Do As I Say, Not As I Do:
An Analysis of Portfolio Development Recommendations Made by Financial Advisors

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John E. Grable, Ph.D., CFP®[iii]

Dr. John Grable is a professor of financial planning at the University of Georgia.

Amy Hubble, Ph.D., CFA, CFP®

Dr. Amy Hubble is the Principal Investment Advisor at Radix Financial, LLC.

Michelle Kruger, ABD

Michelle Kruger is an assistant professor of finance at Loras College.

205 Dawson Hall
Department of Financial Planning, Housing and Consumer Economics
University of Georgia
Athens, GA 30677

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ABSTRACT

Based on a survey of over 200 financial professionals who were asked to describe how they assess, rank, and use client characteristics and risk profiling inputs when constructing asset allocation recommendations, findings suggest that in a scenario free context, financial advisors rank a client's time horizon as the most important risk profiling input. However, when viewed in the context of a specific client scenario; financial advisors appear to alter the importance of certain risk profiling inputs, becoming over reliant upon a client's age and employment status. Results from this study also show that financial advisors are somewhat inconsistent in their use of risk profile inputs across client scenarios; however, findings indicate that older financial advisors with more experience are more apt to consistently recommend portfolios with higher equity ratios than their younger counterparts.

Key Words: Asset Allocation, Risk Tolerance, Portfolio Management, Financial Planning

JEL classification: D14, D81, D9, G11, G41

How do financial advisors arrive at portfolio allocation recommendations for clients? Researchers have been asking this question for over a century. Numerous answers have been proffered. During the first half of the 20th century, financial advisors argued that the allocation choice should primarily be built upon an investor's goal time horizon. This evolved into the widely used "100 – age" rule (Bernstein, 2005; Shiller, 2006). This rule states that an investor should allocate the result of the calculation towards equities (or other risky assets), with the remaining balance allocated to fixed-income and low volatility assets. For example, based on the rule, someone who is age 40 should allocate 60% of portfolio assets into equities and 40% of assets into fixed-income and cash investments. Economics and finance researchers working during the middle part of the 20th century concluded that the "100 – age" rule, and similar practice-derived heuristics, tend to be overly simplistic and often biased. This conclusion lead to the development of numerous normative portfolio allocation theories, most of which are still in use today (Ameriks and Zeldes, 2004).

Although asset allocation modelling tools and techniques have been proposed, few answers have been provided over the years that adequately describe how financial advisors arrive at a portfolio allocation recommendation in practice. Rather than describe how financial advisors arrive at allocation decisions, the thrust of the literature has been devoted to describing how financial advisors should make these decisions (Hickman, Hunter, Byrd, Beck, and Terpening, 2001; Van de Venter and Michayluk, 2007). The general consensus is that financial advisors should use a multi-factor mean-variance efficient model supplemented by the use of a risk tolerance questionnaire (or measure of constant relative risk aversion), as well as household and macroeconomic data and circumstances. It is generally thought that the way in which these and other inputs are assessed and ranked by financial advisors ultimately shapes portfolio decisions and recommendations.

The present study was undertaken for four reasons. First, to identify how financial advisors *rank* risk profile inputs when considering asset allocation decisions for clients. Second, to describe the way financial advisors *weigh* these inputs when faced with a portfolio allocation decision. Third, to determine how consistent financial advisors are in their use of risk profile inputs across client scenarios, and fourth, to create a profile of financial advisors who reliably allocate assets across client scenarios. The remainder of this paper describes the conceptual background of the study, the methodology used to obtain and analyze the data, results related to the paper's purposes, and a discussion of findings.

CONCEPTUAL BACKGROUND AND LITERATURE REVIEW

Financial advisors tend to rely on one (or a combination of) of three methodologies when developing asset allocation recommendations for individual investors: (1) goals-based mean-variant efficient models, (2) heuristic models and tools, and/or (3) professional judgement. Each is described below.

