Who are robo-advisor users?

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Abstract

The purpose of this study is to explore the demand for robo-advising services by analyzing the participants' behavioral characteristics and investment patterns. With the 2015 Financial Industry Regulatory Authority Investor data, we found that robo-advisor users were younger investors with high risk tolerance, whose self-assessment of financial knowledge is comparatively higher than their actual knowledge, and were independent decision-makers. By controlling for those behavioral attributes of robo-advisor users, we also found that robo-advisor users were reluctant to invest in individual stocks, while they showed the largest preference for investing in pooled investment products such as Exchange Traded Funds. Implications of this study's findings can be beneficial to financial planning practitioners, academics, and regulators.

I. Introduction

Robo-Advisors are automated portfolio allocation platforms, many of which apply algorithms based on machine learning. Recent studies suggest an increasing demand for robo-advisory services (Jung, Dorner, Glaser, & Morana, 2018). According to Agarwal, Driscoll, Gabaix, and Laibson (2009), younger investors lack investment knowledge, and many older investors suffer from diminishing cognitive ability. These two groups can benefit most from accessing the services through a low-cost automated investment platform (Fisch, Labouré, and Turner, 2018). Recent reports about the increasing demand for Turnkey Asset Management Programs (TAMP) among financial advisors show that digital integration of technology and the utilization of automated investment platforms are continuing to increase. According to Neal (2019), a Turnkey Asset Management Program (TAMP) is a fee-account technology platform where financial advisors can monitor their clients' investment account. Based on this platform, TAMP programs provide a free digital marketplace where advisors can model their investment strategies. Such a phenomenon shows that the financial advisory industry is entering a new paradigm of reduced transaction costs. While electronic platforms such as TAMPs are not designed to actively let advisors engage in investment activities, many of these platforms make available technology-based tools that facilitate record-keeping and interaction between financial advisors and clients. In other words, it reduces the transaction cost between the financial advisor and its clients that provide technology, investment research, portfolio management, and other outsourcing services for financial advisors.

However, consumers have been slow in warming up to the idea of having their retirement portfolios managed by automated platforms. One recent research on robo-advisors among European investors has shown that 49 percent of the respondents would not utilize a robo platform's service without in-person support from a trained financial advisor (Nicoletti, 2017). In this study, Nicoletti (2017) found that only about 11 percent of the respondents would use a robo-platform instead of accessing a human financial advisor's services. Other factors, such as risk

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tolerance, financial knowledge, and confidence, have been associated with individuals' investment planning decisions (Lusardi & Mitchell, 2008; Wang, 2009). Other recent studies on the demand for robo-advisors have shown that people who used the services of robo-advisors were younger, had higher risk tolerance, and were time-constrained (Fan & Chatterjee, 2020).

This study aims to add to the literature on the demand for robo-advisor platforms by examining whether financial confidence or subjective financial knowledge is associated with the utilization of robo-advisory services. Additionally, this paper investigates the determinants of investment asset selection among those who utilized the services of robo-advisors.

II. Literature review

Current state of robo-advising

Robo-Advisors, or in other words, automated financial advisors, are online platforms that provide investment advice driven by algorithms (Ji, 2017) and machine learning techniques. These investment platforms have emerged as alternative investments compared to traditional human financial advisors. Robo-Advisors have now been around for some time, and their adoption rate has steadily increased over the past decade (Perrin & Duggan, 2015). Indeed, technology has been increasing cost and price efficiencies in the investment arena over the past two decades. For example, a seminal study by Brown and Goolsbee (2000) has found that the internet's democratization reduced the search cost in choosing insurance contracts.

Over the past decade, the financial services market has seen the emergence of robo-advisors or automated investment platforms that provide portfolio management and investment advice to private consumers (Ji, 2017; Woodyard & Grable, 2018). As a low-cost alternative to the traditional financial advisor, robo-advisors provide financial advice by utilizing algorithms programmed to optimize consumers' investment decisions (Ji, 2017; Day, Cheng, & Li, 2018; Kobets, Yatsenko, Mazur & Zubrii, 2018). Robo-Advisory platforms are used by investors and institutions, including financial advisors, investors working with financial advisors, and investors who choose not to work with financial advisors (Financial Industry Regulatory Authority Report (FINRA), 2016). Robo-Advisors help consumers make financial decisions, such as evaluating risk-measurement, selecting portfolios, and rebalancing portfolios.

Recent studies suggest that as technology advances in the long-term, robo-advisors may provide a comparable or a supplementary option to human financial advisors making them increasingly acceptable in the financial services industry (Jung, Glaser, & Köpplin, 2019). Despite the innovation of robo-advisors, consumers' lack of trust has delayed the adoption of robo-advisor solutions by the market (Cheng et al., 2019). One criticism of robo-advisors is that they are designed to only recommend suitable products to consumers (Baker & Dellaert, 2017b). Moreover, although robo-advisors are based on sophisticated algorithmic and machine learning-based frameworks, the capability, integrity, and financial fitness of robo-advisor based services cannot easily be identified and implemented (Baker & Dellaert, 2017b). Research shows that strong customer support and product branding are critical elements of building trust for robo-advisors (Salo, 2017).

Regarding the adoption of robo-advisors, Hohenberger, Lee, and Coughlin (2018) found that subjective assessment of the degree of prior financial experiences can explain the adoption of robo-advisors. Thus, the willingness or motivation to adopt a robo-advisor is positively correlated with previous experiences. People who had more financial transactions in the past were more likely to adopt a robo-advisory system. Regarding the population of robo-advisor users, Woodyard and Grable (2018) found that users of robo-advisors tend to be younger, confident in their financial ability, and distrustful of traditional financial channels.

