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Distribution channel effects on advisor managed investment performance

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Abstract

This study focuses on the effects that business models have on advisor managed portfolio performance by attempting to determine if advisors at Registered Investment Advisory (RIA) firms produce higher net investment results compared with advisors employed at dually registered Independent Broker/Dealer (IBD) firms. Using data from one of the largest investment advisory platforms in the United States, we found qualified supporting evidence that advisors at RIAs outperformed advisors at IBDs in higher-risk portfolios through the use of Turnkey Asset Management Programs and Unified Managed Accounts. © 2022 Academy of Financial Services. All rights reserved.

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1. Introduction

The efficacy of financial advice often compares investment performance to benchmark portfolios. This study segments the financial advice market into two separate distribution channels—Registered Investment Advisors and Independent Broker-Dealers—to determine

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if membership in a particular channel has a significant predictive relationship with advisor managed portfolio performance.

Other than potential philosophical differences, the main difference that separates Registered Investment Advisory (RIA) and Independent Broker/Dealer (IBD) firms is the compensation structures employed. Traditionally, RIA firms derive their compensation from fee-only arrangements. In an assets-undermanagement model, the advisor charges a percentage of the client's portfolio on a quarterly or monthly basis. In typical assets-undermanagement programs, trading securities does not generate a commission for the advisor; the value in such actions lies in the potential of the replacing security outperforming the replaced security and thus increasing the account value, in turn generating a higher dollar amount earned by the advisor.

IBDs employ a dual registration model that allows for fee-for-advice models as well as commission-based compensation programs. The advisor retains the sole discretion as to which model or mixture of the two they utilize. The decision IBDs face about which compensation regime to pursue creates the potential for an advisor's attention to be diverted away from their central task of investment management. Due to this diversion, we seek to determine if the distribution channel affects advisor managed portfolio returns when comparing RIAs and IBDs.

The rest of the paper proceeds as follows: the literature review section provides a detailed background on the efficacy of financial advice, highlighting a gap in the literature regarding segmentation of advisor distribution channel membership. The theoretical framework relates Cognitive Load Theory to the task of investment management. The methods and data employed for the study are then explained, and the results are presented. A discussion of the results precedes the conclusion, which includes limitations and implications of the study as well as areas for future research.

1.1. Literature review

Numerous studies show that the majority of professional money managers do not consistently outperform passive benchmarks (Del Guercio, Reuter, & Tkac, 2010; Desai & Jain, 1995; Gil-Bazo & Ruiz-Verdú, 2009; Jensen, 1968; Malkiel, 1995). Gruber (1996), French (2008), and Reuter (2015) estimate that actively managed mutual funds underperform their benchmark indexes by an average of 64-67 basis points (bps) annually.

Other studies that show advisor recommended mutual funds underperform self-directed portfolios. Karabulut (2013) found that advised investors earned lower raw and risk-adjusted returns compared with self-directed investors even before deducting advisory fees and transactions costs. Bergstresser, Chalmers, and Tufano (2009) found that broker-sold funds had lower raw and risk-adjusted returns than direct-channel funds, even before distribution expenses were deducted. Del Guercio and Reuter (2014) found that broker-sold actively managed mutual funds underperformed both broker-sold index funds and direct channel actively managed mutual funds.

By studying the Oregon University System retirement plan, Chalmers and Reuter (2012) found that employees who retained the services of brokers earned significantly lower after-fee returns and lower risk-adjusted returns compared with those employees who were defaulted into age-based target date funds. The average fee of 0.9% was the largest reason for the underperformance. Chalmers and Reuter (2012) did point out that employee accounts that were self-directed also underperformed the default target date funds, but to a lesser extent than broker advised accounts, echoing the sentiment in Bergstresser et al. (2009). Internationally, Hackethal, Haliassos, and Jappelli (2012) and Foerster, Linnainmaa, Melzer, and Previtero (2017) found similar results when studying German and Canadian investors and advisors' recommendations.

On the other hand, Kinniry, Jaconetti, DiJoseph, Zilbering, and Bennyhoff (2016) suggested that advisor-driven portfolios could outperform self-directed portfolios of clients, assuming the advisor did several tasks deemed to be too difficult, advanced, or time consuming for the novice investor. The study suggests that the so-called *Advisor Alpha* could be as high as 3.0% annually, the most valuable activity being behavioral financial coaching, which could contribute as much as 1.50% annually to a client's portfolio return.