The primary normative asset allocation modelling approach was introduced by Markowitz in 1952. Markowitz argued that investors should develop portfolio allocation decisions primarily based on the optimal expected variance of returns for a given level of risk aversion. What emerged from this recommendation was a methodological approach based on identifying mean-variance efficient portfolios. Campbell and Viceira (2002) explained the outcome associated with this modeling approach as follows:

> The striking conclusion of this analysis is that all investors who care only about mean and standard deviation will hold the same portfolio of risky

assets, the unique best mix of stocks and bonds. Conservative investors will combine this portfolio with cash to achieve a point on the mean-variance efficient frontier that is low down and to the left; moderate investors will reduce their cash holds, moving up and to the right; aggressive investors may even borrow to leverage their holdings of the tangency portfolio, reaching a point on the straight line that is even riskier than the tangency portfolio. But none of these investors should alter their relative proportions of risky assets in the tangency portfolio" (p. 2).

This last point is known as the mutual fund theorem (Tobin, 1958) or the separation theorem (Cass and Stiglitz, 1970). While it remains true that a risk-seeking investor should allocate more of her or his portfolio towards riskier equities compared to a more risk averse investor, Tobin (1958) argued that the composition of assets should be the same for all investors, regardless of risk tolerance, preferences, or other circumstances. Canner, Mankiw, and Weil (1997) reported that few investors actually follow the separation theorem. Canner et al. called this the 'asset allocation puzzle.' Canner and his associates noted that financial advisors, at the time of their study, routinely recommended a higher ratio of bonds to stocks than is appropriate or necessary.

While it is normatively true that the portfolios of all investors can be developed using a linear combination of assets, regardless of an investor's initial wealth level or other constraints (Dybvig and Liu, 2016), this does not appear to be what investors and their financial advisors do in practice. In their study, Canner et al. (1997) documented that few financial experts recommend allocations that match predictions made using the separation theorem. Nearly all financial advisors allocate increasing levels of assets to fixed-income assets as an investor's risk tolerance declines—a procedure described in the theorem—but that the level of fixed-income holdings generally exceeds optimality. Canner et al. attempted to explain this decision-making approach but were unable to fully justify the tendency by financial advisors to make the allocation process systematically more complicated than it should be in practice.

This helps explain the use of the second portfolio development methodology among some investors: heuristic models. Heuristic models help financial advisors simplify the decision-making process by eliminating inputs that are thought to be of minor importance or redundant (Jacobs, Müller, Weber, 2014). One reason heuristic approaches are used is that classical optimization approaches often fail to work efficiently when multiple constraints are entered into models (Billi and Këllezi, 2000). Examples of heuristic optimization include simulated annealing (Kirkpatrick, Gelatt, and Vecchi, 1983), genetic algorithms (Holland, 1975), and threshold accepting (Dueck and Scheuer, 1990). Other heuristic portfolio modelling techniques include GDP weighting, market weighting, equal weighting, minimum-variance allocation, and broad allocation benchmark weighting (e.g., 60% stocks, 25% bonds, and 15% cash) (Chaves, Hsu, Li, and Shakernia, 2011). As noted by Jacobs et al. (2014), these heuristic asset allocation rules can improve investor performance compared to a single asset class portfolio. Additionally, the use of heuristic approaches does not automatically lead to lower risk-adjusted returns compared to traditional optimization models.

While a heuristic model can accelerate the analysis stage of the recommendation development process, this often comes at the expense of accuracy (Hickman et al., 2001). Consider the oldest and widely used portfolio allocation heuristic: the "100-age rule" (Gilli and Kellezi, 2000; Hickman et al., 2001; Shiller, 2006). While making the allocation decision quite simple, the 100 – age rule fails to account for increasing longevity, financial capacity, or an investor's willingness to take risk. The rule is shaped by the assumption that as one ages, the time remaining to recoup losses declines, making it important to preserve capital by shifting assets from volatile investments to more price stable assets. Another important criticism of heuristic rules and models is that the concepts of returns and variation associated with assets tends to be underrepresented. As such, the use of the 100-age heuristic approach to crafting an asset allocation framework is rarely advocated (Huber and Kaiser, 2003),

In practice, many financial advisors employ a third methodology when building portfolio allocation recommendations: professional judgement. Even within a mean-variance efficient framework, professional judgement comes into play frequently. Consider the way in which an investor decides on an appropriate portfolio along the efficient frontier. Campbell and Viceira (2002) noted that this decision is almost always influenced by an investor's age, risk capacity (as measured by human capital and wealth), goal time horizon, and risk attitude. Carr (2014) and Nobre and Grable (2015) argued that there are other inputs to consider, including an investor's (a) past investing behavior, (b) financial knowledge, (c) risk perceptions and preferences, (d) market expectations, and (e) risk need or the level of return required to reach a financial goal. For those financial advisors who do not estimate an investor's utility function, at a minimum, it is the way in which a financial advisor blends these inputs together that shapes the decision of which portfolio on the efficient frontier is chosen.