The market for robo-advising has experienced rapid expansion over the past five years. According to Mercadante (2020), there are several ways robo-advisors facilitate a change in the investment industry. The first change that robo-advisors are facilitating comes from the prevalence of information about financial investments and products. The availability of abundant financial information on the web has made many individual investors feel more empowered to make investment decisions by themselves (with robo-advisors serving as facilitators). The second change is related to the lower barrier into the investment world. Falling transaction costs have created greater access for small investors to invest in the financial markets. While these two aspects are mostly related to the industry's general trend, the primary contribution of robo-advising comes from its ability to rebalance a portfolio and the democratization of quality investments for small investors. Due to wider access to investment advisors through a robo-advising platform (e.g., TAMP), now customers have more real-time access to valuable information. Regarding the current state of the robo-advising industry, according to the Corporate Finance Institute (Corporate Finance Institute (CFI), 2020), the five largest robo-advisors currently operating in the market are Betterment, Charles Schwab, TD Ameritrade (recently bought over by Charles Schwab), the Vanguard group, and Wealthfront. Neal (2019) provides a list of current TAMP providers in Table 1, and as shown, most of the services and products do not differ much from each other, and most of them have the same or similar custodians.

According to Royal (2020), the cost of using robo-advisors includes management fees and the fund’s expense ratios. While the management fees range from 0.25 to 0.5 percent, the funds’ expense ratios to which the robo-advisors allocate investor portfolios may range from 0.05 to 0.65 percent. According to this author (Royal, 2020), robo-advisors have highly sophisticated programmed algorithms and let one manage and monitor individual investors’ portfolios in real-time by providing those small investors with reasonable value propositions.

During the 2020 pandemic, Hicks (2020) finds that stock market volatility and market uncertainty have accelerated the adoption of robo-advisors: the five largest robo-advisors saw a growth of 38% during the first half of 2020 compared with the previous year. The range of investment strategies offered by robo-advisors also expanded during this period. The ten best advisors listed in Hicks’ (2020) study ranged from robo-advisory platforms that used strategies similar to hedge funds to robo-advisors that focused on socially responsible investments (SRI), whereby several of them integrated artificial intelligence (AI) and machine learning-based algorithms in their portfolio management models. Here, the portfolio management styles among the robo-advisors ranged from passive buy and hold strategies to sophisticated active portfolio management strategies.

Table 1. List of current TAMP providers

Firm	Custodian	Total Assets ($M)	Fee Structure	Currently offered programs
Envestnet	Fidelity, First Clearing, Pershing Advisor Solutions, Raymond James Investment Advisor Division, RBC, Schwab Advisor Services, TD Ameritrade Institutional, other	$3,300,000	Asset-based fee	ETF wraps, mutual fund wraps, SMAs, UMAs, UMHs
Independent Advisor Solution by SEI	SEI	$67,215	Asset-based fee (0.29% - 1.23%)	ETF wraps, mutual fund wraps, SMAs, UMAs, UMHs
Assetmark Financial Holdings Inc.	AssetMark, Fidelity, Pershing Advisor Solutions, TD Ameritrade Institutional	$56,700	Other	ETF wraps, mutual fund wraps, SMAs, UMAs, UMHs
Loring Ward & Bam Advisor Services	Fidelity, Pershing Advisor Solutions, Schwab Advisor Services, TD Ameritrade Institutional	$34,000	Asset-based fee (0.10% - 0.65%)	ETF wraps, mutual fund wraps, SMAs, UMAs, UMHs
Brinker Capital	Fidelity, Schwab Advisor Services	$23,782	Asset-based fee (0.00% - 0.64%)	ETF wraps, mutual fund wraps, SMAs, UMAs
Orion Portfolio Solutions	TD Ameritrade Institutional	$15,627	Asset-based fee (0.00% - 0.75%)	ETF wraps, mutual fund wraps, SMAs, UMAs
Sawtooth Solutions	Fidelity, Pershing Advisor Solutions, Schwab Advisor Services, TF Ameritrade Institutional	$11,900	Asset-based fee (0.20% - 0.35%)	ETF wraps, mutual fund wraps, SMAs, UMAs, UMHs
Morningstar Investment Services	Fidelity, Pershing Advisor Solutions, Schwab Advisor Services, TD Ameritrade Institutional	$11,200	Asset-based fee (0.05% - 0.55%)	ETF wraps, mutual fund wraps, SMAs, UMAs
Symmetry Partners	Fidelity, Schwab Advisor Services, TD Ameritrade Institutional	$9,400	Asset-based fee (0.15% - 0.50%)	ETF wraps, mutual fund wraps, SMAs, UMAs, UMHs
Frontier Asset Management	Fidelity, LPL Financial, Pershing Advisor Solutions, Schwab Advisor Service, TD Ameritrade Institutional	$4,185	Asset-based fee (0.30% - 0.60%)	SMAs
Advisors Capital Management	Fidelity, LPL Financial, Pershing Advisor Solutions, Schwab Advisor Services, TD Ameritrade Institutional	$2,400	Asset-based fee, Flat fee (0.35% - 0.80%)	SMAs, UMAs
Fusion Capital Management	Schwab Advisor Services, TD Ameritrade Institutional	$1,652	Other (0.05% - 0.45%)	ETF wraps, mutual fund wraps, SMAs, UMAs, UMHs

Axxcess Platform	Fidelity, Schwab Advisor Services, TD Ameritrade Institutional	$1,650	Asset-based fee (0.05% - 0.65%)	SMAs, UMAs, mutual fund wraps
Dunham	Other	$1,500	Asset-based fee (0.25% - 2.25%)	Mutual fund wraps
SmartX Advisory Solutions	Fidelity, Pershing Advisor Solutions, Schwab Advisor Services, TD Ameritrade Institutional	$1,500	Asset-based fee (0.05% - 0.15%)	UMAs, SMAs, UMHs
Lockwood Managed 360	Pershing Advisor Solutions	$1,391	Asset-based fee (0.20% - 0.95%)	ETF wraps, mutual fund wraps, SMAs, UMAs
3D Asset Management	Schwab Advisor Services, TD Ameritrade Institutional	$805	Asset-based fee (0.30% - 0.65%)	ETF wraps, mutual fund wraps, UMAs, SMAs, UMHs

