Insights into the Users of Robo-Advisory Firms

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ABSTRACT

Robo-advisory firms have established a growing presence in the marketplace in the past several years and, while limited in use, have appeal for young, technologically savvy consumers. This analysis of American investors considers the characteristics of those who exclusively use robo-advisory services and how they differ from those who exclusively use brokers and financial advisors. Results indicate users of robo-advisory services are young and confident in their financial abilities yet distrustful of traditional channels of financial advice.

Vol. 72, No. 5 | pp. 56-66

This issue of the Journal went to press in August 2018.

Introduction

The concept of consumers using the services of a robo-advisor—an internet-based automated service—to obtain financial planning advice and implement financial planning decisions was little more than a theoretical possibility 2 decades ago. Today, however, the role of robo-advisors is becoming more ingrained within the consumer finance domain. Broadly defined, a robo-advisor is any online automated investment, financial advisory, or financial planning service that is primarily intended to serve the needs of the mass market or non-high-net-worth market. The principal advantage offered by robo-advisors is low-cost access to information and trading platforms.[1]

Although robo-advisors are generally considered to be a core type of service provider within the financial services marketplace, the actual amount of assets under management held at these firms is still relatively modest. In 2016, robo-advisors held approximately $300 billion in client assets. Compare this with Bank of America's Merrill Lynch, which controlled over $2 trillion in assets under management in 2016. This situation is likely to change over the next 2 decades. Based on data released by A.T. Kearney, assets under management at robo-advisors are expected to increase to more than $2 trillion in 2020, while others project assets managed by robo-advisors to exceed $4 trillion.[2] Much of this growth is expected to come from a shift in assets away from traditional financial service firms and financial planners.

Even though there have been numerous attempts to describe the market for robo-advisory services, there are still questions related to who is more likely to use a robo-advisor as compared with a traditional service provider such as a stockbroker or other financial advisor. What is known comes from work of firms like A.T. Kearney.[3] A team of researchers at the firm provided insights into who is likely to use robo-advisory services. Specifically, robo-advisory services tend to be utilized by those who are under age 35 with a higher-than-average degree of financial knowledge. Traditional financial service firms, on the other hand, tend to be preferred by those who are older (nearing retirement), risk averse, and less knowledgeable.[4]

This study was designed to test whether these profiles are accurate and to add to the field's knowledge of help-seeking preferences by describing who prefers using the services of a robo-advisor compared with a traditional financial services advisor or firm. This study is unique in that it is based on responses from more than 1,000 investors who actively held and traded investment assets at the time of the survey. The remainder of this paper provides a background review of the types of variables often used to differentiate help-seekers. This is followed by a description of the study methodology and results, and a discussion of findings.

Background Review

The first firms to have developed what is now known as the robo-advisory market were entirely based on an Internet interface. These firms offered basic services that were priced in a way that allowed almost anyone with some assets to gain access to the markets. The true selling points were low transaction costs and maximum ease of access.[5] Continuing to the present time, robo-advisors have developed a unique advantage in being able to pass along savings to clients by eliminating, for the most part, direct human interaction. It is important to note, however, that robo-advisors have recently expanded services to include more human interaction. Even so, for those willing to deal in an online environment, the process of automating data collection, data analysis, recommendation formulation, implementation, and monitoring (i.e., the primary steps involved in the financial planning process) allows for low-cost service. It is now possible for a consumer to obtain not only investment advice through a robo-advisor, but also guidance on any number of subjects, including taxes, mortgage financing, legal issues, education funding, retirement planning, financial counseling, and other financial planning topics. Some have noted that one goal of robo-advisory firms is to supplant traditional financial service professionals in an attempt to make financial advisory services available to the most number of individuals and households possible.[6]

Whether this aspiration will ever come to fruition is still being debated. At a minimum, it will take decades to determine the true impact of robo-advisory services. Some have argued, for example, that the robo-advisory revolution may be more hype than reality. A recent critique of robo-advisors noted that while robo-advisory services do help in reducing transaction costs, these services do so with limited consumer transparency.[7] That is, consumers often do not know if the advice provided is based on a suitability standard, a fiduciary basis, or a biased structure formed around undisclosed conflicts of interest. To date, the Securities and Exchange Commission (SEC) has yet to make a determination about the fiduciary status of robo-advisory firms. This has not deterred some consumers from using only robo-advisors for advice, implementation, and monitoring of financial plans although the SEC, in a statement earlier this year, indicated that the agency was aware of issues related to the suitability of some robo-advisory recommendations.[8]