The literature is relatively silent in explaining the most appropriate ways in which an investor should combine investor characteristics and other risk profile inputs into an asset allocation recommendation, although some regulators have attempted to provide guidance on this issue.[iii] Even less has been discussed in relation to describing how financial advisors go about assessing, ranking, and weighing risk profile inputs.[iv] Given the realities that (a) nearly all financial advisors use professional judgement to one extent or another when developing portfolio recommendations and (b) many of the factors used by financial advisors in qualitative estimations are also associated with inputs into mean-variance efficient choices, it seems appropriate to gain a better understanding of the way in which financial advisors conceptualize risk profile inputs associated with the asset allocation process. An anticipated outcome associated with this study was to address this need in the literature.

METHODOLOGY

Data for this study were collected using an online survey that was distributed to financial advisors via email invitations distributed by the research team. A snowball sampling technique was then used to recruit additional participants. Specifically, initial participants were encouraged to recruit additional respondents. The survey was distributed during a two-month period during late spring 2017. It is important to note that this sampling technique is subject to an online-preference bias and non-respondent bias. As such, the sample and results should be considered exploratory.

The survey consisted of questions that queried participants about their demographic and professional background. Over 200 financial professionals provided responses to the survey questions. Surveys that were started but not completed were removed from the database. In cases where some data were missing, missing values were estimated using a multiple imputation technique, with five outputs, within SPSS 25.0. Table 1 shows the demographic and professional characteristics of participants.

Although the sample was not designed to be nationally or internationally generalizable, the participants did exhibit characteristics of what is generally thought to be a ‘typical financial advisor.’ The sample was comprised primarily of middle-aged men with a college degree level of education. The majority of participants were living in North America (i.e., United States or Canada) at the time of the survey; however, the sample included individuals working in Australia, Asia, the middle east, and the United Kingdom. Methods of compensation among participants varied. Slightly more than one in four reported earning a combination of fees and commissions, with about one in five earning a salary. Less than three percent of participants reported charging hourly fees. The largest number of participants reported working in a financial planning firm. Approximately two-thirds of participants held the CFP® credential. The CLU® and ChFC®, both proprietary marks of the American College, were also represented in the sample.

Table 1. Sample Characteristics.

	Mean (SD)	**Frequency (Percent)**
Gender		
Male		149 (73.0%)
Female		55 (27.0%)
Age	49.92 (11.00)	
Education		
High School		10 (5.2%)
Some College		34 (16.7%)
Associate's Degree		11 (5.8%)
Bachelor's Degree		63 (30.9%)
Graduate Degree		73 (38.2%)
Compensation Model		
Commission Only		20 (10.7%)
Fee Only		28 (15.0%)
Fee Based		29 (15.5%)
Hourly		5 (2.7%)
Fees and Commissions		53 (28.3%)
Salary		41 (21.9%)
Other		11 (5.9%)
Location		

Israel		12 (6.4%)
North America		117 (62.6%)
United Kingdom		12 (6.4%)
Other		46 (24.6%)
Type of Firm		
Bank/Trust Company		21 (10.3%)
Registered Investment Advisor		55 (27.0%)
Insurance Company		17 (8.3%)
Wire House/Brokerage		1 (0.5%)
Institutional		3 (1.5%)
Mutual Fund Company		8 (3.9%)
Financial Planning Firm		80 (39.2%)
Other		35 (17.2%)
Financial Risk Tolerance	7.27 (1.72)	
Years Providing Financial Advice		
< 1 year		4 (2.2%)
1-3 years		6 (3.3%)
4-7 years		22 (12.1%)
8-10 years		24 (13.2%)
11+ years		126 (69.2%)
Professional Designations		
CFP®		138 (67.6%)
CFA		4 (2.0%)
ChFC®		12 (5.9%)
CLU®		24 (11.8%)
Other		26 (12.7%)

Participants were first asked to rank order risk profile inputs that are generally thought (see Carr, 2012 and Nobre and Grable, 2015) to be important when determining how to allocate a client's investment portfolio independent of a portfolio or client context. When making their rankings, participants were asked to give what they believed to be the most important input a score of 1 and the least important input a score of 12. Ties were not allowed. Advisors were allowed to create a category and incorporate this input in their ranking although this was not required.