Although Hackethal et al. (2012) found that the self-directed portfolios outperformed advised portfolios on average, advised accounts exhibited far greater diversification. Hackethal et al. (2012) suggests that a potential reason clients pay for advice lies in the convenience of outsourcing the task rather than to outperform other alternatives. Gennaioli, Shleifer, and Vishny (2015) put forth the concept of "Money Doctors" and posit that professional money managers instill confidence in the client by having a professional at the helm. This confidence reduces anxiety created by investing in risk-based assets and allows the client to invest more aggressively than they would on their own. Gennaioli et al. (2015) recognize that advisors' recommendations are costly, at times generic, and occasionally self-serving, which lead to consistent underperformance compared with passive benchmarks. While a client might earn negative market-adjusted returns after an advisor's fees, the excess return generated compared with a counterfactual portfolio with limited risk-based assets is another measure of the value of an advisor (Gennaioli et al., 2015). Warshcuer and Sciglimpaglia (2012) asked clients to rate the perceived value of financial planning services. Making sure the client is holding a sufficiently diversified portfolio and holding investments that meet each of the client's goals' time horizons and cash flow needs were viewed as more important than recommending investments that beat the market averages.

Although advisors in general are unable to consistently outperform passive benchmarks (and in some cases self-directed portfolios), little attention has been given to determine if the efficacy of financial advice improves across different advisor business models. We seek provide insight about the differences in advisor performance based on their distribution channel.

1.2. Theoretical framework

Cognitive Load Theory (CLT) describes the limits of mental effort used in working memory during problem-solving (Sweller, 1988). The amount of cognitive load levied on an individual engaged in a complex problem-solving exercise can be an explanatory factor in the individual's performance (Sweller, 1988). The heavier the cognitive load, the lower the expected level of performance.

Cognitive load is separated into three different types: intrinsic, extraneous, and germane. The first two forms of cognitive load are additive and together cannot exceed the capacity of working memory if the task is to be completed effectively (Paas, Renkl, & Sweller, 2003). Intrinsic cognitive load is the inherent level of difficulty associated with a particular task (Chandler & Sweller, 1991). It depends on the level of elemental interactivity in the problem-solving action (Paas et al., 2003). The more interrelated the elements of the task are, the higher the intrinsic cognitive load. High elemental interactivity imposes a heavy cognitive load because each element must be processed simultaneously. In contrast, problem-solving involving large numbers of unrelated elements would not impose as heavy a cognitive load because each element could be processed individually without reference to the other elements (Leppink, van Gog, Paas, & Sweller, 2015). Examples of intrinsic cognitive load for investment management include conducting due diligence and investment research and implementing portfolio decisions through trading, rebalancing, and ongoing monitoring.

Extraneous cognitive load, also known as ineffective cognitive load, is present when confounding variables are introduced into the problem-solving activity and interfere with its efficient completion (Paas et al., 2003). These variables or processes are related to the problem-solving activity but create unnecessary and inefficient additional steps to complete the problem, which hinder performance (Leppink et al., 2015). Due to the additive nature of the cognitive load architecture, the presence of extraneous cognitive load is particularly important when intrinsic cognitive load is high. Because cognitive load cannot exceed working memory capacity, when intrinsic cognitive load is high, there is less capacity for extraneous cognitive load (Paas et al., 2003). Examples of extraneous cognitive load that financial advisors may face include addressing client servicing tasks and related paperwork, developing and marketing the business, conducting administrative tasks, and engaging in professional development.

Germane cognitive load is used to explain any unused excess working memory capacity that can be refocused into activities that support intrinsic cognitive load (Sweller, Van Merrienboer, & Paas, 1998). The presence of germane cognitive load is desirable as it helps lessen the strain of intrinsic cognitive load and improves cognitive performance in problem-solving.

Since intrinsic cognitive load cannot be altered, in situations where the cognitive load level is high, reducing or eliminating extraneous cognitive load improves the overall cognitive process (Leppink et al., 2015; Sweller, 1988; Sweller et al., 1998). The split-attention effect provides an example of the toll extraneous cognitive load can have in explaining a limitation of human information processing (Chandler & Sweller, 1991). Extraneous cognitive load increases when a subject's focus is split between multiple elements in a cognitive process.

