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Technology Usage to Manage Client Growth: Understanding Robo-Advisor Adoption Among Registered Investment Firms

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Technology Usage to Manage Client Growth: Understanding Robo-Advisor Adoption Among Registered Investment Firms

by

Kevin B. Chalk

A Dissertation Submitted in Partial Fulfillment of the Requirements for the Degree

Of

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ACCEPTANCE

This dissertation was prepared under the direction of the *KEVIN B. CHALK* Dissertation Committee. It has been approved and accepted by all members of that committee, and it has been accepted in partial fulfillment of the requirements for the degree of Doctor of Philosophy in Business Administration in the J. Mack Robinson College of Business of Georgia State University.

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ABSTRACT

Technology Usage to Manage Client Growth: Understanding Robo-Advisor Adoption Among Registered Investment Firms

by

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The purpose of this study was to examine the effects of fee discounts offered by Registered Investment Advisors (RIA) on the adoption of a robo-advisor solution by their clients within a hybrid investment services model. The analysis of fee discounts within the RIA model is based on assets under management, those less than $250 million and those above $250 million. In addition to analyzing fee discounts offered by an RIA, this study looks at the characteristics of clients using an RIA that has adopted a robo-solution. The findings suggest that RIA firms over $250 million, that offer a fee discount on a robo-solution, are likely to have higher adoption rates than smaller RIA firms. This study also finds that younger clients and clients with lesser investment knowledge have higher adoption of robo-solution offered by the RIA.

INDEX WORDS: Robo-Advisor, Robo-Advising, Registered Investment Advisor, Registered Investment Advisors, Fintech, Wealth Management Technology

I INTRODUCTION

There have been a few technologies that have been introduced in the financial services sector in recent years. Referring to the financial industry, Alt et. al (2018) state that an industry had remained rather stable over decades was apparently confronted suddenly with new market participants and the acceleration of digital innovation. This digital innovation has included the onset of technologies geared to managing investment portfolios, specifically the rise of automated investment solutions which is synonymous with the term, robo-advisor. Jung et. al (2017) references work by Maedche et. al (2016), Sironi (2016), and Ludden et. al. (2015) to define robo-advisors as digital platforms comprising interactive and intelligent user assistance components that use information technology to guide customers through an automated (investment) advisory process. Much of the current literature has focused on the performance aspects of robo-advisors as it relates to portfolio construction and asset allocation methods (D'Acunto et. al., 2019, Beketov et. al., 2018), predictive modeling (Gu et. al., 2019), household balance sheet and personal finance choices (D'Acunto and Rossi, 2021) or comparing robo-advisors vs. traditional investment advisors (Uhl and Rohner, 2018, Harrison and Samaddar, 2020). There is little research addressing the revenue implications of adopting a robo-advisor solution within a financial services organization that offers traditional wealth management services. Traditional wealth managers have viewed robo-advisors as competition, as they are typically offered at lower costs, and not as a solution that can be complementary to the existing services they provide. Robo-advisors can assist firms in the overall client experience for certain clients of the firm. As a segment of the fintech trend, robos have broadened the means of delivering financial advice (Fan and Chatterjee, 2020). An increasing body of research suggests that the future of the financial planning industry lies in a hybrid approach which combines a robo-advisor with the traditional wealth management offering (Sarpong, 2020; Thompson, 2018; Lopez et. al., 2015; Kitces et. al, 2015; Stich, 2018).

The existing research that relates to the hybrid model focuses mainly on the theoretical concepts of integrating a robo-advisor such as, pricing strategies (Ludden et. al., 2015; Edwards, 2018; Garmhausen, 2015; Woodyard and Grable, 2018) and cannibalization of existing business (Lopez et. al., 2015). The tension that exists in wealth management firms choosing to offer a robo-advisor to their clients lies in the notion that adopting a robo-solution could potentially address capacity constraints, which comes with a growing client base, but also potentially cannibalize higher revenue streams of business. A robo-advisor can be utilized by investors without the assistance of a financial advisor. Wealthfront, Betterment, and Sig-Fig are examples of firms that offer a robo-advisor at annual fees ranging from zero to 0.25%.[1] Additionally, wealth managers that utilize a custodial platform such as Charles Schwab, Fidelity, or TD Ameritrade (which are known as custodians), have access to a customizable robo-advisor that is offered by the custodian. For examples of wealth managers, RIA Channel.com[2] ranks the top 100 wealth managers of 2020 based on size, growth, and quality. Creative Planning, Plante Moran and Wealth Enhancement Advisors are ranked as the top three wealth managers with assets under management of $45B, $17B and $13B, respectively. Wealth managers with assets under management of $100M or more are required to register with the Securities and Exchange Commission (SEC) and file a Form ADV and a 13F filing. These filings can be found on the SEC website at www.sec.gov.

[1] https://www.businessinsider.com/best-robo-advisors
[2] https://www.riachannel.com/top-100-wealth-manager-list-2020/

The question that arises, for wealth management firms that choose to offer a robo-advisor, as part of their offering, is do they price the robo-solution at 0.25%? In doing so, would this potentially cause clients that are being charged a traditional wealth management fee structure (roughly 1%) to want to be in a lower priced investment solution that is offered by their advisor?

This study will add to the current literature by proposing a framework to understand robo-advisor adoption of investors, through the lens of wealth management firms. Specifically, this study aims to address the following research question: For assets managed by an RIA, are fee discounts associated with higher allocation of client assets to an automated investment solution versus a traditional solution?

RIABiz, an online journal that targets the financial services industry states “In simple terms, an RIA is a registered investment adviser. This generally means a financial firm that engages in advising others about investing in securities, gets paid for it and is subject to oversight by the SEC or their equivalent regulator at the state level. A confusing factor is that people often believe that the term “RIA” applies to an individual that works for the advisory firm. However, this is inaccurate. Individuals who provide advice on behalf of the firm are referred to as investment adviser representatives. It’s the firm itself that is called an RIA”.[3] For the purpose of this study, RIA will be used to refer to the firm.

RIAs have outpaced traditional broker dealers such as Merrill Lynch, UBS, Morgan Stanley, in terms of asset market share. A 2019 Investment News Report[4] stated “in the financial advice industry, money and margins are moving slowly and inexorably away from the bank-owned wirehouses to independent registered investment advisers, along with other business models that either pay more or give advisers equity in their practices.” Cerulli Associates, in

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[3] https://riabiz.com/a/2011/10/4/what-exactly-is-an-ria.
[4] https://www.investmentnews.com/wall-street-is-going-ria-ish-80224.

their U.S. RIA Marketplace 2019 report[5], state “RIAs are expected to control a combined 29.6% of industry asset market share by year-end 2023.” The report further states, “from a percentage-point perspective, hybrids and independent RIAs are expected to increase 3.5 and 2.0 points, respectively, versus the wirehouses’ –4.8 points”. With this growth comes capacity constraints. The typical RIA firm starts out by bringing on any client they can, regardless of asset size. This strategy is the way most firms survive in the early years, serve whomever they can. After 10 or 15 years in business, an RIA firm might have amassed hundreds of clients and will have a heavily concentrated number of smaller clients that generate a very small amount of revenue. The capacity constraint issue is one that all wealth management firms must wrestle with and is an important issue to address, otherwise firm growth could stall. Michael Kitces, former practitioner editor of the *Journal of Financial Planning* and frequent contributor to RIA industry publications, states in reference to an Investment News benchmarking study, the average advisor (which includes both lead, service, and support advisors working with clients) was responsible for 57 clients, and $477,000 of revenue in 2017. By contrast, back in 2013, the average advisor’s productivity was 73 clients and $561,000 of revenue. In other words, despite the rise of more advanced technology tools to support advisory firm efficiency, the number of clients that an advisor supports dropped by nearly 22%, and the associated revenue/advisor dropped 15%, likely buoyed by the fact that the client’s portfolio and AUM fees themselves grew over this time period, thanks to market returns, and partially ameliorated the 22% decline in clients/advisor (Kitces, 2018). To shed light on how an RIA firm might utilize a robo-advisor to address capacity constraints, this study will focus on the characteristics of investors using an RIA, for financial services, that have adopted a robo-solution.

[5] The Cerulli Report, U.S. RIA Marketplace 2019.

The importance of this study can be gauged from a 2020 benchmarking survey[6] of 1010 RIAs (survey done by Charles Schwab Advisor Services) which lists improving productivity with new technology, improving satisfaction for existing clients, and increasing firm capacity as three of the top seven strategic initiatives. Figure 1 highlights the findings from the study. The top two initiatives are growing via client and center of influence referrals. RIAs are clearly focused on growing their businesses'; however, capacity is becoming an increasing issue. The traditional way to manage capacity is to hire more staff, which is a costly solution. RIAs, that want to continue to grow, must find a way to embrace technology to help alleviate capacity constraints to continue to maintain their growth trajectory.

Top strategic initiatives remain consistent year-over-year, with acquiring new clients a priority.