Participants were then given information about two hypothetical clients and asked to describe how they would use risk profile inputs when developing portfolio allocation recommendations. Specifically, participants were asked to indicate how important each input was, in each scenario, when making a recommendation. Similar to Van de Venter and Michayluk (2007), participants were also asked to recommend an appropriate asset allocation among equities, fixed income, and cash. Table 2 shows the narrative for the two scenarios.

Although combined here, the two scenarios were presented on separate pages of the survey and intentionally offered identical client risk profile information. The only difference between the two were the descriptive narrative presented about the prospective client. The "scores" represent hypothetical answers provided by each client on a client data-gathering form. As an example, clients in both scenarios indicated that they perceived the stock market as not very risky (i.e., a score of 9 on a 10-point scale with 1 being very risky and 10 being not all risky). Participants were also provided the following market data and assumptions to apply across the scenarios: (a) 8% average equity return, (b) 2% average fixed-income yield, (c) 0% average cash yield, (d) inflation less than 2%, and (e) tax rates have been and will remain stable over time.

Table 3. Risk Profile Scenarios.

SCENARIO 1 **YOUR CLIENT IS A MARRIED COUPLE. PARTNER 1 IS 45 YEARS OLD. PARTNER 2 IS 57 YEARS OLD. THEY ARE BOTH EMPLOYED PROFESSIONALLY AND HAVE A HIGH COMBINED FAMILY INCOME. THEY**

OWN THEIR OWN HOME AND HAVE A NET WORTH IN EXCESS OF $1 MILLION. THEY WOULD LIKE TO BUILD A RETIREMENT PORTFOLIO CONSISTING OF TAXABLE AND TAX-ADVANTAGED INVESTMENTS.

Input	*Client Assessment Score*
Couple's perception of the riskiness of the stock market: (1 = Very Risky; 10 = Not at all Risky)	9
Couple's financial knowledge: (1 = Not at all Knowledgeable; 10 = Very Knowledgeable)	4
Couple's investment experience: (1 = Very Little; 10 = Extensive)	3
Couple's level of risk needed to achieve financial goal: (1 = Very Low; 10 = Very High)	3
Time Horizon for Achieving Financial Goal	20 Years
Couple's Need for Liquidity: (1 = Very Low; 10 = Very High)	8
Couple's capacity to deal with a financial loss: (1 = Very Low; 10 = Very High)	9
Couple's willingness to take financial risk: (1 = Not at all Willing; 10 = Very Willing)	6
Couple's history of holding position(s) when faced with a loss: (1 Sell Immediately; 10 = Buy More)	2
Couple's preference for holding risky assets: (1 = Maximize Safety; 10 = Maximize Return)	2

SCENARIO 2

YOUR CLIENT IS A MARRIED COUPLE. PARTNER 1 IS 68 YEARS OLD. PARTNER 2 IS 66 YEARS OLD. THEY ARE BOTH RETIRED. THEY OWN THEIR OWN HOME AND HAVE A NET WORTH OF ABOUT $1.5 MILLION.

Input	*Client Assessment Score*
Couple's perception of the riskiness of the stock market: (1 = Very Risky; 10 = Not at all Risky)	9

Couple’s financial knowledge: (1 = Not at all Knowledgeable; 10 = Very Knowledgeable)	4
Couple’s investment experience: (1 = Very Little; 10 = Extensive)	3
Couple’s level of risk needed to achieve financial goal: (1 = Very Low; 10 = Very High)	3
Time Horizon for Achieving Financial Goal	20 Years
Couple’s Need for Liquidity: (1 = Very Low; 10 = Very High)	8
Couple’s capacity to deal with a financial loss: (1 = Very Low; 10 = Very High)	9
Couple’s willingness to take financial risk: (1 = Not at all Willing; 10 = Very Willing)	6
Couple’s history of holding position(s) when faced with a loss: (1 Sell Immediately; 10 = Buy More)	2
Couple’s preference for holding risky assets: (1 = Maximize Safety; 10 = Maximize Return)	2

Based on the information in each scenario, participants were asked to report how important each input was, on a scale of 0 to 100, as an input into the development of a portfolio allocation recommendation for the clients.[v] For example, a participant who thought that a input was not particularly important might report a weight of 5 out of 100. The survey required each total scenario score, based on all inputs, to sum to 100.