Determinants of Help-Seeking Behavior

Robo-advisor users tend to be younger and more technologically advanced than those who rely on traditional advisory services.[9] The primary outcome associated with this study was to determine whether this commonly held profile of robo-advisory users—younger with more knowledge—matches the typology of consumers who are actively engaged in managing household assets. The financial help-seeking literature was used to obtain a broader description of the factors that can be used to differentiate advisor choice behavior. In this study, help-seeking refers to the choice of using either a robo-advisor or a traditional advisory service.

When viewed broadly, the literature suggests that common demographic and socioeconomic factors often help shape help-seeking behavior. According to Gentile et al., household income and investment wealth set apart those who work with a paid professional from those who seek lower-cost help solutions.[10] Age (younger), gender (men), education (higher), and race (white) tend to be general descriptors of those who seek advice and guidance from financial professionals. Other than age and education, little is known about the effect these variables have on the selection of robo-advisory services compared to traditional services.

Behavioral and attitudinal factors can also shape help-seeking behavior. To date, nearly all studies devoted to the topic of help-seeking in the financial services domain have compared and contrasted professional help providers against free or low-cost providers, such as friends, colleagues, and family members. This makes it difficult to develop hypotheses about the effect of certain variables in describing who is more or less likely to use a robo-advisor. Even so, the literature does indicate that subjective and objective financial knowledge, confidence, and expectations are likely related to help-seeking behavior.[11]

If this study were designed to describe the typical person who uses the services of a professional financial advisor, the profile would look like this: high income with a significant portion of wealth in investment assets, well educated, and knowledgeable (when measured as a subjective opinion). Beyond age and education, it is difficult to describe the profile of a user of robo-advisory services. Although unlikely, the profile may look similar to that of someone who uses a traditional advisory service. An outcome of this study was to provide such as profile.

Methods

Data for this study were obtained from the most recent 2015 FINRA Investor Education Foundation National Financial Capability Study (NFCS), which has been administered since 2009 and has been repeated every 3 years. The sample included 2,000 adults over the age of 18 who also completed the 2015 State-by-State NFCS Survey and indicated that they had investments outside of retirement accounts. For the purposes of this study, respondents were required to be the primary decision maker or the person who shared decision-making responsibilities regarding investments in the household. The selected sample was a subset of the larger state-by-state survey. Respondents were selected at random from three online panels. According to the FINRA Investor Education Foundation, these panels were designed to validate the inclusion of respondents based on current demographic characteristics. The survey instrument was delivered and completed using a website link during summer of 2015. Findings reported in this study were weighted to approximate the U.S. population in terms of age and education. No additional weighting was used to account for nonresponse bias. Given missing data and coding limitations, the final sample size used in the study was 1,152.

Data Analysis Approach

Given the exploratory nature of the study, and the lack of a clear set of hypotheses regarding the profile of robo-advisor users, this study used a computer learning system that created rules to classify respondents into one of two groups: those who use traditional financial advisory services and those who use robo-advisory services. The two groups were mutually exclusive. Respondents were first asked, "Which of the following information sources do you use when making an investment decision?" Those who answered "stockbrokers" and "financial advisors" were classified together as traditional help-seekers. Respondents were then asked to indicate if they had "…ever used an automated financial adviser that provides investment advice and makes trades on your behalf?" Answers were coded: 1 = yes and 2 = no. Those who indicated "yes" were called robo-advisory help-seekers. Within the larger sample, it was possible to be both a traditional and robo-advisory help-seeker. To make the classification system more accurate, those who used both services were omitted from the analysis. Coding for the help-seeking variable was 1 = used a broker/advisor and 2 = used a robo-advisor. The two groups were mutually exclusive.

Table 1 shows the variables that were used in the computer learning system analysis. The table also indicates the distribution of respondents across each variable and the way the variables were coded for statistical purposes.

A computer learning system is sometimes referred to as a decision tree.[12] A decision tree analysis procedure is designed to derive a set of decision rules based on multiple samples from a data set. The goal of the process is to identify variables that create the best classification system. Typically, a decision tree is presented. The tree begins with a root node that shows how the original sample was distributed. In this study, approximately 5 percent of respondents reported working only with a robo-advisor. This low percentage was not surprising. Even though robo-advisory services have grown quickly over the past decade, the nationwide impact of robo-advisors continues to be limited. Given the weighted nature of the sample, it is reasonable to conclude that no more than 5 percent of the investing public was using solely a robo-advisor in 2015.