Rank		Percent of firms 2020	2019
1	Acquire new clients through client referrals	42%	37%
2	Acquire new clients through business referrals	26%	26%
3	Improve productivity with new technology	22%	24%
4	Enhance strategic planning and execution	22%	24%
5	Recruit staff to increase firm's skill set/capacity	21%	24%
6	Improve satisfaction for existing clients	17%	16%

Figure 1: Top Strategic Initiatives

Schwab's 2020 benchmarking survey expanded questions, as it relates to standardizing procedures and increasing use of technology in managing clients, to include RIAs focused on using automated investment solutions. Of the 1,010 participants, only 19% said they are currently using or plan to use an automated investment solution in the next 12 months. Citywire,

[6] https://content.schwab.com/web/retail/public/about-schwab/schwab_ria_benchmmarking_study_2020_0720-0WBV.pdf

a news resource targeted at RIAs, stated in a December 2019 article[7] "While digital advice has made gains in recent years with investors, particularly smaller and younger investors, industry experts say adoption of the technology by advisors remains nascent. Actual use cases for robo-advisors at RIAs are still largely experimental – or very niche. Through my own interactions with RIAs, as a relationship manager for over 16 years to the RIA market, the main concern that some RIAs have with robo-advisors is the potential need to lower their fees for offering services that are traditionally delivered in a more traditional face-to-face setting. The notion of having to lower fees poses a threat to revenue, however, by not implementing some form of technology to assist in managing client growth, there is a threat to overall client growth in the form of firm inefficiencies. In addition to a low adoption rate, as previously noted in the 2019 Charles Schwab benchmarking study, RIAs still potentially see the robo-advisor as an external threat. Research done in January 2019 by Statista, shows 45% of RIAs are concerned robo-advisors pose a threat to their firm.[8] While the Statista research highlights the perceived threat of robo-advisors to RIAs externally, those RIAs that have adopted a robo-solution within their firm grapple with how to charge for such a solution vs. their traditional services that are delivered face to face. The first contribution this study will make is to examine the effects of an RIA offering fee discounts as it relates to the adoption rate of a robo-solution.

The decision to adopt a robo-advisor is twofold: the first being that the RIA choses to adopt and offer such a solution to their clients, and secondly that the client accepts the proposed solution by the RIA. It is important to note that in the RIA model, while the firm typically has discretion when it comes to investment decisions, in most cases a product offering like a robo-

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[7] https://citywireusa.com/registered-investment-advisor/news/why-are-rias-shying-away-from-robo-advisors/a1295712

[8] https://www.statista.com/statistics/533278/level-of-concern-about-robo-advisors-posing-threat-to-us-ria/.

advisor would involve the client in making that choice. This implies there are two units of analysis that should be considered in the research question. The firm, which this study will explore from a fee perspective as previously mentioned but secondly from the individual perspective as the client can ultimately choose to proceed with having their assets managed by a robo-solution with the RIA or not.

There is limited research to date that has investigated FinTech adoption (D'Acunto et. al., 2019) or robo-advisor adoption behavior (Fan and Chatterjee, 2020). The existing literature focuses exclusively on the retail consumer and the characteristics of those consumers. Woodyard and Grable (2018) address the typical profile of the users of robo technology. They validate that the typical user is under age 35, is technologically savvy and confident in their decision-making abilities. Additionally, Charlotte Beyer (Beyer 2017) addresses the shifts in wealth management due to the younger generation and trends in technology. Like the work by Woodyard and Grable, Beyer discusses how wealth is getting younger and the value propositions of financial advisors are changing. There is a view that millennials are much more likely to adopt the use of technology in all facets of their lives to include their finances (Cutler 2015, Kirchenbauer and Jones, 2018). The millennial age group tends to be more educated, are willing to do their own research and tend to be less trusting of financial service professionals (Cutler, 2015). Additionally, millennials carry more debt (result from educational spending) and therefore have smaller asset amounts to invest. These reasons make the robo solutions ideal for millennials according to the literature reviewed. Fulk et. al (2018) find that robo-advisor users generally (1) had lower income, (2) had lower net worth, (3) had received no or less inheritance, and (4) were less impulsive financially. The second contribution this study will make is to extend the research done on retail adoption of robo-advisors to that of investors that are using an RIA for financial guidance.

The remainder of the study is organized as follows: Section II presents the hypothesis development. Section III describes the methods used in the study along with a description of the data, summary statistics for key variables, and analysis of the results. Section IV is a discussion of the results, and Section V concludes with the limitations of the study along with recommendations for future research.

II HYPOTHESIS DEVELOPMENT

Although existing literature provides insights into the individual investor behavior as it relates to robo-advisors, to the best of my knowledge, there is little work on the adoption of robo-solutions related to the RIA industry. As noted earlier, the decision to adopt a robo-advisor is twofold: first that the RIA choses to adopt and offers a robo-solution to their clients, and second that the client accepts the RIA's proposed solution. The first set of hypotheses explores the relationship of the adoption rate of a robo-solution and RIA discretionary AUM along with offering fee discounts for the robo-solution. The motivation for this set of hypotheses (H1a-H1c) is that fee discounts for a robo-solution are related to adoption rates by clients, specifically for smaller RIAs (up to $250M). Firms with AUM under $250M have a median total staff of 4 serving 132 clients while firms over $250M have a median total staff of 12, serving 389 clients.[9] New client acquisition, client service, firm management, investment management, compliance, and operations are among some of the firm activities that all firms face, smaller firms often must "outsource" some of these firm activities.

Building on the work done by Adam Smith (1965) on the division on labor among workers, Becker and Murphy (1992) state a worker who does not specialize and performs all tasks allocates their time among tasks to maximize common output. Kumar et al. (2019) states individual employee's specialization is in proportion to the size of the firm. Firms under $250M often do not have specialized roles relating to investment management and if a robo-solution is being used, this study hypothesizes (H1d) that there is an association between the percentage of employees performing the investment advisory role and the adoption rate of a robo-solution.

[9] https://content.schwab.com/web/retail/public/about-schwab/schwab_ria_benchmmarking_study_2020_0720-0WBV.pdf

Smaller firms could lean more on the efficiencies and scale the robo-solution offers than larger firms.

Cyert and March (1963) state that prices are often set on conventional practice. As a consultant to the RIA industry, I have noted numerous conversations where RIA firms are likely to discount the fee for the robo-offer versus traditional services. This is a tension that can exist across RIA firms. Figure 2 highlights the fees of the top 10 robo-advisors according to Ignites, a source for news regarding the mutual fund industry. With the exposure in the popular press that robo-advisors are receiving, RIA firms tend to use the marketplace as the “conventional” pricing standard in order to avoid competing on price, which could potentially drive better adoption of the robo-solution.

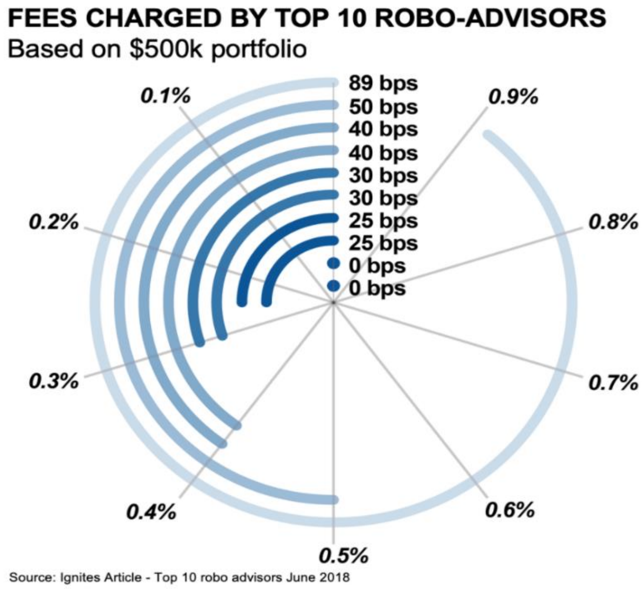


Figure 2: Fees Charged by Top Robo-Advisors

The first set of hypotheses are stated as follows:

H1a. The percentage of assets allocated to a robo-solution is associated with an RIA firm's discretionary assets under management (AUM).

H1b. The percentage of assets allocated to a robo-solution is associated with RIA firms that offer a fee discount on the robo-solution.

H1c. The percentage of assets allocated to a robo-solution is associated with the interaction of RIA firm AUM and offering a fee discount on the robo-solution.

H1d. The percentage of assets allocated to a robo-solution is associated with the percentage of employees performing investment advisory functions within RIA firm.

The second set of hypotheses relates to the characteristics of investors that adopt a robo-solution. This study hypothesizes that age along with other investor traits can influence the adoption rate of a technological solution such as a robo-advisor. The motivation for these hypotheses comes from the Diffusion of Innovation Theory (Rogers, 1995) which is used in explaining how an idea or product gains traction and spreads (diffuses) through a group or social system. Mahajan et. al (1990) state that the purpose of the diffusion model is to predict the successive increases in the number of adopters.

Rogers offers some socioeconomic and personality characteristics of early adopters that can be used to help develop a profile of the typical RIA client that might be willing to adopt a robo-solution. Rogers states: a) “early adopters have a greater rationality than later adopters. Rationality in this sense is defined as the most effective means to reach a given end; b) earlier adopters are not different from later adopters in age. There is inconsistent evidence about the relationship of age and innovativeness; and c) earlier adopters have a greater ability to deal with abstractions than do later adopters. Innovators must be able to adopt a new idea largely on the basis of rather abstract stimuli.” While the research from Rogers is inconclusive as it relates to age and technological adoption, there have been several studies that have used the Diffusion of Innovation Theory to hypothesize age relating to technological adoption (Baldrige and Burnham, 1975; Gora, 2020; Robertson, Zielinski, and Ward, 1984 quoted in Gatignon and Robertson, 1985) and recently Fan and Chatterjee (2020) used Diffusion of Innovation theory in their study of robo-advisor utilization for individual investors. Also, practitioner literature makes the claim that robo-adopters are younger (Huxlex and Kim, 2016; Cutler, 2015; AT Kearney Report, 2015; Munk, 2005; Woodyard and Grable, 2018; Fulk et. al., 2018; Lourenço et. al., 2020). In addition to the previous research on age relating to technology adoption, this study extends the profile of robo-adopters to include investment goals (Lourenço et. al., 2020; Agnew and Mitchell, 2018), active vs. passive investors, investment knowledge (Fulk et. al., 2018; AT Kearney Report, 2015) and experience with market corrections. This background leads to the second set of hypotheses:

H2a. The percentage of assets allocated to a robo-solution is associated with an investor's goals.

H2b. The percentage of assets allocated to a robo-solution is associated with an investor's actions (or proposed actions) during a market correction.