Participant responses were analyzed using descriptive, bivariate, and multivariate statistical techniques, including *t* tests and a discriminant analysis. The purpose of the tests was to determine how consistent participants were in using their ranking of inputs when faced with a client scenario and to determine participants’ level of consistency between scenarios. Another purpose was to describe the characteristics of those who were more likely to recommend an equity allocation above the sample average.

RESULTS

Table 3 shows how participants in the study first ranked the portfolio inputs without client scenario context. Rankings were based on the median rank response across the sample and are shown in highest to lowest order. For example, time horizon was ranked as the most important input associated with allocating a client's investment portfolio. External factors and other self-imposed inputs were the least important. The inputs suggested by participants are shown on the last row of the table.

Table 3. Ranked Inputs Relevant to Investment Portfolio Allocation.

Rank	Risk Profile Inputs
1	Time horizon for achieving financial goal.
2	Client's need for liquidity.
3	Client's capacity to deal with a financial loss.
4	Client's level of risk needed to achieve financial goal.
5	Client's willingness to take financial risk (risk tolerance).
6	Client's financial knowledge.
7	Client's investment experience.
8	Client's history of holding positions when faced with a loss (risk composure).
9	Client's perception of the riskiness of the stock market.
10	Client's preference towards holding risk assets.
11	External factors (i.e., average equity return, average fixed-income and cash returns, inflation, tax rates, etc.)
12	Other inputs (Each of the following received one vote: age of client, client engagement in the planning process, client financial goals, tax implications, client priorities, client fears, client debt profile, and client body language.)

Table 4 shows the average participant scores for the two scenarios. Each score represents a percentage weight for the input representing the importance of the input in making a portfolio allocation decision. For instance, in Scenario 1, participants, on average, gave the client's perception of risk a weight of 5.72% in the asset allocation decision framework. In Scenario 2, risk perception was given a weight of 6.00%. The difference in weights is reported in the fourth column. The last two columns of Table 4 show the *t* test results comparing the weights for Scenario 1 and 2. Overall, participants were relatively consistent when developing their portfolio recommendations, but they were rarely perfectly aligned; this was surprising given that there were no input differences between the scenarios.

In general, participants in Scenario 2 tended to underweight inputs related to client financial knowledge, risk need, and external factor inputs, while they over-weighted liquidity need and other self-imposed inputs. While time horizon was a dominant input in both models, it appeared that participants were including some other input(s) or client characteristic(s) in their allocation calculus.

Table 4. Average Scores for Each Risk Profile Input.

	Scenario 1	**Scenario 2**	**Change**	***t***	**Sig.**
Perception	5.72	6.00	-0.28	-0.95	0.342
Knowledge	8.00	6.84	1.16	4.47	0.001
Investment Experience	7.52	7.46	0.06	0.25	0.804
Risk Need	11.91	10.43	1.48	3.47	0.001
Time Horizon	14.95	14.31	0.64	1.47	0.144
Liquidity Need	13.44	14.38	-0.94	-2.48	0.014
Capacity	9.87	9.60	0.27	0.7	0.486
Risk Tolerance	6.82	7.38	-0.56	-1.04	0.298
Composure	8.06	8.28	-0.22	-0.81	0.421
Preference	6.89	7.76	-0.87	-1.64	0.103

External Inputs	5.39	4.34	1.05	3.08	0.002
Other	1.66	3.32	-1.66	-3.34	0.001

Note: Columns do not sum to 100 due to rounding.