After the root node (node 0), a series of exclusive subsets of data are categorized according to a variable (called child nodes). The most important variables for use in classifying respondents into a category are presented at the top of the tree; the least important are near the bottom. A classification and regression tree (C&RT) method was used in this study. The C&RT model used Gini splits based on maximization of the homogeneity of the child nodes with respect to the value of the target variable. The Gini measure was based on squared probabilities of grouped membership for each target category. Given the sample size, the minimum number of cases per node was 25, with each child node set at 15. The maximum tree depth was limited to five levels.

Once the C&RT decision tree was identified, the significant variables in the model were validated using a logistic regression procedure. The outcome variable in the logistic regression was the source of help: 1 = traditional financial advisory service or 2 = robo-advisory service.

Results

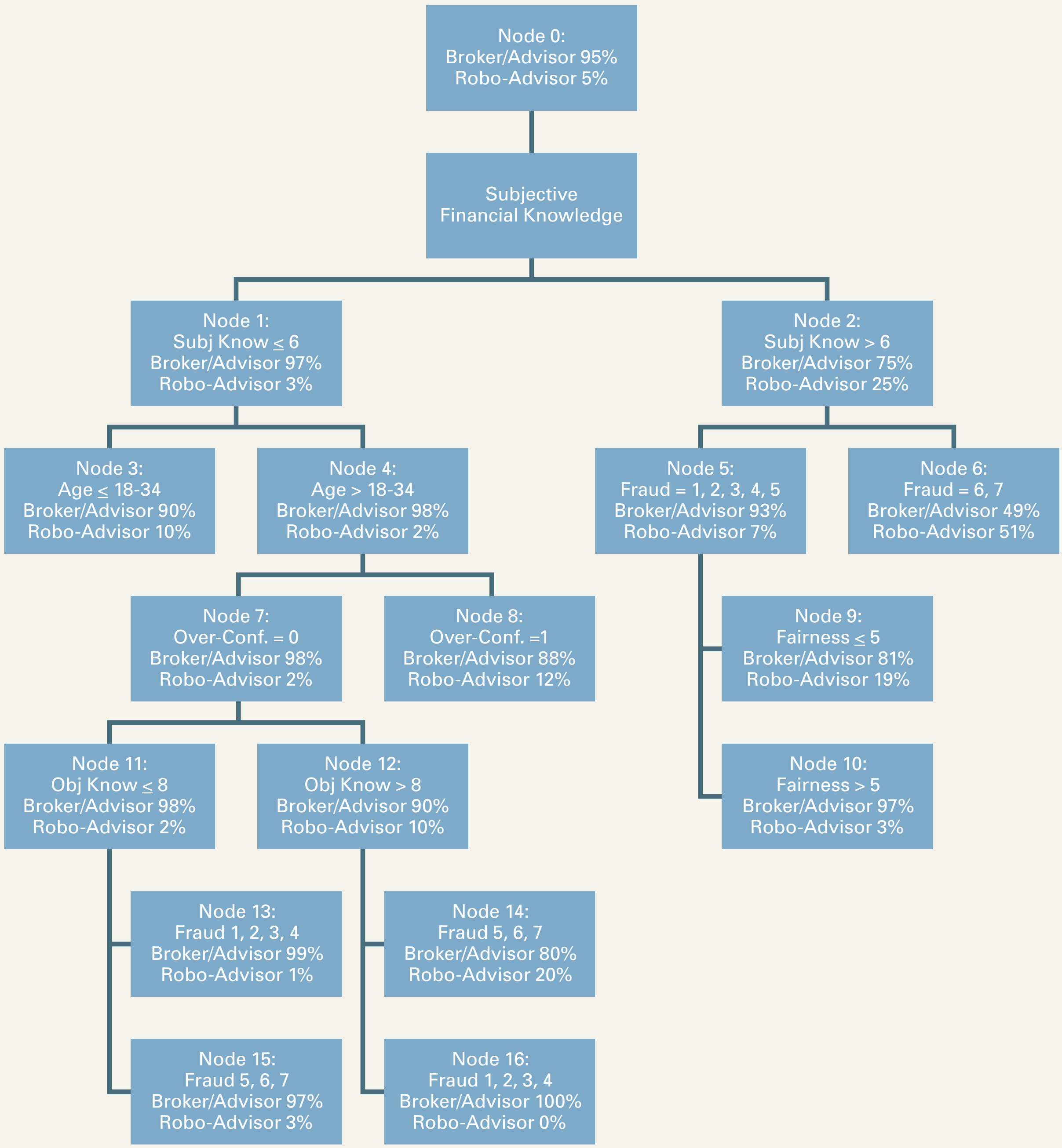
Figure 1 shows the results of the C&RT analysis weighted to represent the U.S. population. As noted previously, 95 percent of respondents self-identified as using a traditional financial advisory service, whereas 5 percent were exclusively robo-advisory users. Information in Figure 1 can be used to better understand the similarities and differences between these two groups.