Note. Exchange-traded fund (ETF) wrap accounts, mutual fund accounts, separately managed accounts (SMAs), unified managed accounts (UMAs), unified managed households (UMHs); Reproduced with permission from "Competition among TAMPs heats up: Financial advisors' growing interest in outsourcing is luring new entrants to the Turnkey Asset Management platform space," by Ryan W. Neal, 2019, *Investment News*, September 2-6, p.11. Copyright 2019 by Investment News. The robo-advisors listed in this table are not representing all the products out in the market. The five largest robo-advisor companies are Vanguard, Wealthfront, Charles Schwab, TD Ameritrade, and Betterment (i.e., the custodians). Products and firms listed in Table 1 provide a Turnkey Asset Management Program (TAMP): an interactive robo-advising tool for financial advisors. A TAMP helps financial advisors to reduce the time of due diligence (e.g., investment research and selection, portfolio rebalancing, maximization of tax efficiency). They let the firms in this table (i.e., custodians) build their clients' investment portfolios at an asset-based fee. A TAMP can be an outsourcing tool, but it is also a streamlined platform where the financial advisor can monitor a client's account and make suggestions. Since a financial planner or advisor is restricted to advising only, a TAMP platform improves communication by providing better and faster information to the clients, whereby the clients make the ultimate decision of investments. Most of those services charge an asset-based fee, and the types of products are listed in the last column.

Issues revolving around robo-advising

Robo-Advisors face system-wide scaling issues such as not addressing specific individual investor concerns (Baker & Dellaert, 2017b). The challenge of providing individualized solutions for financial advisement may hinder the widespread use of robo-advisors as an overall effective solution. In other words, robo-advisors are missing the qualities that human advisors possess may be a determining factor in consumer acceptance of robo-advisors versus their human alternatives (Faloon & Scherer, 2017).

However, other studies indicate that robo-advisors have the potential to become the preferred investment advisory solution for regular clients and high-net-worth clients alike (Uhl & Rohner, 2018). Offering a low-cost advisory solution, robo-advisors have appealed to young, technologically knowledgeable consumers who are averse to utilizing traditional channels of financial advice provided by human advisors (Woodyard & Grable, 2018).

A recent study suggested a consumer's willingness to engage with a robo-advisor solution depends significantly on its usability (Jung, Dorner, Weinhardt, & Pusmaz, 2018). Consumers report experiencing a range of emotions when using robo-advisors (Hohenberger, Lee, & Coughlin, 2018). For example, one study indicated that consumer experience positive emotions such as joy when using robo-advisors. Conversely, negative responses of anxiety can diminish interest in the use of robo-advisors (Hohenberger, Lee, & Coughlin, 2019). Investors may be more likely to follow the advice of a robo-advisor when the advisor exhibits fewer human characteristics. Many investors also decreased their use of robo-advisors when robo-advisor managed portfolios underperformed other investment opportunities over the short term (Hodge, Mendoza, & Sinha, 2020).

The emergence of new technology such as Artificial Intelligence (AI) can make robo-advisors provide even more cost-effective portfolio management solutions for investors (Lee, Kwon, & Lim, 2017). One example of AI implementation is the ability to recreate human decision-making in a robo-advisory solution with the help of self-learning AI algorithms (Tokic, 2018). Robo-Advisor solutions are typically based on the lack of human interactions in hopes consumers will comprehend and retain the information given without the need to ask questions (Salo, & Haapio, 2017). The use of technology to improve financial advisement is not without concerns from industry and consumers.

The introduction of robo-advisors technology to the financial industry has unmasked legal and policy limitations in providing automated advisory services to the financial sector. Investment Advisors Act of 1940 was designed with a human interaction behavior focus. It is argued that robo-advisors are incapable of providing a comparable amount of care a human advisor offers to meet the Advisers Act's standards (Ji, 2017). In a FINRA report, human investment advisers are deemed fiduciaries under the Investment Advisors Act of 1940 (FINRA, 2016). The financial advisor's fiduciary responsibility requires the adviser to provide investment advice in the client's best interest. According to the FINRA report, one way to integrate the portfolio management solutions that robo-advisors provide would be to make these available to clients as a deliverable by a human financial advisor who can play the primary fiduciary function (FINRA, 2016). Robo-Advisors' services do not fill the standard of a fiduciary. Therefore, studies have suggested not to hold robo-advisors to the same regulatory standard that human advisors are subject to (Baker & Dellaert, 2017a).

Despite this efficient system of robo-advising, a question continues to remain in academia: How reliable and consistent is a robo-advisor or an automated investment platform? And what are consumers' perceptions of using a robo-advisor? Pertinent to the first question, Ciccotello and Wood (2001) conducted a real-life simulation based on three types of investors and found that robo-advisors are doing an excellent job recommending financial products. Ciccotello and Wood's (2001) argument is that automated investment platforms have a more consistent recommendation than real-life advisors in certain product types. Such an observation might come from the fact that robo-advisors are run based on a mathematic algorithm that predicts the same output when the input data is similar. The only difference in the outcome by different platforms came from different assumptions and methods used by the robo-advisor. By measuring the coefficient of variation of the output of different robo-advisors, the authors (Ciccotello & Wood, 2001) found that all robo-advisor brands had similar outputs in terms of Roth conversions or life insurance products rather than in investment portfolio related results, while asset allocation or estate tax estimations were better performed with real-life financial advisors. Regarding portfolio allocation, contrary to the pundits' expectations, robo-advisors had difficulties in predicting a consistent output for clients with a complex composition of assets and wealth. Instead, real-life advisors tend to project a more consistent asset allocation strategy than robo-advisors, even though a human financial advisor might exhibit inconsistent investment strategies and philosophies. Additionally, Belanche, Ariño, and Flavian (2019) found that individual investors, who had a deeper understanding of information technology and robots, were more likely to trust and utilize rob-advisors' services. The authors (Belanche, Ariño, & Flavian, 2019) also found that attitudes towards robo-advisors and the utilization of these services varied by the investors' socio-economic and individual characteristics.