The notion that participants assessed and weighted inputs differently between the two scenarios, even though the only substantive differences were the clients' ages and employment statuses, prompted a further evaluation of the data. Consider the correlation coefficients shown in Table 5. The coefficients point to some inconsistencies among the participants from one scenario to another. Given that the two scenarios were identical, it would be reasonable to hypothesize that the weights used by participants to guide the development of a portfolio allocation should have been effectively the same and consistent with the baseline ranked inputs. This was generally true, but the effect size of the associations was lower than what some might expect. In the case of financial risk tolerance, the association was particularly weak, suggesting that the weighting of this input between the two scenarios was inconsistent.

Table 5. Correlations for Weights of Inputs between Scenario 1 and Scenario 2.

		Perception	**Knowledge**	**Experience**	**Risk Need**	**Time Horizon**	**Liquidity Need**	**Capacity**	**Risk Tolerance**	**Composure**	**Preference**	**External Inputs**	**Other**
Perception	*R*	.385											
	Sig.	.000											
Knowledge	*R*		.675										
	Sig.		.000										
Experience	*R*			.538									
	Sig.			.000									
Risk Need	*R*				.616								
	Sig.				.000								
Time Horizon	*R*					.709							
	Sig.					.000							

Liquidity	*R*	.463						
Need	*Sig.*	.000						
Capacity	*R*		.275					
	Sig.		.008					
Risk	*R*			.123				
Tolerance	*Sig.*			.245				
Composure	*R*				.598			
	Sig.				.000			
Preference	*R*					.287		
	Sig.					.006		
External	*R*						.751	
Inputs	*Sig.*						.000	
Other	*R*							.472
	Sig.							.000

Table 6 summarizes how participant rankings of risk profile inputs differed from Scenario 1 to Scenario 2, as well as from the original (client neutral) rankings. When asked to rank inputs free of a specific client context, participants ranked the financial knowledge and financial risk tolerance of their clients relatively high. In practice, client risk composure and risk preference received higher rankings. The rankings shown in columns three and four of Table 6 were based on the weights shown in Table 4.

Table 6. Original Input Rankings and Rankings in Practice.

	Original Rank	**Scenario 1 rank**	**Scenario 2 rank**	**In Practice …**
Perception	9	10	10	Consistent
Knowledge	6	6	9	Less Important
Investment Experience	7	7	6	Consistent
Risk Need	4	3	3	Consistent
Time Horizon	1	1	2	Consistent
Liquidity Need	2	2	1	Consistent

Capacity	3	4	4	Consistent
Risk Tolerance	5	9	8	Less Important
Composure	8	5	5	More Important
Preference	10	8	7	More Important
External Inputs	11	11	11	Consistent
Other	12	12	12	Consistent

Table 7 shows the average and median asset allocation recommendation, as well as the range of recommendations, for Scenario 1. The portfolio was slightly over-weighted towards equities, with approximately 10% of assets allocated to cash.

Table 7. Scenario 1 Portfolio Allocation Recommendations.

	AVERAGE	**AVERAGE RATIO OF FIXED-INCOME TO EQUITIES**	**MEDIAN**	**AVERAGE RATIO OF FIXED-INCOME TO EQUITIES (MEDIAN)**	**RANGE (%)**
EQUITIES	48.88	0.84	50.00	0.80	10.00 – 100.00
FIXED-INCOME	40.97		40.00		0.00 – 75.00
CASH	10.15		10.00		0.00 – 50.00

Table 8 shows the same statistics based on Scenario 2 recommendations. Compared to Scenario 1, participants reduced the exposure to equities, while increasing the amount allocated to fixed-income assets. The cash allocation, at the median level, remained at 10%; however, on average, participants recommended a higher allocation of assets to cash compared to Scenario 1.

Table 8. Scenario 2 Portfolio Allocation Recommendations.

	AVERAGE	AVERAGE RATIO OF FIXED-INCOME TO EQUITIES	MEDIAN	AVERAGE RATIO OF FIXED-INCOME TO EQUITIES (MEDIAN)	RANGE (%)
EQUITIES	36.17	1.39	40.00	1.25	0.00 – 85.00
FIXED-INCOME	50.28		50.00		0.00 – 100.00
CASH	13.56		10.00		0.00 – 100.00

Table 9 shows the results from the *t* tests used to determine if the recommended allocations for Scenario 1 and Scenario 2 were different. As noted above, the allocation to fixed income and cash assets was significantly higher in Scenario 2.