To begin with, subjective financial knowledge was the best discriminating variable in the model. As shown in node 1, those with a financial knowledge equal to or less than 6 (on a scale of 1 to 7) were more likely to use a traditional help provider. Only 3 percent of those with this level of subjective knowledge reported using a robo-advisory service. Following the tree downward, age was the next-best classifier among those with a subjective knowledge equal to or less than 6. Those in the 18-to-34 age group (node 3) were slightly less likely to use a traditional advisor. Older respondents (node 4) were less likely to use a robo-advisor. Being overconfident was the next-best classifier. As shown at node 8, those who were older with less subjective financial knowledge but who were overconfident in their knowledge were less likely to use a traditional financial advisory service. Those with the same characteristics who were not overconfident were more likely to use a traditional advisor. The effect of knowledge can be seen at nodes 11 and

TABLE 1
Descriptive Statistics for the Independent Variables (n = 1,152)

Variables	Distribution	Mean (SD)	Coding
Gender			1 = Male; 2 = Female
Male	55.1%		
Female	45.0%		
Age			
18 to 34 years	16.2%		1
35 to 54 years	31.6%		2
55+ years	52.3%		3
Ethnicity			1 = White; 0 = Other
White	80.3%		
Nonwhite	19.7%		
Education			1 = Some college or less; 2 = College (bachelor's)
Some college or less	39.0%		
College (bachelor's) or more	61.0%		
Income			
< $50,000	21.0%		1
$50,000 to $100,000	44.7%		2
$100,000 +	34.4%		3
Value of investments			
<$2,000	5.1%		1
$2,000 to <$5,000	4.3%		2
$5,000 to <$10,000	5.8%		3
$10,000 to <$25,000	7.3%		4
$25,000 to <$50,000	8.1%		5
$50,000 to <$100,000	15.0%		6
$100,000 to <$250,000	19.9%		7
$250,000 to <$500,000	15.9%		8
$500,000 to <$1,000,000	10.5%		9
$1,000,000 or More	8.0%		10
Risk tolerance			1 = Some risk; 0 = No risk
Some risk	90.5%		
No risk	9.5%		
Long-term market confidence		M = 7.05 (SD = 2.03)	1 = Not at all confident; 10 = Extremely confident
Confidence in fairness of markets		M = 5.81 (SD = 2.47)	1 = Not at all confident; 10 = Extremely confident
Importance of fees		M = 8.20 (SD = 1.89)	1 = Not at all important; 10 = Extremely important
S&P 500 Market Expectations			
<0%	1.2%		1
0% to 4.9%	18.%		2
5% to 9.9%	50.%		3
10% to 14.9%	18.6%		4
15% to 19.9%	6.7%		5
20% or more	4.5%		6
Worry about investment fraud		M = 3.92 (SD = 1.81)	1 = Strongly disagree; 7 = Strongly agree
Comfort with investments		M = 7.09 (SD = 1.97)	1 = Not at all comfortable; 10 = Extremely comfortable
Subjective financial knowledge		M = 4.86 (SD = 1.39)	1 = Very low; 7 = Very high
Objective financial knowledge[15]		M = 4.66 (SD = 2.23)	0 = None correct; 10 = All correct
Overconfident[16]			
Yes	16.0%		1
No	84.0%		0
Underconfident			
Yes	15.6%		1
No	84.4%		0
Nonbiased confidence			
Yes	68.0%		1
No	32.0%		0