An additional deterrent to minimizing cognitive load is choice overload. As the choice set grows, the number of characteristics needing comparison increases and cognitive costs rise, potentially giving way to overload (Greenleaf & Lehmann, 1995; Shugan, 1980). When choices are consequential and/or involve numerous options, the decision-making process becomes more effortful, which can lead to cognitive overload (Botti & Iyengar, 2006; Huberman, Iyengar, & Jiang, 2004).

Cognitive load is also more likely to be exhausted when processing more complex tasks (Jacko & Ward, 1996). Campbell (1988) suggests that a complex task must minimally have either multiple paths, multiple outcomes, conflicting interdependence among paths, or uncertain probabilistic linkages. Using this definition, portfolio management can be defined as a complex task that requires considerable cognitive resources to perform and is more likely to exhaust cognitive load.

The effects on performance due to multitasking are also noteworthy. Gonzàlez and Mark (2005) discovered that task switching was equally created by external interruptions as well as internal self-interruptions, called *discretionary switching*. Discretionary switching is the type most associated with tasks that require multiple related, but separate subtasks, and is most closely related to our study. Like split-attention, discretionary task switching diverts cognitive resources from the primary task to a secondary or tertiary task, potentially before the completion of the primary task. Czerwinski, Horvitz, and Wilhite (2004) found that complex tasks were more difficult to resume once interrupted. Hodgetts and Jones (2006) found an inverse relationship between primary task difficulty and resumption times; the more difficult or complex the primary task, the slower the resumption time once it was interrupted. Gillie and Broadbent (1989) found that primary task accuracy after interruptions declined as task complexity increased. Jin and Dabbish (2009) identified seven categories of discretionary switching. Most relevant for this study is *inquiry*, which is switching to a secondary task to gain information that aides in completing the primary task.

Independent RIAs are typically fee-only planners whose compensation is derived either as a set fee (e.g., a flat or per hour charge for services), a percentage of the assets under management (AUM), or a combination of the two. Independent Broker/Dealers maintain a dual compensation model: (1) commission-based product placement and (2) a fee-based model similar to Independent RIAs. With investment management as the primary task, an advisor at an IBD must first complete a secondary task and determine (i.e., inquire and engage in discretionary switching) what amount of the client's investible net worth and/or discretionary income will be implemented through an asset-undermanagement compensation program and what amount will be implemented through a commission-based compensation program. Because advisors at IBDs have the additional process of determining a client's compensation program, this adds extraneous cognitive load to the investment management task for IBD advisors, what we call, the *Compensation Puzzle*. In addition, because commission-based compensation is not impacted by subsequent returns, when IBD advisors place client assets in commission-based products, they may have lower incentives than RIA advisors for their clients' portfolios to perform well in the future.

The Compensation Puzzle can be framed as a goal conflict between generating the highest return for clients and generating higher upfront compensation for an advisor. Campbell (1988) states that the presence of goal conflict increases task complexity. Thus, investment management is made more complex for IBD advisors due to the presence of the Compensation Puzzle. Because the relationship between task complexity and performance is negative, we expect RIAs to perform better than IBDs on the complex task of portfolio management. Further, because financial planning involves an ongoing relationship, an advisor could be required to revisit this Compensation Puzzle multiple times, switching from primary to secondary tasks in the process.

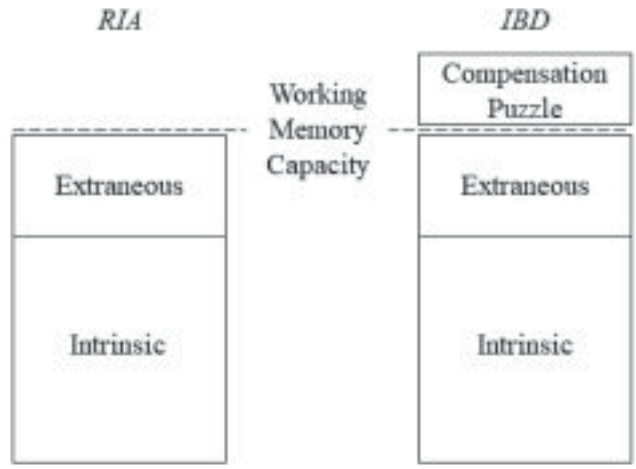

Fig. 1. Representation of the cognitive load and working memory capacity faced by advisors at RIA and IBD firms.