H2c. The percentage of assets allocated to a robo-solution is associated with an investor's age.

H2d. The percentage of assets allocated to a robo-solution is associated with an investor's knowledge.

H2e. The percentage of assets allocated to a robo-solution is associated with an investor's experience with a market correction.

H2f. The percentage of assets allocated to a robo-solution is associated with account ownership and account taxability.

III METHODS

III.1 Data

This paper used data from a brokerage firm that provides asset custody to RIAs. This brokerage firm has built a customizable robo-solution for their RIA clients to use. This robo-solution is completely customizable by the RIA to incorporate over 1,300 ETFs or 2,700 mutual funds that are chosen by the RIA. The brokerage firm has no oversight or input into the investment allocation of the models built within the robo-advisor. The only caveat that the RIA firm must adhere to is a cash allocation requirement for the models they build. Currently, the brokerage firm does not charge a fee for the RIA to use the robo-solution.

A data file was created that consisted of all RIA firms that are currently using the brokerage firm's robo-solution, along with the clients that are linked to each RIA firm where the RIA firm has employed the robo-solution to manage the client's assets. The data file was created according to the brokerage firms' approach to serving RIAs based on AUM. Table 1 summarizes the data from the brokerage firm. To maintain the confidentiality of the brokerage firm's service model, the classification was changed to Service Model 1, Service Model 2, and Service Model 3.

Table 1: Population Descriptives

RIA Service Model	RIA Firms in Population Set	Clients in Population Set	Client Percentage of overall Population
Service Model 1	182	2,888	16%
Service Model 2	365	12,187	68%
Service Model 3	101	2,803	16%
Total	648	17,878	100%

A sample set for this study was created as the data file mentioned above did not include all the variables needed for the study (the brokerage firm uses multiple databases that contain the information needed for this study), therefore a second sample data set was created. A sample set of 1,000 client accounts was chosen based on suggestion in Burns and Burns (2008) to use a relationship between effect size and power to determine the sample size. Table 2 and Table 3 from Burns and Burns (2008) highlight the proposed relationships. Table 2 in Burns and Burns (2008) notes that large N (sample size) is a factor for increasing power in a statistical test. Additionally, to detect small effect sizes at a significance level of 5%, a sample size of 1,000 is needed.

Table 2: Factors That Influence Power

Feature of the study	Factor increasing power	Factor decreasing power
Effect size	*Large effect size*	*Small effect size*
Predicted difference between population means	Large differences	Small differences
Population standard deviation	Small population SD	Large population SD
Sample size (N)	Large N	Small N
Significance level (alpha)	Lenient (such as .05 or even .10)	Stringent (such as .01 or even .001)
One-tailed versus two-tailed test	One-tailed	Two-tailed

Table 3: Same Sizes

Sample sizes needed to detect various effects at p = .05 two-tailed

	Effect sizes (r)						
Power	.10	.20	.30	.40	.50	.60	.70
.15	85	25	10	10	10	10	10
.20	125	35	15	10	10	10	10
.30	200	55	25	15	10	10	10
.40	300	75	35	20	15	10	10
.50	400	100	40	25	15	10	10
.60	500	125	55	30	20	15	10
.70	600	155	65	40	25	15	10
.80	800	195	85	45	30	20	15
.90	1000	260	115	60	40	25	15

Based on Cohen (1988) *Statistical Power Analysis for the Behavioural Sciences*, Lawrence Erlbaum, p. 92).

As it relates to this study, a simple percentage weighting method was used to determine the number of clients to sample from each service model in Table 1. For example, Service Models 1 and 2 have 16% of the overall clients in the population set, Service Model 2 has 68%

of the overall population set. Using a target of 1,000 clients, a sample of 160 clients was collected from Service Models 1 and 3, and 680 clients from Service Model 2. To collect the sample, a simple random sampling technique was used (Trochim et. al, 2016) where the population data was loaded into excel for each service model and then all client identifiers were removed (to protect client confidentiality) and a random number was assigned by excel to each client. The random number assignment was then sorted from lowest to highest and the first 160 clients were taken from Service Models 1 and 3 and the first 680 clients were taken from Service Model 2. Table 4 highlights the variables, along with a definition of each variable, which was collected from the client level along with their associated RIA-level variables.

Table 4: Variable Descriptives

RIA-Level Variable	Variable Definition	Client-Level Variable	Variable Definition
RIA assets in robo-solution	Total amount of assets that the RIA manages for their clients using the brokerage firm's robo-solution.	Age	Age of the client
The variables below were collected from a database independent of the brokerage firm (www.sec.gov)	RIA Firms must file a form ADV, with the SEC or State (depending on AUM). Each RIA that uses the brokerage firms robo-solution discloses its use on their ADV as well as their total amount of assets under management for the entire firm.	Total assets with RIA	The total amount of assets the client has placed with the RIA
RIA discretionary assets	Amount of assets under management, of the RIA, that is under the discretionary control of the firm	Total assets in robo-solution	The total amount of assets that are in the robo-solution that is linked to the RIA
RIA-Level Variable	Variable Definition	Client-Level Variable	Variable Definition
Fee discounts offered on robo-solution	RIA discloses any fee discounts that are different from their "regular" fee schedule.	Percentage of assets in robo-solution	Represents total assets in the robo-solution divided by the total assets with the RIA
Percentage of Employees Performing Investment Advisory Function	The RIA reports the total number of employees performing the investment advisory functions and the total number of employees overall.	Stated investment goal	When clients enroll in the robo-solution, they choose their intended investment goal which could be one of the following: *prepare for*

			retirement, build long term wealth, generate income, save for something special, build a rainy-day fund or save for an upcoming expense
		Investment Knowledge	When clients enroll in the robo-solution they choose their investment knowledge which could be one of the following: *none, some, good or extensive*
		Experienced a market decline of 20% or more (Yes or No)	When clients enroll in the robo-solution they indicate *(yes or no*) if they have ever experienced a market decline of 20% or more.
		Action Taken During Market Decline	When clients enroll in the robo-solution and they answer "yes" to having experienced a market decline of 20% or more, they choose from the following regarding action they took: *did nothing, bought more, reallocated my investment, sold everything or sold some.* If the client answered no, they were asked what they would likely do from the following options*: do nothing, buy more; reallocate my investments, sell everything, sell some*
		Account Registration	Joint, Individual, Custodial or IRA
		Taxable or Non-Taxable	From the registration label, a variable was created to indicate if the account was taxable or non-taxable.

I decided that the service model classification, for RIAs, by the brokerage firm would not create results that could be generalized (Trochim et. al, 2016) therefore the RIA firms were broken into categories based on discretionary AUM. The categories created are as follows: under

$100M, $100M-$250M, $250M-$500M, $500M-$750M, $750M-$1B and $1B+. Table 5 summarizes the data set based on the new RIA firm categories.

Table 5: RIA AUM Descriptives

(A) RIA AUM Category	(B) Number of RIAs in Population	(C) Number of RIAs in Sample	(D) Clients in population set	(E) Percentage of clients (within RIA AUM category) relative to overall population	(F) Clients in Sample Set
<$100M	133	37	2,825	16%	160
$100M-$250M	155	50	6,023	34%	302
$250M-$500M	116	49	4,644	26%	280
$500M-$750M	57	28	1,133	6%	74
$750M-$1B	27	14	349	2%	30
$1B+	160	55	2904	16%	154
Total	648	233	17,878	100%	1,000

It should be noted that the clients in the sample set (column F) do not exactly match the respective percentages in (column E) as the number of clients to include in the sample set were determined from the service model classification outlined in Table 1.

III.2 Variables

Based on the research question, "are fee discounts associated with higher allocation of client assets to an automated investment solution vs a traditional solution", the dependent variable for both hypotheses was the percentage of client assets allocated to a robo-solution. This variable was calculated by taking the assets allocated to the robo-solution offered by the RIA divided by the total assets the RIA manages for the client. Table 6 offers summary statistics for assets managed by the RIA versus those allocated to a robo-solution from the sample set (see Appendix A for further comparisons). The independent variables for the first set of hypotheses (H1a-H1d) are RIA discretionary AUM, fee discounts (yes or no) and the percentage of employees dedicated to the investment function. For the second hypotheses (H2a-H2e), independent variables are age, investment knowledge, investment goals, market decline (participation in a 20% market correction) and actions taken if the client participated in a market correction or what they would do if a 20% market correction occurred. For H2f, the independent variables are account ownership type and taxability of the account (see Table 7 for descriptive statistics). Independent variables are chosen with the goal of providing some direction to RIAs on fee structure for a hybrid model and whether a client might be a good fit for a robo-solution. Additionally, these variables (H2a-H2f) can be determined during the client on-boarding process.

Table 6: Continuous Variable Summary Statistics

Table 6. reports summary statistics for the continuous variables of Firm Discretionary AUM, Percentage of Employees Performing Investment Advisory Function (see Appendix A for Scatter Plot), Client AUM with RIA Firm, Client Robo-Advisor AUM, and Percentage of client assets in a robo-solution. As defined in Table 4., Firm Discretionary AUM represents a firm's reported assets under management, Percentage of Employees Performing Investment Advisory is calculated by dividing the reported number of employees performing the investment advisory role by the total number of firm employees, Client AUM with RIA Firm represents assets clients place with an RIA firm, Client Robo-Advisor AUM represents assets placed in a robo-solution, Percentage of client assets in robo solution represents the percentage of assets in a robo solution compared to amount of assets a client has with an RIA Firm. Age represents the age of clients (see Appendix B for Scatter Plot).