FIGURE 1
Weighted Classification and Regression Tree Classifying Traditional and Robo-Advisory Users



12. At node 11, those with less objective knowledge reported using a traditional advisory service. Those with the highest levels of objective knowledge were less likely to use a traditional financial advisor. The last classifier was fear of investment fraud. Following node 11, those who were less worried about fraud (node 13) were slightly more likely to seek help from a traditional advisor, compared to those at node 14. Similarly, following node 12, none of the respondents with little fear of fraud reported using a robo-advisor, whereas those who had some fear of fraud (node 15) were a bit more likely to use a robo-advisor. It is important to keep in mind, however, that this classifier, being at the bottom of the tree, was not particularly powerful as a classification factor.

The right side of Figure 1 shows the profile of respondents who were more likely to use a robo-advisor. After subjective financial knowledge (node 2), fear of investment fraud was the next-best classification variable. Those with high subjective knowledge and elevated levels of fear (node 6) were more likely to use a robo-advisor. At Node 5 the opposite was true. Respondents with higher levels of subjective financial knowledge and low to modest fear of fraud

TABLE 2
Importance of Each Variable in the Classification and Regression Tree Model

Independent Variable	Importance	Normalized Importance
1. How strongly do you agree or disagree with the following statement?—I am worried about being victimized by investment fraud.	0.009	100.0%
2. On a scale from 1 to 7, where 1 means very low and 7 means very high, how would you assess your overall knowledge about investing?	0.008	90.1%
3. Overconfident	0.007	79.5%
4. Objective knowledge	0.007	79.3%
5. Age	0.007	78.2%
6. What is the approximate total value of all your investments in nonretirement accounts?	0.005	61.1%
7. How confident are you that U.S. financial markets…are fair to all investors?	0.005	52.6%
8. Ethnicity	0.002	27.4%
9. What do you expect the approximate average annual return of the S&P 500 stock index to be over the next 10 years (without adjusting for inflation)?	0.002	25.9%
10. Household income	0.002	20.2%
11. Gender	0.002	18.5%
12. How important to you were the fees and pricing structure when opening your nonretirement investment account(s)?	0.001	14.8%
13. How confident are you that U.S. financial markets…—[o]ffer good long-term opportunities for investors?	0.000	3.9%
14. How comfortable are you when it comes to making investment decisions?	0.000	3.0%
15. Unbiased confidence	0.000	0.9%
16. Underconfident	0.000	0.9%
17. Education	0.000	0.9%

were more likely to work with a traditional financial advisor. Following node 5, confidence in the fairness of markets emerged as a useful classification factor. Respondents with high subjective knowledge, low to moderate fear of fraud, but lower confidence in the fairness of the markets, were less likely to use a traditional advisor. At node 10, those fitting the same general profile who felt the markets were generally fair were less likely to report working with a robo-advisor. Table 3 provides a tabular review of the findings.

As a model, the C&RT was able to accurately predict respondent classification 95 percent of the time. Given the sample dispersion, it is not surprising that the greatest accuracy was among those who used a traditional financial advisory service. Table 2 provides a summary of the importance of each variable included in the model. Two statistics are shown. The importance of each variable is represented by a figure showing the contribution an item provided to the explanation of the difference between the two groups. The normalized importance figure represents the same information as a percentage of magnitude within the model. Given that worry about investment fraud was used multiple times in the model, its importance emerged as the most notable classification variable.

Table 3 shows the results from the confirmatory logistic regression. The regression was run to verify the classification split variables shown in Figure 1. The dependent variable was coded 1 = used a robo-advisor, otherwise 0. For the purposes of the regression, the significant variables in Figure 1 were included as independent variables in the model. The model was statistically significant (χ^2 = 97.80, p < .001). The Hosmer-Lemeshow test was not significant (χ^2 = 8.22, p =.41), suggesting no evidence of a poor fit. The overall model prediction classification was close to 96 percent.