III. Empirical analysis

The estimation strategy of this paper was based on a two-phase analysis of robo-advisor users. The first part is an analysis based on the characteristics of those users (see Table 3). In this phase, we found distinctive behavioral patterns of investors who use automated advisory systems (i.e., robo-advisors). This was done by regressing a binary probability model (i.e., a logit model in this study) of whether one is a robo-advisor user (dependent variable) on the characteristics of an investor (independent variables). These included variables pertinent to demography, risk tolerance, own assessment of financial knowledge, financial literacy score, and investment style. Based on the regression results, we determined the characteristics of robo-advisor users by identifying statistically significant variables.

In the second phase of our empirical analysis, we ran another logit model. The dependent variables were financial products invested by the survey respondent in the Financial Industry Regulatory Authority (FINRA) survey (see Table 4). Each financial product was then regressed on whether one is a robo-advisor user, the respondent's risk tolerance level, own assessment of financial knowledge, financial literacy score, and investment style. Except for excluding the demography variables and instead including the robo-advisor variable (which previously was the dependent variable in the first model), the rest of the variables were practically the same as in the previous model: they were used as control variables (i.e., the model in Table 3).

FINRA investor data and variables

As mentioned before, this study uses the Financial Industry Regulatory Authority (FINRA) National Financial Capability Study (NFCS) dataset. This study uses the 2015 wave of the NFCS (state-by-state version) and the merged 2015 FINRA Investors' data. The merged dataset includes information about participants: Their socio-demographic characteristics, invested financial products, risk-tolerance level of investors, investment styles, own assessment of financial knowledge, financial literacy, and whether one uses an automated financial advisor (i.e., robo-advisor). The entire sample size of our investment data contained 2,000 observations, while all the questions used in this study were questions asked in a binary fashion. Additionally, we controlled for the respondents' state of residence, which was later used for State-based fixed effects to subdue different State legislatures affecting investments and different internet infrastructures.

Again, it is emphasized that only the 2015 version had the pertinent question regarding the use of automated advisors. Unfortunately, the most recent FINRA survey dropped question C11, so that the 2015 version is the 'only' survey that has a question regarding the use of robo-advisors. As for challenges that might argue that the data set used in this study is a little outdated, we argue that our study bases on the behavioral attributes of robo-advisor users. In other words, our study is exploring the fundamental characteristics of certain types of investors and, based on their attributes, how they invest. Thus, unless the investors' behavioral characteristics investing in a certain financial product change, or unless there is a financial product that is different from the conventional products in the market, our argument firmly stands with the notion that the patterns of investments would not change because investors' characteristics do not change easily.

Table 2. Summary statistics

VARIABLES	(1) Obs.	(2) Mean	(3) Median	(4) St. Dev.	(5) Min	(6) Max
Financial products						
STOCK	2,000	0.748 (74.8%)	1	0.435	0	1
BOND	2,000	0.347 (34.7%)	0	0.476	0	1
MFUND	2,000	0.665 (66.5%)	1	0.472	0	1
ETF	2,000	0.221 (22.1%)	0	0.415	0	1
ANNU	2,000	0.326 (32.6%)	0	0.469	0	1
WLIFE	2,000	0.416 (41.6%)	0	0.493	0	1
CMMFTRE	2,000	0.112 (11.2%)	0	0.315	0	1
OTHER	2,000	0.147 (14.7%)	0	0.354	0	1
Risk Tolerance						
Substantial risk	2,000	0.0985 (9.85%)	0	0.298	0	1
Above avg. risk	2,000	0.294 (29.4%)	0	0.456	0	1
Avg. risk	2,000	0.498 (49.8%)	0	0.500	0	1
Investment style						
Own decision	2,000	0.407 (40.7%)	0	0.491	0	1
Variable of interest						
Robo-Advisor	2,000	0.129 (12.9%)	0	0.335	0	1
Own finance assessment						
Very high	2,000	0.117 (11.7%)	0	0.321	0	1
Fees						

Fixed fee	2,000	0.316 (31.6%)	0	0.465	0	1
Controls						
Gender (Male)	2,000	0.550 (55.0%)	1	0.498	0	1
Age (35-54)	2,000	0.316 (31.6%)	0	0.465	0	1
Age (55+)	2,000	0.522 (52.2%)	1	0.500	0	1
Ethnicity (White)	2,000	0.803 (80.3%)	1	0.398	0	1
Education (College)	2,000	0.610 (61.0%)	1	0.488	0	1
Income (50K-100K)	2,000	0.447 (44.7%)	0	0.497	0	1
Income (100K+)	2,000	0.344 (34.4%)	0	0.475	0	1
Financial literacy						
State + Investment data	2,000	8.905	9	3.260	0	16

Note. The total number of observations in the 2015 FINRA investor dataset was 2,000. The percentages in the parentheses only apply to binary variables.

More than half of the respondents answered that they would hire a financial advisor because they want to avoid loss (64.7%) and improve performance (67.5%). Others answered that they would like to improve their portfolio performance (51.6%) or access to investment opportunities (44.3%) that they would not have had without a financial advisor.

Regarding financial knowledge, ten questions were asked in the investor data and six in the primary state-by-state population data. The original survey used the same financial literacy questions of Lusardi and Mitchell's work (2014) and asked those questions to the survey respondents. In this sense, they are 'not' the same survey respondents as in the original study conducted by Lusardi and Mitchell (2014). By putting together Lusardi and Mitchell's financial literacy metrics (2014) and the FINRA financial literacy questions (that were asked to all the survey respondents in the 2015 FINRA survey, we created a comprehensive financial literacy score that incorporated survey questions originated from both. Based on these two measurements, we gave each right question one point so that the maximum achievable financial literacy score was 16. The average was 8.91 points, close to the mean of 8 points, and the standard variation was 3.26 points. Contrary to the well-distributed financial literacy scores, only a few people in the survey answered that they have a very high finance knowledge level. Only 11.7% of the respondents self-assessed themselves as having a very high knowledge base, which indicated that many respondents lacked confidence and faith in their knowledge base.