	No. of Obs.	Mean	Median	Std. Deviation	Range	Minimum	Maximum
Firm Discretionary AUM	1000	$1,961,147,471	$502,532,536	$4,109,555,345	$45,080,159,794	$1,602,052	$45,081,761,846
Percentage of Employees Performing Investment Advisory	1000	67%	64%	22%	89%	11%	100%
Client AUM with RIA Firm	1000	$244,884	$66,019	$629,852	$8,451,792	$56	$8,451,849
Client Robo-Advisor AUM	1000	$116,981	$52,170	$187,378	$2,065,373	$56	$2,065,429
Percentage of client assets in robo solution	1000	88%	100%	28%	99.68%	0.32%	100%
Age	1000	46.16	43.00	14.753	68	18	86

Table 7:Categorical Variable Summary Statistics

Table 7 reports summary statistics for the categorical variables of investment knowledge, investment goals, experience with market declines, action taken if a market decline has been experienced or action that would be taken if a person were to experience a market decline, account ownership and taxability. As mentioned in Table 4, variable descriptives, these categorical variables are collected as clients enroll in a robo-solution.

Variable	Frequency	Percentage of Sample
Stated Investment Knowledge		
None	130	13%
Some	550	55%
Good	241	24.1%
Extensive	79	7.9%
Stated Investment Goal		
Build Long Term Wealth	293	29.3%
Build a rainy-day fund	13	1.3%
Generate income	33	3.3%
Prepare for Retirement	613	61.3%
Save for an upcoming expense	28	2.8%
Save for something special	20	2.0%
Experienced a Market Decline of 20% or more		
Yes	435	43.5%
No	565	56.5%
Action Taken (If Yes to Decline)		
Bought More	93	9.3%
Did Nothing	242	24.2%
Reallocated my investments	83	8.3%
Sold Some	12	1.2%
Sold Everything	5	0.50%
Action Taken (If No to Decline)		
Buy More	86	8.6%
Do Nothing	218	21.8%
Reallocate my investments	229	22.9%
Sell Some	30	3.0%
Sell Everything	3	0.20%
Ownership		
Individual	930	93%
Joint	70	7%
Taxability		
Taxable	270	27%
Non-Taxable	730	73%

III.3 Analyses and Results

Robo-Advisor Assets-RIA AUM and Fee Discounts

This study hypothesizes that RIA Discretionary AUM, employee specialization and if the RIA firm offers a fee discount on a robo-solution should explain the cross-sectional variation in the assets an investor allocates to a robo-solution (see hypotheses H1a, H1b, and H1c and H1d). To understand how firm size, fee discounts and the percentage of employees performing investment advisory functions (H1a, H1b, H1c, H1d) interact to explain the percentage of assets held in a robo-solution, I conduct multivariate analysis by estimating the following models:

(1) % assets in robo = $b_0 + b_1$*AUMSize* + b_2*FeeDiscount* + b_3*AUMSize*Fee* + *e*

(2) % assets in robo = $c_0 + c_1$*AUMSize* + c_2*FeeDiscount* + c_3*AUMSize*Fee* + c_4*%age of Advisory Employees + e*

(3) % assets in robo = $d_0 + d_1$*SmallNoFee*+ d_2*SmallFeeDiscount* + d_3*LargeFeeDiscount* + *e*

where *% assets in robo* represents the percentage of assets a client of the RIA holds in the robo-solution in Models 1, 2 and 3. For Model 1, *AUMSize* represents the total discretionary AUM of an RIA firm. If the RIA firm is under $250M, the indicator variable *AUMSize* takes on a value of 1, and if the RIA firm is over $250M, *AUMSize* = 0. *Fee Discount* represents whether the RIA firm offers a fee discount on the robo-solution, if yes then the indicator variable takes on a value of 1, and if they do not offer a fee discount then the variable = 0. I also create an interaction variable (represented by *AUMSize*FeeDiscount*) between *AUMSize* and whether the RIA firm offers fee discounts (*FeeDiscount*) to capture the incremental effect of fee discount over the RIA size on the percentage investment in robo-solution. For Model 2, the variables take on the same values as in Model 1, with the addition of *%age of Advisor Employees* representing the percentage of employees of an RIA firm that perform the investment advisory function. For Model 3, *SmallNoFee* represents RIAs that are under $250M and do not offer a fee discount.

SmallFeeDiscount represents RIAs that have under $250M in AUM and offer a fee discount and *LargeFeeDiscount* represents RIAs that have over $250M in AUM and offer a fee discount.

The results from Models 1, 2 and 3 are reported in Table 8.

Table 8: Robo-Advisor Assets- RIA AUM and Fee Discounts

Table 8 reports the results of regressing the percentage of investor assets in a robo-solution on RIA Discretionary AUM (*AUMSize*), fee discounts (*FeeDiscount*) and the interaction variable of AUM and fee discounts (*AUM*FeeDiscount*) which is shown in Model 1. *AUMSize* equals 1 if RIA AUM is under $250M, and 0 if RIA AUM is over $250M. *FeeDiscount* equals 1 if an RIA firm offers a fee discount, and 0 if it does not offer a fee discount. *AUM*FeeDiscount* equals 1 if RIA AUM is under $250M and RIA firm offers a fee discount on its robo-solution, and 0 otherwise. These indicator variables take on the same values in Model 2. The additional indicator variable in Model 2 is *%age of Advisory Employees*, which represents the percentage of employees performing an investment advisory role. For Model 3, *SmallNoFee* represents RIAs that are under $250M and do not offer a discount, *SmallFeeDiscount* equals 1 if the RIA is under $250M and offers a fee discount, and 0 otherwise. *LargeFeeDiscount* equals 1 if the RIA is over $250M and offers a fee discount, and 0 otherwise. The bottom panel provides the results of the pairwise comparison tests for the mean coefficients in Model 3. *p*-values are reported in parentheses, *** indicates significance level at 1%.

	Model 1 Beta (*p*-value)	Model 2 Beta (*p*-value)	Model 3 Beta (*p*-value)
Constant	85.54 (0.001)***	82.85 (0.001)***	85.54 (0.001)***
AUMSize (Small/Large)	-2.16 (.370)	-2.73 (.270)	
Fee Discount (Y/N)	7.46 (0.001)***	7.49 (0.001)***	
%age of Advisory Employees		.04 (.317)	
Interaction (AUMSize*FeeDiscount)	-1.20 (.817)	-1.10 (.831)	
SmallNoFee			-2.16 (.370)
SmallFeeDiscount (Y/N)			4.10 (.280)
LargeFeeDiscount (Y/N)			7.46 (0.001)***
R^2	0.02	0.02	0.02
F Statistic	6.64 (0.001)***	5.23 (0.001)***	6.64 (0.001)***
No. of Obs.	1000	1000	1000
Test for linear combinations of coefficients			
SmallNoFee-LargeFeeDiscount(Y/N)			-9.62
F Statistic			15.27 (0.001)***
SmallNoFee-SmallFeeDiscount(Y/N)			-6.26
F Statistic			1.74 (.188)
LargeFeeDiscount(Y/N)-SmallFeeDiscount(Y/N)			3.36
F Statistic			.54 (.464)

I conduct preliminary analyses to ensure no violation of the assumption of multicollinearity (see Appendix C), and none existed. The observations from the analysis in Model 1 (shown in Table 8) indicate that clients of small RIA firms would hold 2.16% less in a robo solution than a client associated with a larger RIA firm (over $250M). However, the indicator variable, *AUMSize*, is not significant. This is somewhat of a surprising result based on my observations as a consultant to the RIA Industry. Not surprising is that advisors offering a fee discount would hold just over 7% more assets in a robo-solution. For clients associated with smaller RIAs, the interaction of firm AUM and fee discounts, although statistically insignificant, indicates that smaller firms offering a fee discount, clients would hold roughly 1% less in a robo-solution. The *F*-statistic reported for Model 1 is statistically significant, which indicates *AUMSize*, *FeeDiscount* and the interaction of *AUMSize* and *FeeDiscount* are reliable predictors of the percentage of the assets held in a robo-solution. However, the low R^2 indicates overall low explanatory power of Model 1 in explaining the variation in the percentage of assets held in a robo-solution.

For Model 2, I test if adding the percentage of employee performing an investment advisory function (*%age of Advisory Employees*) to the model would increase the explanatory power of the model. The results show that for every unit increase in the percentage of employees performing the advisory function, the percentage of increase in a robo-solution is very minimal. The *F*-statistic continues to be significant for Model 2. However, the overall explanatory power of the model remains low ($R^2 = 2\%$).

In Models 1 and 2, the interaction variable, *AUM*FeeDiscount*, compares the percentage of assets in a robo-solution between RIA firms that are less than $250 million and offer a fee discount with all other RIA firms. Therefore, it does not allow pairwise comparison across RIA firms categorized on the basis of AUM and fee discount. Therefore, in Model 3, I refine the specification, as mentioned previously, where *SmallNoFee* represents RIAs that are under $250M in AUM and do not offer a fee discount, *SmallFeeDiscount* represents RIAs that are under $250M in AUM and offer a fee discount, and *LargeFeeDiscount* represents RIAs that are over $250M in AUM and offer a fee discount. Like in Models 1 and 2, for the association of RIA size and fee discounts, an interaction variable (represented by *SmallFeeDiscount* and *LargeFeeDiscount*) was created between the independent variable of RIA AUM and those RIAs that offer fee discounts. To create the interaction variable, I separate RIA AUM into two categories, AUM < $250M and AUM ≥ $250M, both of which are indicator variables that take a value of 1 if RIA AUM meets the criterion, and 0 otherwise. I create a third category, fee discount, that consisted of whether the RIA offered a fee discount on their robo-solution offer, with yes=1 and no=0. A fourth category was created, small fee category interaction (*SmallFeeDiscount*), which is equal to 1 if the advisor offered a fee discount, and 0 if there is no fee discount.