Surprisingly, subjective financial knowledge was not significant in the model, even though it was the primary split variable in the C&RT model. The lack of statistical significance was likely related to the effects of the three significant variables, although it should be noted that there was a high correlation between subjective financial knowledge and overconfidence (r = 0.57). Older respondents were less likely to use a robo-advisor. Those who worried about investment fraud were more likely to use a robo-advisor, as were those who exhibited overconfidence in their financial knowledge. This last effect may have canceled out the effect of subjective financial knowledge. Although important in the C&RT, confidence in the

TABLE 3
Confirmatory Logistic Regression Results

	B	*S.E.*	*Wald*	*df*	*Exp(B)*
Subjective financial knowledge	0.150	.198	.572	1	1.161
Age	–0.867***	.207	17.582	1	.420
Worry about investment fraud	0.332***	.098	11.373	1	1.394
Overconfidence	1.179*	.505	5.458	1	3.250
Confidence in fairness of markets	0.054	.074	.540	1	1.056
Objective financial knowledge	0.052	.086	.368	1	1.054
Constant	–4.262***	1.105	14.870	1	.014

Notes: ***p < .001; χ^2 = 97.80, Nagelkerke R^2 = .26

fairness of the markets and objective financial knowledge were not significant in the regression.

A second logistic regression was run as a robustness check. When overconfidence was excluded as a variable in the regression, subjective financial knowledge was significant in the model. As shown in Table 4, age was negatively associated with the use of a robo-advisor, whereas robo-advisor users were more likely to be worried about investment fraud. These findings indicate that financial knowledge, either subjectively measured or proxied by overconfidence, is an important factor associated with the use of robo-advisory services.

Discussion

The first interface between technology and the financial services sector, for most consumers, occurred through an automated teller more than 40 years ago. Since that time, numerous advances have been made in linking human financial decision making with automated systems. Today, robo-advisory services have entered the marketplace and show every indication of becoming an entrenched provider of financial advice, either as a complete service provider for consumers or as an entry path to a more personalized financial services program. The appeal of robo-advisory services appears to be stronger for younger consumers and those with more confidence in their ability to manage financial matters. There may indeed be some self-selection involved among younger consumers as their use of any financial advisor indicates awareness of the need for financial services beyond those required to meet basic needs.

One of the most interesting insights from this analysis is the role of perceived fraud within the financial services industry as an indicator of robo-advisory use. Investors are known to react to negative shocks to trust by moving assets to less risky investments and by shying away from financial advisors.[13] This may be an indication of past instances, either as an individual or vicariously through a family member or acquaintance, of a negative experience with a financial professional. Exposure to a negative experience, recognition of the need for financial services, confidence in one's own ability, and the appeal of a perceived neutral player in the form of a highly sophisticated financial tool make the robo-advisor channel attractive to some consumers. Traditional financial advisors have an opportunity to capitalize on this by adopting strict practice standards and by providing a website link to a regulatory site such as FINRA BrokerCheck to attract clients who may have been previously exposed to negative advisory outcomes.

The distinction between a consumer's confidence in his or her ability to handle financial issues and overconfidence, as related to objective financial knowledge, has interesting implications for the use of robo-advisors. Overconfidence can lead to riskier behavior at

TABLE 4
Logistic Regression Model Omitting Overconfidence

	B	*S.E.*	*Wald*	*df*	*Exp(B)*
Subjective financial knowledge	0.483***	0.146	10.940	1	1.621
Age	–0.842***	0.201	17.535	1	0.431
Worry about investment fraud	0.354***	0.096	13.521	1	1.424
Confidence in fairness of markets	0.099	0.085	1.352	1	1.104
Objective financial knowledge	–0.048	0.078	0.386	1	0.953
Constant	-5.762***	1.080	28.467	1	0.003

Notes: ***$p < .001$; $\chi^2 = 92.32$, Nagelkerke $R^2 = 0.24$

least when dealing with current financial issues such as cash management and credit card usage.[14] From the results of this study, it appears that users of robo-advisors are more likely to be in the overconfident category. However, as shown in the confirmatory logistic regression that omitted overconfidence, those who seek help from robo-advisors have significant levels of subjective financial knowledge and confidence in the markets.

Financial professionals can take note that the propensity of younger, more financially confident consumers' use of robo-advisors does not mean that traditional financial service channels are in jeopardy. On the contrary, there is much to encourage those who provide traditional services based on person-to-person interactions. Younger consumers who are wary of being "burned" by the financial services industry, as they may have seen happen with others, appear to have confidence in channels of financial advice that project neutrality associated with the quality of advice. The perceived neutrality and quality of the advice available through robo-channels may be an assumption made by these consumers. However, there may be a message for financial service providers that young consumers in search of guidance in the financial markets are seeking high-quality advice. A potential challenge for traditional providers of financial services, going forward, may be making a stronger case for the value added through traditionally provided services. As current clients transition out of the marketplace, replaced by those who have known nothing but robo-advisors, some financial service professionals may need to become more proactive in describing their market value and leveraging their own use of technology. Whereas the existing clients may have been intimidated by the overt use of technology in financial planning, the younger generation may see it as reassuring and as evidence of latest and best practices employed in financial planning solutions.