1.3. Hypothesis

The main hypothesis of this study states that due to the additional extraneous cognitive load levied against IBD advisors' working memory capacity due to the presence of the Compensation Puzzle, net investment performance of IBDs will be lower than that of Independent RIAs. As such, we propose the following null and alternative hypotheses:

H_0: RIAs will not have significantly different net returns than IBDs.

H_1: RIAs will have higher net returns compared with IBDs, regardless of portfolio management approach.

CLT serves as the main justification for the hypothesis that RIAs will outperform IBDs. The activity of investment portfolio creation and management is akin to a problem-solving exercise. Modern Portfolio Theory (MPT) states that portfolios are created such that expected return is maximized for a given level of risk. Each asset should be assessed based on its individual risk and return characteristics and how that asset contributes to the overall portfolio's risk and return, emphasizing the importance of the correlations between the assets within the portfolio (Markowitz, 1952). Due to the high levels of elemental interactivity when engaging in portfolio construction and management, the intrinsic cognitive load placed on an advisor is high, requiring significant working memory capacity. Because working memory capacity is limited, the potential addition of extraneous cognitive load from the Compensation Puzzle could lead to working memory capacity being exceeded and therefore, a reduced effectiveness in investment management. Fig. 1 provide a graphical representation of the Compensation Puzzle and how it relates to the cognitive load and working memory capacity of advisors at RIAs and IBDs.

2. Method

2.1. Data

Data were obtained through the generosity of a large, anonymous investment advisory platform. This platform provides a uniform tool that delivers advisor managed portfolios

(AMP), unified managed accounts (UMA), as well as turnkey asset management programs (TAMP). They serve Independent RIA firms, IBDs, Insurance Broker/Dealers, banks, and trust companies. For purposes of this study, banks and trust companies were excluded due to the nature of their product and service offerings. Banks and trust companies offer ancillary products and services that are outside the focus of investment management, and such offerings could influence the results. Insurance Broker/Dealers were combined with IBDs and referred to collectively as IBDs because their dual registration as fee-for-service and commission-based advisors are quite similar for the two distribution channels. All advisors at the RIA and IBD firms in this study receive fee-based compensation for the portfolios included in our analysis that they manage. In other words, IBDs advisors in this study have decided to place their clients' assets into fee-based models similar to those used by RIAs rather than to place them into commission-based products.

AMP are investment portfolios where the advisor maintains the responsibilities for the day-to-day investment management process, including formulating an investment strategy and asset allocation, conducing due diligence on the individual investments, implementing the strategy, and monitoring the portfolio and its component parts. AMP can contain only individual securities, mutual funds, and/or exchange-traded funds (ETFs). The AMP data contains 1,585 records for AMPs for the one-year time period, 1,151 records for the three-year time period, and 858 records for the five-year time period.

TAMP are investment portfolios where the day-to-day investment management process is completely handled by a third-party investment service provider. Benefits of a TAMP include outsourcing time-consuming activities such as investment research, portfolio allocation, and asset management tasks. A drawback of using TAMPs is that the originating advisor does not have direct control or input into the asset management process (Kenton, 2018). The TAMP contains the lowest amount of advisor responsibility for the investment management program of the three styles studied. The data contains 3,789 records for TAMPs for the one-year time period, 3,132 records for the three-year time period, and 2,434 records for the five-year time period.

Unified Managed Accounts (UMA) are investment portfolios that act as a hybrid between AMP and TAMP portfolios. Under a UMA program, an advisor has the responsibility to create a high-level asset allocation for a portfolio as well as to conduct the due diligence on the component parts of the portfolio. The advisor is not responsible for rebalancing the portfolio like they would be in an AMP; rather, these duties are handled by the investment platform. UMA portfolios do not contain individual securities. Instead, they contain mutual funds, ETFs, TAMPs, and Separately Managed Accounts (SMAs). While the advisor's overall responsibility is less in the UMA program compared with the AMP, there are still day-to-day investment management responsibilities. The data contains 1,484 records for UMAs for the one-year time period, 1,163 records for the three-year time period, and 857 records for the five-year time period.