The results from Model 3 indicate that clients associated with a small RIA (under $250M) that offers a fee discount would increase their percentage of assets held in a robo-solution by 4.10%. However, this finding is not statistically significant. For clients associated with large RIAs (over $250M), they increase their holdings by roughly 7.5%, this finding is statistically significant. For Model 3, the *F*-statistic and R^2 values remain similar to those for Models 1 and 2. Pairwise comparison tests show that only the estimated coefficients on *SmallNoFee* and *LargeFeeDiscount* are different from each other, which indicates that large advisors offering a fee discount would attract a greater percentage of assets in a robo-solution compared to the small advisors that do not offer a fee discount.

To better understand these results, I isolate the independent variables of RIA discretionary assets, and RIAs offering a fee discount. Table 9 shows these results. RIA AUM was isolated as a continuous variable vs. a categorical variable as there is a possibility that statistical power is reduced by dichotomizing the data for RIA AUM. In Table 9, Model 4 (*DiscAUM*) represents RIA AUM as a continuous variable. The results of regressing the *percentage of assets held in a robo solution* against *DiscAUM*, indicates that for every dollar increase in discretionary assets of an RIA, the assets held in a robo solution would actually decrease. This regression shows no significance at conventional levels (p-value = 0.198) in addition to the model having a low R^2.

Comparing the previous analysis shown in Table 8, of RIA AUM (represented by *AUMSize*) the results seem to suggest that non-linearity exists in the data as it relates to RIA Discretionary AUM. As previously mentioned, the results shown in Table 8 for Model 1 and Model 2 indicated an RIA firm over $250M would hold more assets (2.16% and 2.73% respectively) in a robo-solution vs. an RIA firm under $250M. By changing RIA AUM to a continuous variable, the results indicate an opposite relationship. The scatter plot in Figure 3 confirms that a nonlinear relationship exists in the data relating to RIA Discretionary AUM and the percentage of assets held in a robo-solution. There is a large number of smaller RIAs under $100M that hold a high percentage of assets in a robo-solution, however that percentage declines up until approximately $10B at which time the percentage of assets held in a robo solution begins to increase.

Given the nonlinear relationship of RIA AUM and the percentage of assets held in a robo-solution, I estimate a quadratic regression by squaring the continuous variable for RIA AUM. Results are shown in Model 5 in Table 9. The squared term confirms that as RIA firms grow larger, they will hold more in a robo-solution. Both *DiscAUM* and *DiscAUM*^{2} (Model 5), are significant at the 1% level when I estimate a quadratic regression. However, explanatory power continues to be low (R^2 is 1%). Table 9 also shows RIA AUM (AUM < $250M) as a categorical variable (Model 6) instead of using RIA AUM as a continuous variable. The regression output shows significance at the 5% level (*p*-value = 2.7%), but still shows little explanatory power (R^2 is 0.4%). Finally, Model 7 shows the results of RIAs that offer a fee discount. RIAs that offer a fee discount were coded as a 1 or 0, with 1 representing RIAs offering a fee discount. The results show that offering a *fee discount* is significant at the 1% level (*p*-value = 0.001). However, the contribution to explaining the variation in percentage of assets held in a robo solution remains low, R^2 = 2%.

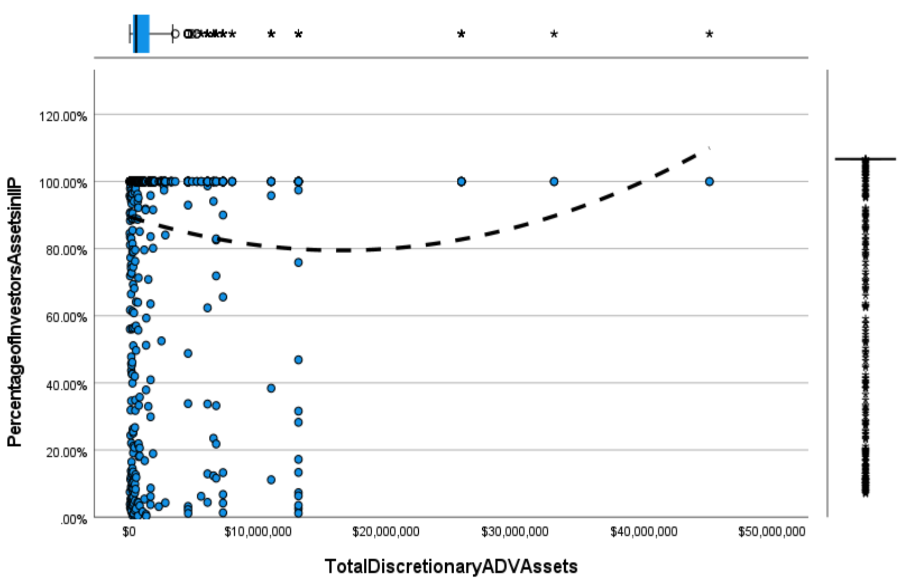


Figure 3:Robo Advisor Percentage – RIA AUM Scatter Plot
Total Discretionary ADV Assets is scaled down by a factor of 1000.

Given that using a continuous variable, for RIA AUM, does not increase the explanatory value of the regression model, I use the categorical approach as the data for this study was segmented based on RIA AUM and some of the practitioner press is geared towards advisor AUM segments.

Referring to the models presented in Table 8, the models are significant at the 1% level (*p*-value < .001) and based on these results H1b and H1c could be supported. However, there is little support for H1a and H1d.

Table 9: Robo-Advisor Assets- RIA AUM

Table 9 reports the results of regressing the percentage of investor assets in a robo-solution on RIA's Discretionary AUM (*DiscAUM*), and Fee Discounts (*FeeDiscount*). *DiscAUM* and $DiscAUM^2$ were scaled down by *DiscAUM*/1000000 and DiscAUM^2/10^20. Model 1 shows the results of *DiscAUM* independently as a continuous variable. Model 2. combines *DiscAUM* and the quadratic variable $DiscAUM^2$. Model 3 shows the results of isolating RIA Firm AUM as a categorical variable (*SmallCat*). If an RIA has discretionary AUM of less than $250M, then the variable is assigned a 1, otherwise 0. Model 4 shows the results of fee discounts (*FeeDiscount*) independently. *p*-values are reported in parentheses, *** and ** indicates significance level at the 1% and 5% respectively.

% asset in robo

	Variable	Variable Type	Intercept	Coefficient(s) *p*-values are in parentheses	R^2	No. of Obs
Model 4	DiscAUM	Continuous	88.43 (0.001)***	-.000280 (.198)	0.002	1,000
Model 5	DiscAUM DiscAUM^2	Continuous	89.47 (0.001)***	-.001 (0.01)*** 3.71 (.014)**	0.01	1,000
Model 6	SmallCat	Categorical	89.025 (0.001)***	-4.589 (.027)**	0.004	1,000
Model 7	FeeDiscount	Categorical	84.802 (0.001)***	7.837 (0.001)***	.02	1,000

Determinants of Robo Assets

This study also hypothesizes that an investor's goals, age, knowledge, experience with market corrections, action taken (or potential action taken) after a market decline, account ownership type and account taxability are associated with the percentage and assets in a robo-solution (see H2a-H2f). To test these hypotheses, I combined these variables to estimate the following model:

(8) % assets in robo = $e_0 + e_1 \textit{Goals} + e_2 \textit{Actions} + e_3 \textit{Age} + e_4 \textit{Knowlege} + e_5 \textit{MktDecline} + e_6 \textit{Taxability} + e_7 \textit{Ownership} + e$

where *% assets in robo* represents the percentage of assets a client of the RIA holds in the robo-solution. Investor goals are the goals of the investor, which were segmented into two categories consisting of long term and short term. Long-term goals (build long-term wealth and prepare for retirement) = 1, and short-term goals (generate income, save for upcoming expenses, and build a rainy-day fund for emergencies) = 0. Actions represented specific actions that investors took if they experienced a market correction of 20% or more or potential actions an investor would take if they have not experienced a market correction. If an investor either did nothing or would do nothing, if a market correction were experienced, a value of 1 was assigned. If an investor took any action or would take any action, which would include buying more, sell some or all, or reallocating investments), a value of 0 was assigned. Client's age were grouped according to Pew Research[10] and are associated with Gen Z (under 22), Millennials (23-38), Gen X (39-54), Boomers (55-73), and Silent Generation (74-91). I assign the following values for different age groups: Gen Z = 4, Millennials = 3, Gen X = 2, Boomers = 1 and Silent Generation = 0. I also use Age as a continuous variable to determine if there is greater explanatory power, and find no benefit to the analysis in doing so. Knowledge represents an investor's knowledge with an investor having no knowledge being assigned a code of 0, 1= some knowledge, 2= good knowledge and 3= extensive knowledge. *MktDecline* represents if an investor has experienced a market decline of 20% or more, with 0 = having experienced a market decline and 1 = having not experienced a market decline. Taxability represents the tax effects of the account, where 1= taxable and 0 = qualified (non-taxable). And finally, *Ownership* represents the account ownership where 1 = individual ownership and 0 = joint ownership. I report the results from regression (2) in Table 10.

[10] https://www.pewresearch.org/fact-tank/2019/01/17/where-millennials-end-and-generation-z-begins/.

Table 10: Robo-Advisor Assets- Investor goals, actions, age, knowledge, and experience with market corrections

Table 10 reports the results of regressing the percentage of investor assets in a robo-solution on investor *Goals*, *Actions*, *Age* (using both categorical and continuous variables), investor *Knowledge*, *MktDecline* (experience with market corrections of 20% or more), account *Taxability* and account *Ownership*. Investor goals were coded as long term = 1. Long Term is defined as building long term wealth or preparing for retirement. Short term goals =0. Short term goals were defined as generating income, saving for upcoming expenses, or building a rainy-day fund. Investor actions are coded as did nothing or do nothing =1, all other actions =0. Age (categorical) is coded as Gen Z = 4, Millennials = 3, Gen X = 2, Boomers = 1 and Silent Generation = 0. Knowledge was coded as none =0, 1= some, 2= good and 3= extensive. Experiencing a market correction of 20% or more was coded as 0 and no experience with a market correction coded as 1. For taxability, 1 represents accounts that are taxable, 0 represents IRAs and account ownership, 1 = individual ownership and 0 = joint ownership. *** indicates significance level at 1% level.