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(15) Objective financial knowledge was measured with the following questions:

1. In general, investments that are riskier tend to provide higher returns over time than investments with less risk.
   True: 76%; False: 14%; Don't know: 9%
2. If you buy a company's stock:
   (a) You own a part of the company: 73%
   (b) You have lent money to the company: 14%
   (c) You are liable for the company's debts: 1%
   (d) The company will return your original investment to you with interest: 6%
   (e) Don't know: 5%
3. If you buy a company's bond:
   (a) You own a part of the company: 10%
   (b) You have lent money to the company: 65%
   (c) You are liable for the company's debts: 4%
   (d) You can vote on shareholder resolutions: 5%
   (e) Don't know: 16%
4. Over the last 20 years in the U.S., the best average returns have been generated by:
   (a) Stocks: 55%
   (b) Bonds: 8%
   (c) CDs: 2%
   (d) Money market accounts: 6%
   (e) Precious metals: 8%
   (f) Don't know: 19%
5. If a company files for bankruptcy, which of the following securities is most at risk of becoming virtually worthless?
   (a) The company's preferred stock: 13%
   (b) The company's common stock: 53%
   (c) The company's bonds: 15%
   (d) Don't know: 19%
6. Which of the following best explains why many municipal bonds pay lower yields than other government bonds?
   (a) Municipal bonds are lower risk: 32%
   (b) There is a greater demand for municipal bonds: 10%
   (c) Municipal bonds can be tax-free: 34%
   (d) Don't know: 23%
7. What has been the approximate average annual return of the S&P 500 stock index over the past 20 years (not adjusted for inflation)?
   (a) –10%: 0%
   (b) –5%: 2%
   (c) 5%: 25%
   (d) 10%: 26%
   (e) 15%: 7%
   (f) 20%: 4%
   (g) Don't know: 36%
8. You invest $500 to buy $1,000 worth of stock on margin. The value of the stock drops by 50%. You sell it. Approximately how much of your original $500 investment are you left with in the end?
   (a) $500: 21%
   (b) $250: 35%
   (c) $0: 23%
   (d) Don't know: 20%
9. Which is the best definition of "selling short"?
   (a) Selling shares of a stock shortly after buying it: 11%
   (b) Selling shares of a stock before it has reached its peak: 20%
   (c) Selling shares of a stock at a loss: 26%
   (d) Selling borrowed shares of a stock: 21%
   (e) Don't know: 22%
10. Which of the following best explains the distinction between nominal returns and real returns?
   (a) Nominal returns are pre-tax returns; real returns are after-tax returns: 12%
   (b) Nominal returns are what an investment is expected to earn; real returns are what an investment actually earns: 21%
   (c) Nominal returns are not adjusted for inflation; real returns are adjusted for inflation: 12%
   (d) Nominal returns are not adjusted for fees and expenses; real returns are adjusted for fees and expenses: 9%
   (e) Don't know: 44%

(16) Financial overconfidence, underconfidence, and unbiased confidence were calculated by using objective financial knowledge scores to predict subjective knowledge scores (i.e., "On a scale of 1 to 7, where 1 means very low and 7 means very high, how would you assess your overall knowledge about investing?"). The ordinary least squares regression model was statistically significant ($F_{1,1986} = 125.22$, $p < .001$). The predicted unstandardized value (i.e., predicted knowledge score) was saved for each respondent. The predicted mean, across the sample, was 4.85 ($SD = .34$). This score was then subtracted from each respondent's subjective financial knowledge score. Positive scores indicated knowledge overconfidence, whereas negative scores indicated knowledge underconfidence. Scores were then recoded so that anyone with a knowledge confidence score greater than one standard deviation as being overconfident (coded 1; otherwise coded 0). Those whose score was one standard deviation or lower were categorized as underconfident (coded 1; otherwise coded 0). Everyone else was classified as unbiased in terms of financial knowledge.