Data were provided on a firm level rather than at the account or advisor level. For each variable, the average value for each firm was provided. For example, the one, three, and five-year average returns per firm were provided for RIAs and IBDs, for each of the three portfolio management approaches (i.e., AMP, UMA, and TAMP) and across the risk tolerance categories that the platform uniformly employs. Return data were provided for one, three, and five-year average returns for the time period ending on July 31, 2019, which means that the five-year average return data spanned August 1, 2014, to July 31, 2019. Average account size, advisory fee, number of accounts, as well as number of advisors were provided as of July 31, 2019. Because the data are as of a single point in time, time series analysis was not possible.

Firm-level data were provided to protect the identities of the individual advisors, clients, and firms that utilize the investment advisory platform as customers. The data set contains a total of 694 Registered Investment Advisory firms and 723 Independent Broker/Dealer firms, although many of these firms have a combination of AMP, UMA, and TAMP portfolios.

2.2. Empirical model

The following OLS regression model is used to test the hypothesis, if the distribution channel has a significant relation with one, three, and five-year average performance across the different risk tolerance categories regardless of the portfolio management approach (i.e., AMP, UMA, or TAMP). The empirical model is run separately on subsamples of the data based on the portfolio management approach (AMP, UMA, and TAMP).

$$\begin{aligned} Avg\,1,3,or\,5-Year\,Return &= \beta_0+\beta_1(RIA)+\beta_2(PortRisk)+\beta_3(RIA*PortRisk) \\ &+\beta_4(AvgFee)+\beta_5 In(AvgAcctSize)+\beta_6(NumAccounts)+\varepsilon \end{aligned} \tag{1}$$

2.3. Dependent variables

The dependent variables are the one, three, and five-year average return ending July 31, 2019. These returns are generated net of the advisor fee. Accounts are included in each time frame if they have a long enough history. For example, a portfolio that has two years of return data will only be included in the analysis of one year of return data, whereas a portfolio with four years of return history will be included in the one- and three-year analyses.

2.4. Independent variables

The following independent variables included in the regression to determine if they impact the one, three, and five-year average rates of return of the portfolio.

2.4.1. RIA

This is a dichotomous variable that is positive for RIA firms and zero for IBD firms.

2.4.2. Portfolio risk

The investment advisory platform utilizes five distinct universal risk tolerance levels. Clients complete a questionnaire, which provides a risk tolerance rating. Once the client's risk tolerance rating is established, the platform will provide available TAMP portfolios that meet the client's risk tolerance objective, account size, as well as the advisor's licensing. For advisors who choose to employ AMP or UMA strategies, the client risk tolerance rating provides a risk range that the advisor must adhere to when constructing the portfolio. The platform ranks each available component investment and assigns a composite risk value. As component investments are added to the portfolio, the composite risk score for the portfolio is created and must remain within the client's risk tolerance score to be considered compliant.

The five risk tolerance categories in descending order from most conservative to most aggressive are:

1. Capital Preservation
2. Conservative
3. Moderate
4. Growth
5. Aggressive Growth

We expect that risk tolerance (manifest as portfolio volatility) and average one, three, and five-year returns will have a positive relationship. As portfolio volatility increases across the five risk tolerance categories, total net return will also increase, due to the additional equity allocations and increased risk premium.

*2.4.3. RIA*portfolio risk*

This interaction variable provides a measure of the marginal impact of increased portfolio volatility among RIA firms.

2.5. Control variables

2.5.1. Average advisor fee

This variable represents the average advisor fee (expressed as a percentage) for each portfolio, which does not represent the total cost to the client. Advisor driven portfolios do not have manager fees that TAMPs (and UMAs) could have. Additionally, firms charge different program fees that split revenue with the advisory platform; these fees are not included in the average advisor fee but could influence what the advisor chooses to charge. Fees also tend to work on economies of scale; in other words, the larger the account, the lower the percentage fee charged. Lastly, these fees are not what the advisor actually earns. Each firm has a different compensation structure, and each advisor has a different payout, which could influence what the advisor chooses to charge. We expect the average advisor fee to have an inverse relation with each dependent variable. Average advisor fees range from 0.000046% to 2.293% for IBDs for the one-, three-, and five-year time periods. For RIAs, fees range from 0.0986% to 2.059% for the one-, three-, and five-year time periods.