% assets in robo

Constant	Goals	Actions	Age	Knowledge	Mkt Decline	Taxability	Ownership	No. of obs.	R^2	F Statistic
94.63	-4.10	2.68	3.77	-6.69	1.32	-3.32	-3.65	1000	.065	10.01
(0.001)***	(.179)	(.142)	(0.001)***	(0.001)***	(.518)	(.138)	(.341)			(0.001)***

% assets in robo (age as continuous variable)

Age	Constant	No. of obs.	R^2
-.282	100.84	1000	.02
(0.001)***	(0.001)***		

As in the previous model, I conduct a preliminary analysis for multicollinearity and find it not to be the case (see Appendix C). Results from regression 8 explains slightly more of the variable in assets held in a robo-solution (6.5%). The analysis did confirm what other studies (Fan and Chatterjee, 2020; Woodyard and Grable, 2018; Cutler, 2015; Kirchenbauer and Jones, 2018) have found as it relates to younger investors' adoption of robo-solution. The analysis shows that Generation Z investors would hold 15% (gen z code of 4 x 3.77 % vs. silent generation coding of 0) more of their investable assets in a robo solution than an investor in the Silent Generation. The model also confirms that an investor's knowledge can be used to predict the level of adoption of a robo-solution. An investor with extensive knowledge would tend to hold roughly 20% less in a robo-solution than an investor with no experience. Investor goals, experience with market declines, actions taken with market declines, account taxability and ownership do not appear to make a significant contribution to the percentage of assets an investor holds in a robo-solution. The model is significant at the 1% level (*p*-value < .001), and based on these results, H2c and H2d could be supported. However, there is little support for H2a, H2b, H2e and H2f. Table 11 summarizes the findings from H1a-H1d and H2a- H2f.

Table 11: Null Hypothesis Results

Table 11. shows a summary of the results for each hypothesis tested for H1 and H2. The description summarizes the hypothesis along with the findings. Null Hypothesis represents the alternative conclusion to the hypothesis tested. Fail to Reject represents a finding that the sample tested did not provide sufficient evidence of a relationship between the dependent variable (percentage of assets in a robo-solution) and the independent variable. Reject represents a finding that the sample tested did provide sufficient evidence a relationship exists between the dependent and independent variable.

Hypothesis	Description	Reject or Fail to Reject the Null Hypothesis
H1a	Association of percentage of assets to a robo-solution with RIA AUM	Fail to Reject
H1b	Association of percentage of assets to a robo-solution with offering Fee Discounts	Reject
H1c	Association of percentage of assets to a robo-solution with interaction of AUM and Fee Discounts	Reject
H1d	Association of percentage of assets to a robo-solution with percentage of employees performing investment advisory function	Fail to Reject
H2a	Association of percentage of assets to a robo-solution with an investor’s goals	Fail to Reject
H2b	Association of percentage of assets to a robo-solution with an investor’s actions (or proposed actions) during a market correction	Fail to Reject
H2c	Association of percentage of assets to a robo-solution with an investor’s age	Reject
H2d	Association of percentage of assets to a robo-solution with an investor’s knowledge	Reject
H2e	Association of percentage of assets to a robo-solution with an investor’s experience with a market correction	Fail to Reject
H2f	Association of percentage of assets to a robo-solution with account ownership and account taxability	Fail to Reject

IV DISCUSSION

There have been many advances within the technology sector, or more specifically the FinTech space, that are geared towards support of the growth trajectory in the RIA industry. While robo-advisors have received their fair share of practitioner press, there has been little research devoted to robo-advisor usage within the financial services industry. The difficult challenge RIA firms face today is should they adopt a robo solution to help with capacity constraints and once they decide to adopt, what would be the best pricing structure (Lopez et. al., 2015) and who are the clients they should target for robo usage. Singh et al. (2017) state advances in frontline interface technologies and devices are profoundly disrupting how organizations and customers interact to create and exchange value. The concept of a hybrid model (Sarpong, 2020; Thompson, 2018; Lopez et. al., 2015; Kitces et. Al., 2015; Stich, 2018) brings forth the notion of how a robo-solution might complement the traditional service model of RIAs. In keeping with the hybrid model framework, this research adds to current literature by extending the focus beyond the individual investor level to the RIA level by assessing the effects of fee discounts, RIA AUM and employee specialization on robo-adoption. Secondly, this study extends the current research on the characteristics of individual adopters by considering factors such as investor goals, experience with market declines and investment account attributes. These contributions help RIA firms, seeking to either implement a hybrid model or increase current adoption rates to manage client capacity, with evaluating a pricing structure for the robo-solution and identification of client characteristics of likely robo adopters.

The first contribution, relating to RIA AUM and fee discounts, suggests that offering a fee discount increases the adoption of a robo-solution but not when offered by an RIA under \$250M. Specifically, the findings show a large RIA firm offering a fee discount is a significant contributor to the percentage of assets held in a robo solution. A client working with an RIA over

$250M would hold roughly 7.5% more in robo-solution vs. a client working with an RIA under $250M. As previously mentioned, several practitioner papers (Lopez et. al., 2015, Ludden et. al., 2015, Kitces et. al., 2015) pose the question of the proper pricing structure for a financial planning firm offering a hybrid model. This study, to my knowledge, is the first to begin to answer this question. Even though the findings suggest fee discounts increase adoption for larger RIAs, there are other elements in the data from this study that should be taken into context.

First, referring to the work by Cyert and March (1963), prices are set based on conventional practice. As previously highlighted (see Figure 2 on page 10), the range of pricing for the top 10 robo-advisors was from 0 basis points to 89 basis points. Also, previously noted, the typical RIA charges roughly 1% on their traditional services for clients. This study's findings suggest that RIAs might not follow conventional pricing practices when it comes to offering a robo-solution. Figure 4 shows a 2x2 matrix of clients from this study linked to large RIAs that offer a fee discount vs. clients linked to small RIAs that offer a fee discount. Only 39% (393 out of 1,000 sampled) of the clients in this study are linked to an RIA that offer a fee discount. Table 5, on page 18, points out that 233 RIAs represented the 1,000 clients in this study which indicates an RIA is represented more than once in the sample of clients. Of the 233 RIAs in the sample, only 31% offer a fee discount. This low percentage of firms offering discounts could speak to the notion that RIAs feel there is more value addition in their relationship with the client, beyond just that of the investment solution they provide.

	No Fee Discount	Fee Discount
Large RIA Clients	400	351
Small RIA Clients	207	42

Figure 4: Population RIA AUM-Fee Discount 2x2 Matrix

One possible explanation for fee discounts being significant in this study, specifically in larger RIAs, could be found in Figure 5, which represents a 2x2 matrix of the 233 advisors in the study. Of the large RIAs, 38% offer a fee discount vs. 19.5% of the small RIAs offering a fee discount. Also, large RIAs (over $250M) represent 63% of the sample in this study. As previously mentioned, from the 2020 Schwab Benchmarking Study, large RIAs serve a median of 389 clients vs. small RIAs having a median client base of 132, which could account for the high number of clients from the sample being associated with a large RIA. Another explanation, as to why the findings suggest fee discounts are significant for larger RIAs, could be the pricing strategy of these larger firms. Given larger RIA firms generate more revenue, than smaller firms, they may have more flexibility in offering discounts and are able absorb these discounts more so than smaller firms.

	No Fee Discount	Fee Discount
Large RIAs	91	55
Small RIAs	70	17

Figure 5: Sample RIA AUM- Fee Discount 2x2 Matrix

One of the potential advantages of a hybrid model is the ability to leverage technology to help manage client capacity, as mentioned in the introduction of this study. This study attempts to add to the current literature by leveraging work done by Adam Smith (1965) on the division of labor among workers. Specifically, this study argues that RIA firms under $250M do not have specialized roles relating to investment management. The basis for this argument is from my observations as a consultant to the RIA Industry having worked with RIA firms, ranging from $50M up to $20B in AUM, for over 16 years. As shown in the results (Table 8), the independent variable used to isolate employee specialization, *%age of Advisory Employees*, was not significant. A potential factor causing the low significance is how RIAs report employee specialization. As shown in Table 4, the RIA reports the total number of employees and the total number of employees performing investment advisory functions on their ADV. A limiting factor could be how "investment advisory" function is defined by the RIA. Investment advisory function, could be interpreted to mean, solely focused on investment management or it could be interpreted to be more of an "advisory" function that is client facing which could involve advising clients on their investments. For example, consider a small RIA with 5 employees. Of the 5 total employees, 1 employee is in a front office role and the other 4 are advisors that meet with clients. This particular RIA could answer the question, on the ADV relating to investment advisory functions, as having 4 employees dedicated to the investment advisory role. For comparison, a large RIA with 50 employees with 4 dedicated to specifically investments, could answer the question as having 4 employees dedicated to investment advisory. This variation in how the question is answered could lead to a low significance factor in the model. More research would need to be done, at the advisor level, to isolate the variability in the data.

The second contribution of this study to the existing literature is to extend the research done by Fan and Chatterjee (2020) by using the Diffusion of Innovation Theory (Rogers, 1995) to understand the investor characteristics of robo-adopters. One of the unique characteristics of this study is the data consists of investors that have a chosen to work with an RIA firm and therefore are looking to the RIA firm for investment guidance. Current literature has focused on the "do-it-yourself" investor, and while some of the characteristics of a "do-it-yourself" investor and an RIA might be similar as it relates to age, investment knowledge, or goals, this study adds elements such as account attributes and experience with market declines to further help RIAs refine the ideal client profile for robo-adoption.