In terms of investment style, 40.7 percent answered that they make their own decisions, and 41.1 percent responded that they seek professional advice. In terms of the fee structure, 31.6% were paying a fixed monthly or annual fee. Other than the variable related to the usage of robo-advisors, major variables that were used as dependent variables in this study were related to investment choices. The FINRA investor data asked respondents about what type of financial product one is currently owning. Out of 2,000 observations, on average, 74.8 percent owned stocks (STOCK), followed by 66.5 percent of respondents who owned mutual funds (MFUND). Bonds (BOND) were owned on average by 34.7 percent, annuities (ANNU) by 32.6 percent, exchange-traded funds (ETF) by 22.1 percent, commodities and futures (CMMFTRE) by 11.2 percent, and other investment products such as real estate investment trusts (REITs), options, private placements, or structured notes (OTHER) were owned by 14.7 percent.

The gender composition included 55 percent of males and 45 percent of females regarding the demographic control variables. Also, almost half of the respondents were over 55 years old (52.2%), and 80.3 percent were racially white. The education level of investors showed that, on average, 61 percent were college-educated. The composition of income levels included 44.7 percent of people who earned between $50,000 and $100,000, while around 34.4 percent earned over $100,000.

Table 3. Robo-Advisor regression

VARIABLES	(1) ROBO	(2) ROBO	(3) ROBO	(4) ROBO
Controls				
Gender (Male)	-0.142	-0.114	0.100	0.0893
	(0.172)	(0.165)	(0.182)	(0.183)
Age (35-54)	-0.853***	-0.820***	-0.702***	-0.713***
	(0.190)	(0.209)	(0.213)	(0.213)
Age (55+)	-1.809***	-1.713***	-1.428***	-1.408***
	(0.268)	(0.272)	(0.274)	(0.274)
Ethnicity (White)	-0.392**	-0.319*	-0.225	-0.217
	(0.192)	(0.192)	(0.198)	(0.202)
Education (College)	-0.190	-0.0740	0.110	0.123
	(0.164)	(0.163)	(0.180)	(0.180)
Income (50K-100K)	-0.298	-0.262	-0.202	-0.192
	(0.238)	(0.223)	(0.234)	(0.234)
Income (100K+)	-0.682***	-0.715***	-0.515**	-0.486*
	(0.223)	(0.237)	(0.248)	(0.251)
Risk Tolerance				
Substantial risk	3.912***	3.217***	3.483***	3.420***
	(0.548)	(0.507)	(0.501)	(0.503)
Above avg. risk	2.513***	2.215***	2.568***	2.574***
	(0.546)	(0.537)	(0.534)	(0.530)
Avg. risk	1.565***	1.454**	1.739***	1.741***
	(0.555)	(0.575)	(0.575)	(0.573)
Own finance assessment				
Very high		1.554***	1.481***	1.437***
		(0.269)	(0.278)	(0.272)
Financial literacy				
State + Invest data			-0.153***	-0.156***
			(0.0292)	(0.0292)
Investment style				
Own decision				0.274*
				(0.142)
Constant	-3.678***	-3.968***	-3.457***	-3.470***
	(0.829)	(0.779)	(0.783)	(0.792)
Observations	2,000	2,000	2,000	2,000
State Fixed Effect	applied	applied	applied	applied
Pseudo R-Squared	0.299	0.339	0.356	0.357

Note. The dependent variable ROBO is a binary variable on a question in the 2015 FINRA investor survey:

question C11 (36th question). This question asked in a dichotomous fashion, "Have you ever used an automated financial advisor that provides investment advice and makes trades on your behalf?" This binary variable was then used as the dependent variable in all four models in this table. The robust standard errors are in parentheses. The model was based on a Logit model where the error terms were clustered by States. *** p<0.01, ** p<0.05, * p<0.1

Profile of robo-advisor users

The first analysis was conducted based on a logit regression where the dependent variable was a binary variable of whether one was using an automated financial advisor (i.e., robo-advisor). The results are reported in Table 3, and State fixed effects were applied to exclude idiosyncratic attributes by States, such as the degree of internet service provided and its dissemination among residents of each State or different State legislatures that might affect one's investment. The results in Table 3 are reported in log-odds. In terms of the control variables' significance, all age groups and the income group earning over $100,000 per year showed a significant and negative sign. In this study, the age groups of 35 to 54 and the age group over 55 years were negatively associated with the utilization of a robo-advisor compared to the lowest age group of 18 to 34 (i.e., the reference group). In a similar context, people with income over $100,000 were less likely to make their investment decisions based on this electronic platform than people who earn less than $50,000 (i.e., the reference group). These results suggest that people older in age are reluctant to rely on the services of an automated investment platform, and people with higher income were also negatively associated with the use of robo-advisors.

The risk tolerance variables were compared to the reference group of highly risk-averse individuals (i.e., individuals who would take 'no risk:' highly risk-averse group). In all risk-tolerance levels, survey respondents showed a significant and positive association towards using a robo-advisor. This is an indicator that the use of this electronic platform is highly correlated with taking risks. In all four models, substantial risk-takers had the largest coefficient, followed by above-average risk-takers and average risk-takers. Here, all variables were compared to the risk-averse investor who served as a baseline comparison group.

The financial literacy variables consistently showed a significant negative effect throughout Models 3 and 4. As elaborated before, the financial literacy variable was constructed by incorporating financial literacy test scores from both the State-by-State and Investor data, which ranged from zero to 16 points maximum. Each question was graded by one point if the respondent got the question right. A negative sign alerts that respondents with a low level of financial knowledge have a higher propensity towards using a robo-advisor. Pertinent to this result, the result of the investment style (i.e., "own decision") indicates that robo-advisor users are independent because they prefer to make their own financial decisions rather than rely on acquaintances or third-party advisors.