2.5.2. Ln (average account size)

For all AMP, UMA, and TAMP accounts, the average client account size is reported per firm as of July 31, 2019. Average account size for RIA AMPs ranges from $26,343 to

$15,506,672. Average account size for IBD AMPs ranges from $26,090 to $41,286,141. Average account size for RIA UMAs ranges from $27,221 to $45,829,626. Average account size for IBD UMAs ranges from $26,259 to $4,504,614. Average account size for RIA TAMPs ranges from $25,073 to $13,600,157. Lastly, average account size for IBD TAMPs ranges from $25,137 to $6,875,348.

2.5.3. Number of accounts

This variable represents the total number of accounts for each RIA and IBD in each portfolio management approach. We expect the number of accounts and one, three, and five-year average returns to have an inverse relation with AMP and UMA performance. Incidentally, we also expect the number of accounts and average account size to be inversely correlated.

3. Results

A description of the samples for the one-year time period is included in Table 1. The average return for RIAs over one-year ranges from 3.6% for UMAs and 4.35% for AMPs, while the average return for IBDs ranges from 3.25% for TAMPs and 4.53% for AMPs. Average Portfolio Risk for RIAs and IBDs range from 3.2 to 3.5. Average account sizes by firm vary quite widely, from around $250,000 to over $800,000. The average fee charged is just under 1% across each of the models, and the number of advised accounts is considerably lower for RIAs than for IBDs.

To explore the relation between portfolio performance and business model (RIA vs. IBD), we start by performing *t*-tests on the average returns for each of the nine models (i.e., three reporting time periods for each of the three portfolio management approaches). The results are displayed in Table 2. Four of the nine models had a statistically significant difference in the mean return between RIAs and IBDs. In each of these instances, including all three TAMP models, the returns of the RIAs were higher.

Before analyzing the full empirical model described previously, we performed a series of simplified regression models, as indicated in Table 3. The initial model, Regression #1, is a simple regression consisting of investment performance as the dependent variable and the key variable of interest, RIA, as the only independent variable. Regression #2 adds Portfolio Risk as an independent variable. Regression #3 builds on the previous model by adding an interaction variable of RIA and Portfolio Risk. Finally, Regression #4 incorporates all the control variables, including the average advisor fee, the natural log of average account size, and the number of accounts. Each regression model was run separately on nine subsamples, one for each of the three portfolio management approaches (AMP, UMA, and TAMP) for each of the three time periods (one-, three-, and five-year).

Table 4 shows the results for Regression #1 for each of the portfolio management approaches in each of the three time periods. The main variable of interest (RIA) is positive and significant in four of the models (one-year UMA, and all three TAMP time periods), consistent with the results in Table 2. The other regressions do not have significant parameter estimates for RIAs.

Table 1 Descriptive statistics for the one-year sample, separated by portfolio management approach (AMP, UMA, and TAMP) and by distribution channel (RIA, IBD)

	AMP		UMA		TAMP	
	RIA	IBD	RIA	IBD	RIA	IBD
Average return	4.35%	4.53%	3.60%	3.31%	4.17%	3.25%
Portfolio risk	3.2	3.2	3.5	3.3	3.3	3.2
Average account size	\$432,762	\$377,176	\$824,559	\$437,266	\$389,059	\$250,693
Advisor fee	0.99%	0.97%	0.90%	0.94%	0.99%	0.93%
No. of advisor accounts	76	290	39	274	53	232
n	413	1,172	724	760	1,588	2,201

Table 2 Mean one-, three-, and five-year returns for RIAs and IBDs using AMPs, UMAs, and TAMPs

	One-year return	Three-year return	Five-year return
RIA AMP	4.347%	6.607%	3.690%
IBD AMP	4.527%	6.824%	3.825%
Difference	−0.180%	−0.217%	0.501%
RIA UMA	3.595%	6.211%	3.191%
IBD UMA	3.309%	6.344%	3.134%
Difference	0.286%*	−0.133%	0.057%
RIA TAMP	4.167%	6.272%	3.465%
IBD TAMP	3.247%	5.721%	2.964%
Difference	0.920%***	0.551%***	0.501%***

Note. Significant *t*-test results comparing the differences in the means are indicated with asterisks.
***$p < 0.001$, **$p < .01$, *$p < .05$.