This study, similar to other studies (Fan and Chatterjee, 2020; Fulk et. al; 2018;), finds that age is a significant predictor of the percentage of assets held in a robo-solution. The results show that Generation Z and Millennials would hold roughly 11% and 8% more, respectively, of their investable assets in a robo solution than an investor in the Baby Boomer generation. The willingness to embrace technology is one likely explanation for these findings. But, unlike their parents who might have engaged a financial advisor, younger investors are less likely wanting a face-to-face interaction and find the occasional validation of investment progress as sufficient in a financial advisor relationship. Therefore, a robo-solution allows RIAs to manage capacity and maintain a relationship with younger investors (typically children of older clients) which ultimately could help the RIA maintain the assets of their older clients as they pass to their children. In keeping in line with age being associated with robo adoption, this study hypothesized that there is an association with an investor goals and the percentage of assets held in a robo-solution. Surprisingly, investor goals had little significance as it relates to robo-adoption. A possible explanation for this finding is that investors do not place importance on the type of investment solution or vehicle that helps them accomplish their goals, the importance lies in the achievement of their goals.

I analyzed the client's stated investment knowledge and the findings, while a significant predictor in the model, were contrary to Fan and Chatterjee's (2020) findings. The investor knowledge (as described in Table 4) is collected as a subjective measure in the account opening process. This study's results show that an investor with extensive knowledge would hold 20% less in a robo-solution than an investor with no investment knowledge. While this finding is contrary to that of Fan and Chatterjee (2020), as part of their results, they state it is possible that those who are more knowledgeable are more likely to prefer to work with a human advisor and refrain from delegating their portfolio management to a robo-advisor platform. I would agree with this assessment on the basis of a more knowledgeable investor is likely to be older (and as previously stated less likely to adopt a robo-solution) and if they have hired an RIA, they are more likely to want to have their investments "managed" by a human. D'Acunto and Rossi (2019) state, in their discussion of the spectrum of robo-advisors, that a hybrid model caters to wealthier and older clientele. They go on to state the importance of having a human advisor involved in the elements of the client relationship that cannot be automated, such as financial planning.

For investors that have experienced a market correction, there is comfort in knowing they have someone that is making decisions about how the correction impacts their financial situation. This study also hypothesizes that there is an association with robo-adoption and an investor's experience with a market correction and also their actions (or proposed actions) during a market correction. The notion behind these hypotheses is that for investors that have weathered a market downturn, the image of a robo advisor at the helm of their portfolio would likely be a tough sell for the RIA to their clients. The results show that neither experience with a market correction or action taken make a significant contribution to the percentage of assets held on a robo-solution. A possible explanation for this result lies in one of the limitations of this study. I did not observe the interaction between the RIA and client, and I cannot attest to the approach each RIA included in this study takes when recommending how they would serve each client. There is an assumption that if the RIA proposes a robo-solution, the client makes a choice as to whether to proceed with that recommendation or not. These results could be due to the trust (Rossi and Utkus, 2020), regardless of any previous market experiences, a client places in the RIA when they choose to hire the firm.

Two other variables included in the regression analysis are taxability and account ownership. When it comes to managing taxes for investments, robo-advisors are an effective way to manage tax implications as they employ passive investment strategies and apply rebalancing techniques (Uhl and Rohner, 2018). Additionally, as a consultant to the RIA industry I can attest to the fact that when RIAs have thought about how a robo-solution might fit their client's needs, typically the types of accounts that seem most appropriate are the accounts where parents set aside money for college funds for their children, or investors that are just putting money away for savings after maximizing any retirement accounts. As noted in Table 10, from the data set, taxable accounts were coded as a 1, with IRA accounts coded as 0. Individual accounts were coded as a 1 and joint accounts coded as a zero. The results show both taxability and account ownership are not significant determinants of the adoption of a robo-solution.

Both regression models in this study had very low R^2 values. As it relates to the models associated with RIA AUM and fee discounts (R^2 of 2%), there are a few potential explanations for the low explanatory value. First, the robo-solution involved in this study has evolved since its inception (and since the data sample was collected) and it is possible that this custodian's initial release of the robo-solution did not entice RIA firms to adopt the technology as part of their offering. For example, lower trading costs or additions to investment solutions (such as adding mutual funds) could have an impact on overall adoption that is not examined in this study. Another possible explanation is the previously mentioned cash mandate by the custodian, which the data was obtained from, that RIAs hold a certain amount of the model in cash. This mandate could be viewed by some RIAs as having a negative effect on overall investment performance (as they might hold less cash in their traditional portfolios) and therefore they might use other model portfolio solutions for their clients. The model tested for client attributes also had a low explanatory value (R^2 of 6.5%). One possible explanation for this can be attributed to the association of the client with an RIA in that the client has already decided to hire the RIA and therefore has placed their decision making (as it relates to choosing a robo-solution) in the hands of the RIA.

While neither model has great explanatory power, there are several implications for RIAs that can be drawn from this study. First, this study sets out to answer the question: For assets managed by an RIA, are fee discounts associated with higher allocation of client assets to an automated investment solution vs. a traditional solution. While fee discounts were found to be significant in this study's regression models, when evaluating these findings against the mean assets held by clients in a robo solution, RIAs should not consider having to reduce their traditional fees when adopting a hybrid model as a must. Certainly, there are robo-solutions in the marketplace that are priced much less than the traditional fee structure of RIAs, but the reduction in fees by the RIA appears to have a small overall impact to the percentage of assets held in a robo-solution. Additionally, clients of RIAs might place more value in the overall relationship and not focus as much on the fee as some RIAs might think. And secondly, the hybrid model might offer a real opportunity for RIAs to engage the younger generation in an effective way, given the results relating to age and investment experience. The engagement of the younger generation could come in the form of the children of older clients or an opportunity to grow a segment of the market.

V LIMITATIONS AND FUTURE RESEARCH

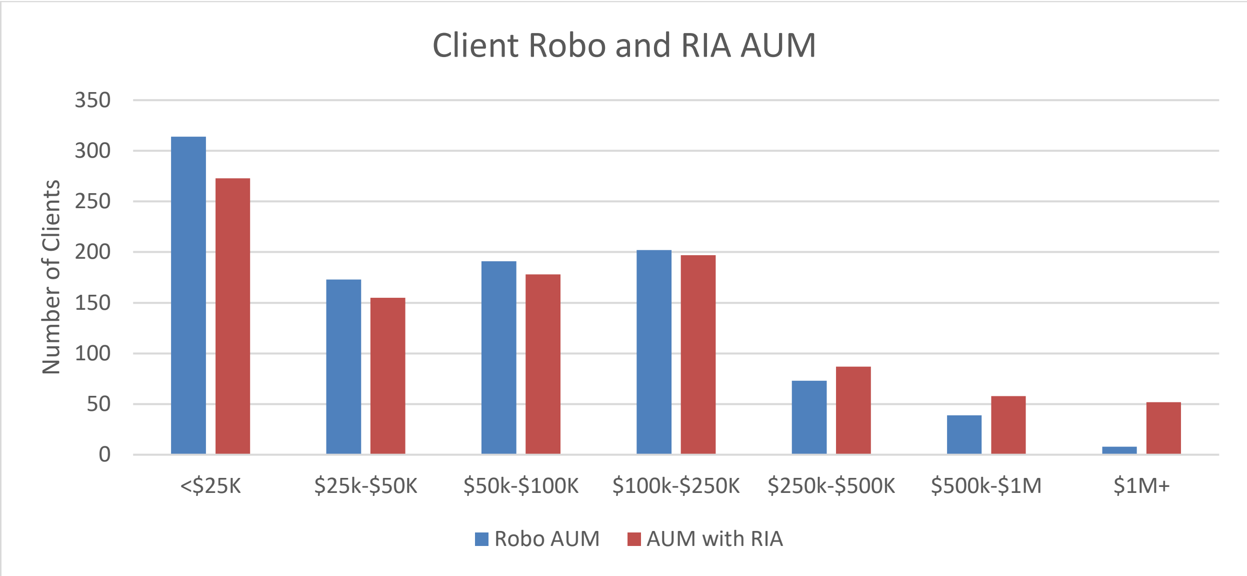
There are several limitations associated with the data used in this study. First, as mentioned previously, the data set was collected from a single brokerage firm which poses a few issues regarding the generalizability of the findings. While the brokerage firm does represent a large population of RIAs, this study does not consider RIAs that are not using the firm's custodial services and potentially use other brokerage firm's robo-solution. This limitation introduces a potential selection bias within the data in that the firms included in the study have already chosen to use a particular robo-solution and firms that offer a fee discount have already made that choice. Second, as it relates to selection bias, there is an implication that the RIAs included in this study have taken other robo-solutions into account in making the choice to use this firm's solution. That decision process is not within the scope of this study as it does not review the merits of one robo-solution over another. Third, while the RIAs included in this study have discretion over the investment process, the decision to adopt a robo-solution is not specifically known as to how much influence the RIA had in actual adoption. Finally, this study uses the Diffusion of Innovation Theory (DOF) to examine the characteristics of investors that adopt a robo-solution. As, previously noted, DOF (Rogers, 1995) is used to explain how an idea or product gains traction and spreads through a group or social system. Therefore, there is a time-series element to DOF, in that it assumes the diffusion process is over a period of time. However, this study does not use time-series data, and only considers a single point in time.