The paradox of robo-advisor users regarding their actual knowledge and self-assessment can be observed by two opposite significant financial literacy results and one's financial knowledge assessment. The positively significant result of one's own financial assessment indicates that the robo-advisor users tend to have high confidence in their knowledge. This is further supported by the investment style variable, where investors who make their financial decisions on their own have a strong inclination to be a robo-advisor user.

Table 4. Investment patterns

VARIABLES	(1) STOCK	(2) BOND	(3) MFUND	(4) ETF	(5) ANNU	(6) WLIFE	(7) CMMFTRE	(8) OTHER
Variable of Interest								
Robo-Advisor	-0.142	0.689***	0.943***	1.093***	0.835***	0.378*	0.985***	1.017***
	(0.222)	(0.168)	(0.268)	(0.237)	(0.178)	(0.203)	(0.232)	(0.188)
Risk Tolerance								
Substantial risk	0.821***	0.294	0.371	2.088***	0.0276	0.193	1.815***	0.615*
	(0.275)	(0.230)	(0.266)	(0.466)	(0.252)	(0.246)	(0.367)	(0.361)
Above avg. risk	1.143***	0.298	0.855***	1.756***	-0.190	0.231	1.735***	0.710**
	(0.208)	(0.194)	(0.194)	(0.448)	(0.193)	(0.160)	(0.400)	(0.297)
Avg. risk	0.603***	0.191	0.734***	1.541***	-0.0145	-0.0420	0.802*	0.460
	(0.179)	(0.184)	(0.220)	(0.441)	(0.190)	(0.156)	(0.427)	(0.283)
Own finance assessment								
Very high	0.493**	0.834***	0.223	0.814***	0.279	0.398**	0.684***	0.794***
	(0.203)	(0.169)	(0.231)	(0.196)	(0.193)	(0.180)	(0.244)	(0.196)
Financial literacy								
State + Invest data	0.0432**	-0.0171	0.109***	0.0660***	-0.0459***	-0.0567***	-0.0632**	0.0852***
	(0.0208)	(0.0166)	(0.0160)	(0.0197)	(0.0153)	(0.0182)	(0.0274)	(0.0286)
Investment style								
Own decision	0.303**	-0.544***	-0.917***	-0.0141	-0.764***	-0.327***	0.0646	0.410***
	(0.153)	(0.133)	(0.106)	(0.124)	(0.104)	(0.123)	(0.210)	(0.147)
Fees								
Fixed fee	-0.259*	0.433***	0.401***	0.243**	0.535***	0.636***	0.497**	-0.0410
	(0.145)	(0.107)	(0.132)	(0.118)	(0.121)	(0.110)	(0.213)	(0.163)
Constant	-0.120	-0.971***	-0.836***	-3.748***	-0.323	-0.362	-3.527***	-3.434***
	(0.229)	(0.207)	(0.245)	(0.456)	(0.223)	(0.650)	(0.603)	(1.123)
Observations	2,000	2,000	2,000	2,000	2,000	2,000	2,000	2,000
State Fixed Effect	applied	applied	applied	applied	applied	applied	applied	applied
Pseudo R-Squared	0.0593	0.0899	0.0957	0.148	0.0882	0.0703	0.205	0.109

Note. The dependent variables are all binary variables that asked the survey respondent whether the respondent was investing in one of the financial products: STOCK (individual stocks), BOND (individual bonds), MFUND (mutual funds), ETF (exchange-traded funds), ANNU (annuities),

CMMFTRE (commodities or futures, or OTHER (REITs, options, private placements, or structured notes). The robust standard errors in parentheses, whereby the error terms were clustered at the State level.
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Investment patterns of robo-advisor users

In order to investigate the investment patterns of robo-advisor users after controlling for other socio-demographic, risk, and financial capability related factors, we ran a logit model based on financial products as dependent variables. The reason for applying a State-based fixed effect was because we wanted to control for dissimilar internet distributions and different State legislatures that might affect one's investment behavior. The dependent variables included in the model of Table 4 were questions regarding one's investment portfolio. They asked whether the respondent was investing in individual stocks (STOCK), individual bonds (BOND), mutual funds (MFUND), exchange-traded funds (ETF), annuities (ANNU), whole life insurance (WLIFE), commodities or futures (CMMFTRE), or other investments such as REITs, options, private placements, and structured notes (OTHER). All were binary variables that correspond to the value of one if one has an investment in one of the investment products above. In Table 4, the variable of interest is the question in the FINRA dataset that asks whether one has ever used an automated financial advisor. Pertinent to this variable, the results in Table 4 show positive and significant results in all product types except individual stocks (Model 1). Regarding the magnitude of the coefficients, Exchange Traded Funds (ETF) showed the largest coefficient, followed by other products (OTHER: REITs, options, private placements, or structured notes) and commodities and futures (CMMFTRE). This result indicates that there is a preference for robo-advisor users to invest in packaged financial products such as ETFs. However, it is also possible that individual investors who used the services of robo-advisors had a preference for the utilization of ETFs because it was suggested by the vendor or the robo-advisor itself. Whether the vendor directed the investor towards investing in ETFs because this vendor is selling those products cannot be confirmed based on the limited data and pool of variables available in the FINRA dataset. However, whether the investor made a certain choice based on the analysis given by the robo-advisor is possible in the sense that the robo-advisor computes the optimal portfolio allocation and types of products based on the behavioral information saved by the investor. From this aspect, a recommendation by the robo-advisor is a reflection of the investor's own predisposition towards ETFs.