Table 9. Statistical Differences between Scenario 1 and Scenario 2

	Mean	SD	*t*	*p*
Scenario 1 Equities	48.88	12.68	55.06	.001
Scenario 2 Equities	36.17	11.11		
Scenario 1 Fixed-Income	40.97	11.20	52.25	.001
Scenario 2 Fixed-Income	50.28	12.15		
Scenario 1 Cash	10.15	6.79	21.34	.001
Scenario 2 Cash	13.56	9.02		

The results presented in Table 9 are perplexing. Participants should have arrived at an average and/or median allocation of assets that was statistically similar for the two scenarios (even if the recommended allocations were not mean-variance efficient). This prompted a question among the research team as to why there might be differences. Participants were encouraged to make notes regarding other inputs that they believed were important. These notes were used to obtain insights into the methodological thinking of participants who shifted away from equities towards fixed-income and cash assets in Scenario 2. The following notes were representative of the comments provided for "other inputs" for Scenario 2:

"A 20-year time horizon leads the clients to be 88 and 86, an age that may be a complicating significant input."

"Lifestyle expenses—health."

"Mortality."

"Their health."

"Their age."

Taken together, it appeared that financial advisors, either objectively or subjectively, included age as a predominant weighting input in Scenario 2. The participants seemed to be following the somewhat controversial 100 - age allocation heuristic.

Although such a heuristic is rarely recommended for day-to-day use, the results from this study certainly give the impression that this is what some financial advisors may be using in practice. Consider the recommended allocation to equities in Scenario 1. The clients in Scenario 1 were approximately 51 years of age. Participants recommended an equity allocation of ≈50%. In Scenario 2, the clients were closer to 67 years of age. Participants recommended an equity exposure close to 36%, which fits closely with the allocation heuristic.

This does not mean that all participants were engaged in shifting allocation recommendations based on the age of the clients. A small number of participants consistently recommended higher equity allocations across both scenarios. Table 10 shows the univariate ANOVA results from a discriminant analysis that was conducted to identify the characteristics of participants who recommended an allocation to equities of at least 50% in both scenarios. For the purposes of the test, each of the variables (inputs) shown in Table 1 were included. Additionally, the ranking data from Table 2 were included as predictors of group membership (1 = recommended 50% or more in equities in both scenarios, otherwise 0).

As shown in Table 10, four characteristics described those who recommended a consistently high allocation to equities: age, type of employer, years providing financial advice, and ranking of risk capacity. Specifically, those who were older with more experience, worked outside of a bank or trust company, and weighed a client's risk capacity as less important were more likely to recommend holding 50% of more in equites across scenarios.[vi]

Table 10. Descriptive Inputs of Those Who Allocated 50% or More to Equities in Both Scenarios.

	Less than 50% Equities (N = 153)	**50% or More Equities (N = 26)**	**Sig.**
Age	49.52	54.58	.025
Employer: Bank or Trust Company: Yes = 1	.14	.00	.045
Years Providing Financial Advice	4.39	4.88	.013
Ranking of Client's Risk Capacity	3.87	4.89	.021

DISCUSSION

The title of this paper describes a conclusion that emerged from the analyses presented here: do as I say, not as I do. When asked to rank risk profile inputs in a context-neutral environment, participants in this study—all professional financial advisors—ranked the following as being the most important: time horizon, liquidity need, risk capacity, risk need, and risk tolerance. These inputs mirror what is generally encouraged in the finance and financial planning literature. Even among those who implement recommendations using mean-variance efficient models, the concepts of time horizon and risk tolerance, as well as other client preferences, are thought to influence the recommendation of a portfolio located on the efficient frontier.

In general, those with a shorter time horizon and a low tolerance for risk should, holding other inputs constant, hold less risky assets. Consider the case when a client's time horizon for goal achievement is constrained. When this happens, the client's exposure to equities for that particular goal, holding all other inputs constant, should fall. This allocation approach is closely related to the concept of risk capacity. As the time available to recoup potential losses is reduced, so should exposure to assets that exhibit greater price volatility. This has been a staple best practice of portfolio management for many years. Similarly, a client's tolerance for risk and ambiguity can be used as a constraining input on portfolio recommendations. Those with a high risk tolerance should, holding other inputs constant, be willing to withstand the emotional consequences associated with greater equity exposure. Liquidity and risk need tend to move in opposite directions. As a client's liquidity need rises, so should exposure to fixed-income and cash assets. Conversely, as the risk need increases, the allocation to these assets should fall. To a great extent, the manner in which risk profile inputs are combined is based on a financial advisor's professional judgement.