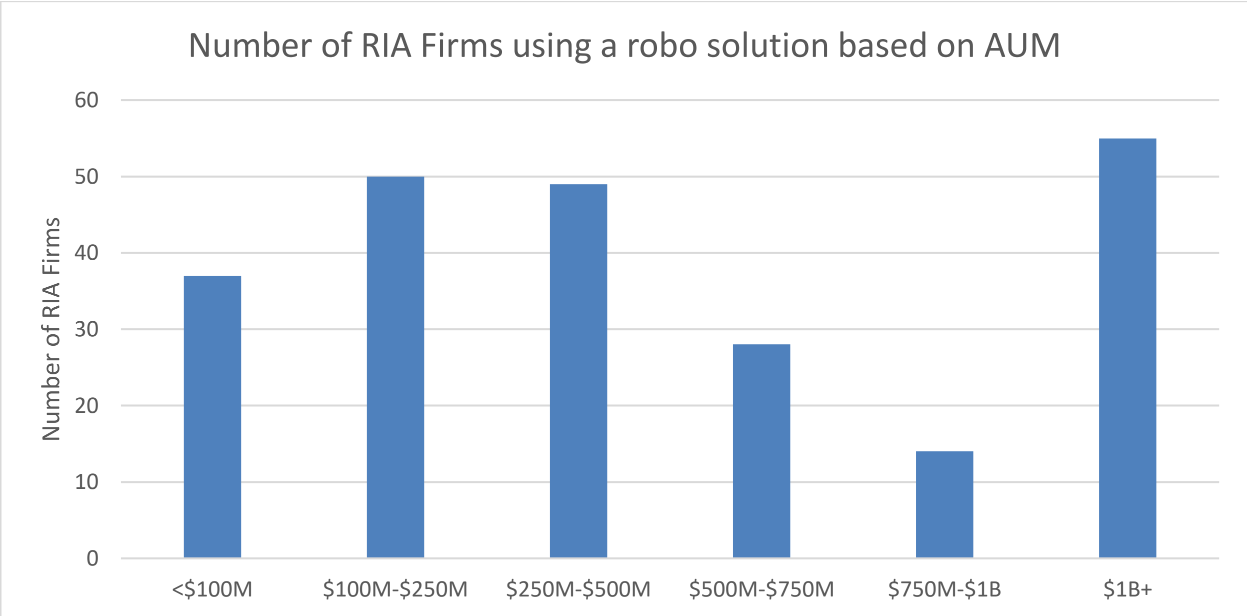
These limitations may offer several opportunities for future research. A more expansive time-series study across multiple robo-platforms would provide greater insights into other potential factors that might affect adoption such as investment solutions within a particular robo-solution or the robo-solution interface itself. This study only focused on whether a fee discount was offered or not, it did not consider the magnitude of the discount. The magnitude of the discount or whether the discount was applied could be a factor that could a part of future research. As mentioned previously, the regression models in this study have very low explanatory power. A possible explanation could be due to the decision-making process a client goes through in hiring an RIA, they have made a decision to hire the RIA and therefore there could be an implied trust in the recommendation of the RIA. A qualitative study could be done across advisors and their clients to better understand the interaction between the RIA and the clients regarding a robo-solution. An additional measure in this qualitative study could look at the satisfaction level of the client as it relates to the hybrid used by the RIA. And finally, to understand if a hybrid model truly helps with capacity constraints, within an RIA firm, a longitudinal study could be done to measure firm performance relating to AUM growth, client growth and retention rates and staff productivity measures.

APPENDICES

Appendix A

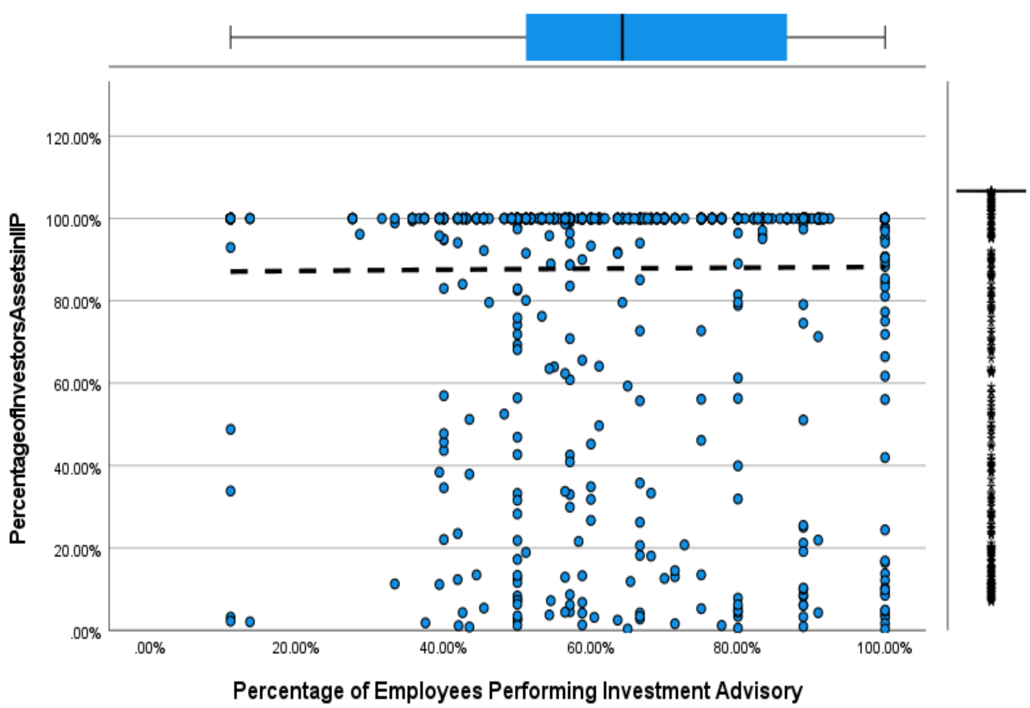
The bar chart below shows the comparison (by category) of client assets held in a robo-solution vs. assets held with the RIA Firm.



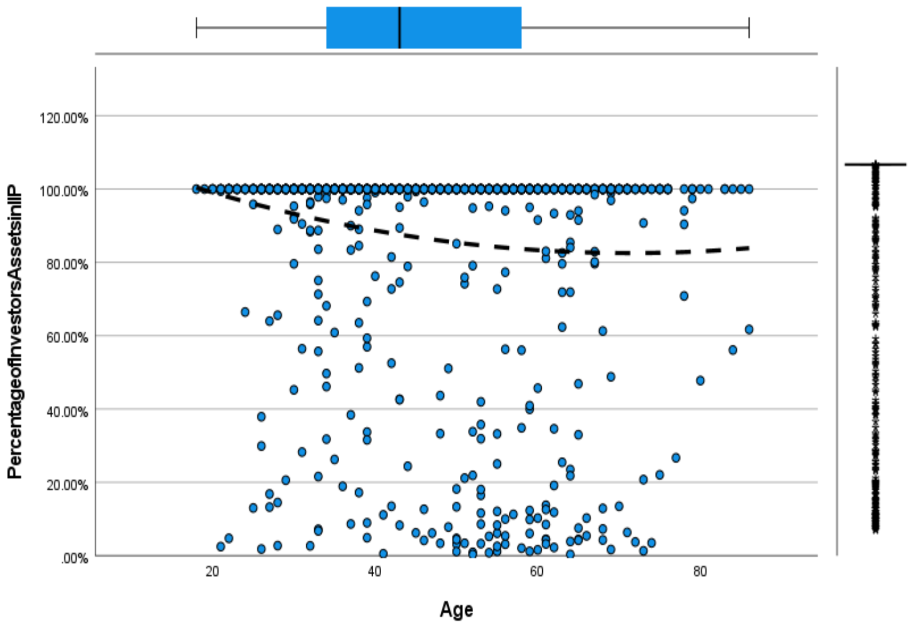


Appendix B

The Scatter Plot below shows the relationship between Percentage of Employees Performing the Investment Advisory Function and Percentage of Assets held in a robo-solution. Percentage of Employees Performing IA (Investment Advisory) Function is calculated by dividing the number of employees an RIA reports that is performing an Investment Advisory role by the total number of employees of the RIA.



The scatter plot below shows the relationship between the percentage of assets held in a robo-solution and age.



Appendix C

Coefficients for Correlation and Multicollinearity

The tables below show correlation and collinearity statistics for the regression models examined in this study. Correlation coefficients take on values between -1 and +1, indicating a perfect correlation. Tolerance and Variance inflation indicator (VIF) values are shown to test for correlation between independent variables (multicollinearity). Tolerance values less than .10 indicates that the multiple correlation with variables is high. VIF values above 10 would indicate the presence of multicollinearity.

Model 1	Correlations			Collinearity Statistics	
	Zero-order	Partial	Part	Tolerance	VIF
AUMSize	-0.070	-0.028	-0.028	0.729	1.371
FeeDiscount	0.135	0.114	0.114	0.784	1.276
AUMSize*FeeDiscount	0.013	-0.007	-0.007	0.731	1.368

Model 2	Correlations			Collinearity Statistics	
	Zero-order	Partial	Part	Tolerance	VIF
AUMSize	-0.070	-0.035	-0.035	0.691	1.448
FeeDiscount	0.135	0.043	0.042	0.867	1.153
%of Advisory Employees	0.009	0.032	0.031	0.929	1.076
AUMSize*FeeDiscount	0.013	-0.007	-0.007	0.731	1.368

Model 3	Correlations			Collinearity Statistics	
	Zero-order	Partial	Part	Tolerance	VIF
SmallNoFee	-0.081	-0.028	-0.028	0.831	1.203
SmallFeeDiscount	0.013	0.029	0.028	0.945	1.059
LargeFeeDiscount	0.133	0.114	0.114	0.821	1.218

Model 8		Correlations			Collinearity Statistics	
		Zero-order	Partial	Part	Tolerance	VIF
	Goals	-0.024	-0.044	-0.043	0.950	1.053
	Actions	0.060	0.047	0.046	0.918	1.089
	Age	-0.147	-0.116	-0.113	0.794	1.260
	Knowledge	-0.216	-0.175	-0.172	0.846	1.182
	Mkt Decline	0.123	0.017	0.017	0.716	1.397
	Taxability	-0.032	-0.046	-0.045	0.764	1.308
	Ownership	0.006	-0.030	-0.029	0.789	1.267

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VITA

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