Regarding the control variables, the risk-tolerance variables show that people who invest in financial products are, on average, risk-takers. The association is positive and significant for all products other than insurance-based products such as annuities and whole life insurance products. Similarly, subjective financial knowledge was also significant and positively associated with investing in all types of investment products except annuities. Objective financial literacy was positively associated with investments in stocks, ETFs, mutual funds, and other investment products. Yet, it was negatively associated with investments in annuities, whole life insurance products, and commodities. Respondents who made their own investment decisions were positively associated with investing in stocks and other products but were negatively associated with investing in bonds, mutual funds, annuities, and whole life insurance products. In order to assess whether a fee structure was affecting one's investment decision, we also controlled for fixed fees in our regression model. The results indicated that the preference for fixed fees was negatively associated with investing in stocks but positively associated with investing in bonds, mutual funds, ETFs, annuities, and whole life insurance products.

IV. Discussion

Robo-Advisory systems or automated financial advisors are emerging as an alternative to the traditional human-based financial advisory profession (Ji, 2017). Our study suggests that robo-advisor users have certain socio-demographic characteristics and investment preferences. The robo-advisor users were relatively young, with a greater risk tolerance level, and a high subjective financial literacy. However, robo-advisor users were negatively associated with objective financial literacy. These findings are consistent with the results found in Hohenberger, Lee, and Coughlin's (2018) study. Regarding robo-advisor users' investment patterns, robo-advisor users showed a strong preference for ETFs, commodity and futures, as well as other products such as REITs, options, private placements, or structured notes.
Lee and Shin (2018) submit that technological advancements are the greatest innovations in the financial industry. It is evolving towards higher speed, deregulation, and lower cost. Certainly, the current state of the robo-advisory technology had evolved beyond the state in 2015 when our dataset was created. Yet, we argued that the behavioral characteristics of robo-advisor users are exogenous so that their preferences for certain financial products would not change. We acknowledge that our study was constrained because a more recent wave of the dataset with this information regarding the utilization of robo-advisory platforms was not available in the later wave of the FINRA dataset. However, given the rapid growth, adaptation, and changes taking place in the FinTech industry, and more specifically, in the robo-advisor market, future studies need to examine these associations with more recent datasets.

As for prospects of the robo-advising industry, according to a survey by Charles Schwab (2018), it is expected that nearly 58% of Americans are expected to use robo-advisors by 2025. Around 45% said that robo-advisors will have a big impact on financial services, whereby 71% of the respondents still wanted human access on the platform. This was noticeable among Millennials. Around 80% of the Millennials preferred robo-advisers that also had access to human advisors. While Millennials were the primary users of robo-advisors, nearly 46% of the Baby Boomers could find their needs by using a robo-advising platform, and 45% of them presumed to use one by 2025. This survey result validates our findings in the sense that in our empirical analysis (Table 2), older generations were less likely to use a robo-advising platform as compared to the youngest reference group in our sample.

Regarding the current state of robo-advisor users in the population, about 60% of robo-advisor users in the United States are Millennials, and 25% are Generation X people. Most of them expressed that managing their investment portfolio on a robo-advising platform is easy.

According to a report by KPMG (2015), the leading FinTech start-ups are found in China and the United States, whereby China is amongst the largest markets in the credit market. Indeed, as Diemers, Lamaa, Salamat, and Steffens (2015) reported, the FinTech industry's ecosystem should not ignore the role of the government. That is, the FinTech industry should not only focus on technological advancement but also should incorporate best practices that are consistent with the prevailing policies and regulations.

Personalization is key in the robo-advising industry. Indeed, every investor has a different risk tolerance level and has a different portfolio based on one's preferences. While these two aspects are always present in any environment, the emergence of robo-advisors empowered the investor with more optimization tools to build, rebalance, and monitor one's portfolio by reducing the labor cost to human advisors. According to Allayannis and Becker (2019), such a phenomenon of customization, compressed transaction cost, and availability of data-driven optimization tools are the trends that will continue to drive the growth of robo-advising in the near future.

References

Agarwal, S., J. Driscoll, X. Gabaix, and D. Laibson (2009). The age of reason: Financial decisions over the lifecycle with implications for regulation. *Brookings Papers on Economic Activity*, *2*, 51-117

Allayannis, Y., & Becker, Y. M. (2019). *A global FinTech overview*. Darden No. UV7736. Retrieved from https://store.hbr.org/product/a-global-fintech-overview/UV7736

Baker, T., & Dellaert, B. (2017a). *Regulating robo advisors: Old policy goals, new challenges* (Volume 6, Issue 7). Retrieved from University of Pennsylvania, Wharton School website: https://repository.upenn.edu/cgi/viewcontent.cgi?article=1049&context=pennwhartonppi

Baker, T., & Dellaert, B. (2017b). Regulating robo advice across the financial services industry. *Iowa Law Review*, *103*, 713.

Belanche, D., Ariño, L. V. C., & Flavian, C. (2019). Artificial Intelligence in FinTech: Understanding robo-advisors adoption among customers. *Industrial Management & Data Systems*, *119*(7), 1411-1430.

Brown, J. R., & Goolsbee, A. (2002). Does the internet make markets more competitive? Evidence from the life insurance industry. *Journal of Political Economy*, *110*(3), 481-507.

Charles Schwab. (2018). *The rise of robo: Americans' perspective and predictions on the use of digital advice*. Retrieved from https://www.schwab.com/automated-investing/what-is-a-robo-advisor

Cheng, X., Guo, F., Chen, J., Li, K., Zhang, Y., & Gao, P. (2019). Exploring the trust influence mechanism of robo-advisor service: A mixed method approach. *Sustainability*, *11*, 1-20.

Ciccotell, C. S., & Wood, R. E. (2001). An investigation of the consistency of financial advice offered by web-based sources. *Financial Services Review*, *10*, 5-17.

Corporate Financial Institute (CFI). (2020). *Who are the five largest robo-advisors*. Retrieved from https://corporatefinanceinstitute.com/resources/knowledge/trading-investing/the-five-largest-robo-advisors/

Day, M. Y., Cheng, T. K., & Li, J. G. (2018, August). AI robo-advisor with big data analytics for financial services. In *2018 IEEE/ACM International Conference on Advances in Social Networks Analysis and Mining (ASONAM)* (pp. 1027-1031). IEEE.