In the context of this study, participants over-weighted age and employment status. As noted by Klement and Miranda (2012), this appears to be an almost unconscious preference. Recall that participants were allowed to indicate specific other inputs that they used when developing portfolio recommendations. Of the more than 200 participants, less than a handful specifically noted that age was such a input; however, in practice, client age certainly appeared to be the dominant input shaping portfolio recommendations. It is important to note that the results from this study do not, and should not be used to, indicate that the participants in this study did anything unusual or incorrect. The primary takeaway is this: participants in this study (a) shifted their allocation recommendation when presented with nearly identical case scenarios, and (b) the shift in recommendation was based not on a dramatic re-weighting of risk profile inputs, but rather on the use of the age heuristic and/or other unspecified client characteristics (e.g., employment status).

This leads to a concluding observation. The shift toward fixed-income assets across the sample and the two scenarios may be representative of what Canner et al. (1997) called the 'asset allocation puzzle.' Given the 20-year time horizon in both scenarios, a greater exposure to equities would have been expected. So, who was more likely to provide this type of recommendation? It turns out that older more experienced financial advisors were consistently apt to recommend a riskier asset allocation with a higher ratio of equities to fixed income. There was some evidence to suggest that those fitting this profile also under-weighted a client's risk capacity in favor of other inputs, such as time horizon.

Although the results of this study are noteworthy, it is important to acknowledge relevant limitations. To begin with, the data used in this study were exploratory, and as such, results are not necessarily nationally or internationally generalizable. Additionally, it is possible that a selection bias was present in the data. This may have occurred based on the online nature of the survey and the length of the questionnaire. Some financial advisors may have opted out of the survey process or may not have received an invitation to participate, which could have skewed results. Issues related to endogeneity may also be present. While attempts were made to account for the primary inputs associated with portfolio decision making, it is possible that one or more key variables were omitted or unobserved. Even so, the data and findings do offer a unique insight into the way financial advisors assess, rank, and weigh portfolio allocation inputs. Additional research is needed to determine whether a model can be developed to help financial advisors and investors blend these inputs in a way that maximizes optimality.

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[ii] Contact Information: Corresponding author: 205 Dawson Hall, Department of Financial Planning, Housing and Consumer Economics, University of Georgia, Athens, GA 30677; email: grable@uga.edu; phone: 706-542-4758; website: fpplab.org

[iii] As an example, European Union legislation known as The Markets in Financial Instruments Directive (MIFID) regulates firms that provide services to clients who use financial instruments and the markets where those instruments are traded. Starting in 2014, financial advisors must ensure that investment recommendations are suitable and appropriate. A key element of this requirement is the accurate assessment of a client's risk preferences, profile, and tolerance, which must be measured through reliable assessment tools and techniques.

[iv] A measure of constant relative risk aversion is most often used within a mean-variance optimization framework to capture an investor's risk preference. As noted by Barsky, Juster, Kimball, and Shapiro (1997, p. 540), "[an] expected utility maximizer will choose the 50-50 gamble of doubling lifetime income as opposed to having it fall by the faction $1 - \lambda$ if $\frac{1}{2}U(2c) + \frac{1}{2}U(\lambda c) > U(c)$." Often, constant relative risk aversion or its inverse, constant relative risk tolerance, will be measured as lottery choices based on 50-50 choice scenarios rather than income gambles. When an investor answers enough choice scenario items, a measure of lambda can be derived. This can then be used to estimate a utility function for the investor. In practice, however, few financial advisors go through the process of estimating utility functions for investor clients.

[v] An attentive reader will notice that the input scores were identical across the two scenarios. The primary difference between the two scenarios was the age and employment status of the clients. In Scenario 1, the clients were saving for retirement, whereas in Scenario 2 the clients were already retired. In either case, both clients shared a portfolio-funding goal of 20 years.

[vi] Although research participants weighed risk capacity as less important (1 = most important), risk capacity was still ranked highly in terms of the inputs.