Diemers, D., Lamaa, A., Salamat, J., & Steffens, T. (2015). *Developing a FinTech ecosystem in the GCC: Let's get ready for take off* (Strategy&). Retrieved from https://www.strategyand.pwc.com/m1/en/reports/developing-a-fintech-ecosystem-in-the-gcc.pdf

Faloon, M., & Scherer, B. (2017). Individualization of robo-advice. *Journal of Wealth Management*, *20*(1), 30-36.

Fan, L., & Chatterjee, S. (2020). The utilization of robo-advisors by individual investors: An analysis using diffusion of innovation and information search frameworks. *Financial Counseling and Planning*, *31*(1), 130-145.

Financial Industry Regulatory Authority (FINRA), Report on Digital Investment Advice (2016), Retrieved from https://www.finra.org/sites/default/files/digital-investment-advice-report.pdf

Fisch, J. E., Labouré, M., & Turner, J. A. (2018). The Emergence of the robo-advisor. *Wharton Pension Research Council Working Papers, 10,* 1-46.

Hicks, C. (2020, December). 10 best robo advisors of 2020. *U.S. News*. Retrieved from https://money.usnews.com/investing/investing-101/slideshows/the-best-robo-advisor-for-different-types-of-investors?slide=11

Hodge, F. D., Mendoza, K. I., & Sinha, R. K. (2020). The effect of humanizing robo-advisors on investor judgements. *Contemporary Accounting Research*, Forthcoming. doi: http://dx.doi.org/10.2139/ssrn.3158004

Hohenberger, C., Lee, C., & Coughlin, J. F. (2018). Acceptance of robo-advisors: Effects of financial experience, affective reactions, and self-enhancement motives. *Financial Planning Review*, *2*(e1047), 1-14.

Ji, M. (2017). Are robots good fiduciaries? Regulating robo-advisors under the Investment Advisors Act of 1940. *Columbia Law Review*, *117*(6), 1543-1584.

Jung, D., Dorner, V., Glaser, F., & Morana, S. (2018). Robo-advisory. *Business and Information Systems Engineering*, *60*(1), 81-86.

Jung, D., Dorner, V., Weinhardt, C., & Pusmaz, H. (2018). Designing a robo-advisor for risk-averse, low-budget consumers. *Electronic Markets*, *28*, 367-380.

Jung, D., Glaser, F., & Köpplin, W. (2019). Robo-Advisory: Opportunities and risks for the future of financial advisory. In: Nissen V. (Eds.), *Advances in Consulting Research* (pp. 405-427). Cham, Switzerland: Springer.

Kobets, V., Yatsenko, V., Mazur, A., & Zubrii, M. (2018, May). Data analysis of private investment decision making using tools of robo-advisers in long-run period. In *ICTERI Workshops* (pp. 144-159).

KPMG. (2015, December 14). *H2 Ventures KPMG FinTech 100: Announcing the world's leading FinTech innovators for 2015*. Retrieved from https://home.kpmg.com/xx/en/home/ insights/2015/12/ventures-kpmg-FinTech-fs.html

Lee, K. Y., Kwon, H. Y., & Lim, J. I. (2017, August). Legal consideration on the use of artificial intelligence technology and self-regulation in financial sector: Focused on robo-advisors. In *International Workshop on Information Security Applications* (pp. 323-335). Cham, Switzerland: Springer.

Lee, I. & Shin, Y. J. (2018). FinTech: Ecosystem, business models, investment decisions, and challenges. *Business Horizons*, *61*, 35-46.

Lusardi, A., & Mitchell, O. S. (2008). Planning and financial literacy: How do women fare? *American Economic Review*, *98*(2), 413-17.

Lusardi, A., & Mitchell, O. S. (2014). The economic importance of financial literacy: Theory and evidence. *Journal of Economic Literature*, *52*(1), 5–44.

Mercadante, K. (2020, December 6). Five ways robo-advisors are changing the investment industry. *Investor Junkie*. Retrieved from https://investorjunkie.com/robo-advisors/5-ways-they-changed-industry/

Neal, R. W. (2019, September). Competition among TAMPs heats up: Financial advisors growing interest in outsourcing is luring new entrants to the Turnkey Asset Management platform space. *Investment News*, September 2-6, 8-11.

Nicoletti, B. (2017) *The Future of FinTech*. Cham, Switzerland: Springer.

Perrin, A., & Duggan, M. (2015). Americans' internet access: 2000-2015. *Pew Research Center*, *26*(6). Retrieved from http://assets.pewresearch.org/wp-content/uploads/sites/14/2015/06/2015-06-26_internet-usage-acress-demographics-discover_FINAL.pdf.

Royal, J. (2020, December). Best robo-advisors in 2020. *Bankrate*. Retrieved from https://www.bankrate.com/investing/best-robo-advisers/

Salo, A. (2017). *Robo advisor, your reliable partner? Building a trustworthy digital investment management service* (Master's thesis).

Salo, M., & Haapio, H. (2017, February). Robo-Advisors and investors: Enhancing human-robot interaction through information design. In *Trends and Communities of Legal Informatics. Proceedings of the 20th International Legal Informatics Symposium IRIS* (pp. 441-448).

Tokic, D. (2018). BlackRock Robo-Advisor 4.0: When artificial intelligence replaces human discretion. *Strategic Change*, *27*(4), 285-290.

Uhl, M. W., & Rohner, P. (2018). Robo-Advisors versus traditional investment advisors: An unequal game. *Journal of Wealth Management*, *21*(1), 44-50.

Wang, A. (2009). Interplay of investors' financial knowledge and risk-taking. *Journal of Behavioral Finance*, *10*(4), 204-213.

Woodyard, A. S., & Grable, J. E. (2018). Insights into the users of robo-advisory firms. *Journal of Financial Service Professional*, *72*(5), 56-66.