Table 5 shows the results using Regression #2, which adds portfolio risk as an independent variable. Portfolio Risk is significant in all but one of the regressions. The parameter estimates for RIAs in each of the three TAMP time periods are positive and significant. The parameter estimate for RIAs in the one-year UMA time period is still positive but is no longer significant. Once we control for Portfolio Risk, the parameter estimate for RIAs in the three-year AMP and UMA models are now significant and negative.

Table 6 shows the results using Regression #3, which adds the interaction variable of RIA and Portfolio Risk as another independent variable. In all but two of these regressions (the one-year AMP and the five-year TAMP), the parameter estimate for RIA is now significant and negative. However, the parameter estimate for the interaction variable is also significant but positive in all but two of the regressions, suggesting the relationship between RIAs and investment returns includes a marginal effect dependent on the risk of the portfolio.

The results seen in Tables 5 and 6 suggest that the relative performance of RIAs may depend on the level of Portfolio Risk. To further explore this potential interaction, we perform t-tests on the returns of RIAs and IBDs after separating the sample by Risk Category. The results are included in Table 7. In the column for the Capital Preservation risk category, IBDs have a statistically significant higher mean return than RIAs for the three- and five-year TAMP time periods. At the opposite end of the risk spectrum, however, the column for the Aggressive Growth risk category shows statistically significant outperformance of RIAs

Table 3 Progression of the regression models, indicating the independent variables that are included in each regression

Independent variables	Regression #1	Regression #2	Regression #3	Regression #4
RIA	X	X	X	X
Portfolio risk		X	X	X
RIA*Portfolio risk			X	X
Average advisor fee				X
Ln (average account size)				X
Number of accounts				X

Table 4 Regression #1 results for each of the portfolio management approaches, where one-, three-, and five-year returns are the dependent variables

	One-year return	Three-year return	Five-year return
AMP			
Intercept	0.0453***	0.0682***	0.0383***
RIA	−0.0018	−0.0022	−0.0014
R^2	0.0005	0.0008	0.0007
N	1,585	1,151	858
UMA			
Intercept	0.0331***	0.0634***	0.0313***
RIA	0.0029*	−0.0013	0.0006
R^2	0.0028	0.0007	0.0003
N	1,484	1,163	857
TAMP			
Intercept	0.0325***	0.0572***	0.0296***
RIA	0.0092***	0.0055***	0.0050***
R^2	0.0233	0.0073	0.0132
N	3,789	3,132	2,434

***$p < 0.001$, **$p < .01$, *$p < .05$.

over IBDs by a considerable margin in five of the subsamples, including the five-year AMP time period, the one-year UMA time period, and all three TAMP time periods.

Table 8 shows Regression #4, which incorporates all the control variables in the empirical model. Not surprisingly, advisor fees in almost every regression are significant and

Table 5 Regressions #2 results for each of the portfolio management approaches, where one-, three-, and five-year returns are the dependent variables

	One-year return	Three-year return	Five-year return
AMP			
Intercept	0.0435***	0.0253***	0.0177***
RIA	−0.0018	−0.0037*	−0.0024
Portfolio risk	0.0006	0.0134***	0.0065***
R^2	0.001	0.31	0.17
N	1,585	1,151	858
UMA			
Intercept	0.0270***	0.0170***	0.0082***
RIA	0.0024	−0.0041***	−0.0010
Portfolio risk	0.0019***	0.0140***	0.0070***
R^2	0.010	0.45	0.26
N	1,484	1,163	857
TAMP			
Intercept	0.0347***	0.0017	0.0020*
RIA	0.0093***	0.0041***	0.0039***
Portfolio risk	−0.0007*	0.0171***	0.0086***
R^2	0.024	0.59	0.33
N	3,789	3,132	2,434

Note. Portfolio risk is included in each of the regressions as an independent variable.
***$p < 0.001$, **$p < .01$, *$p < .05$.

Table 6 Regressions #3 results for each of the portfolio management approaches, where one-, three-, and five-year returns are the dependent variables

	One-year return	Three-year return	Five-year return
AMP			
Intercept	0.0434***	0.0278***	0.0194***
RIA	−0.0016	−0.0166**	−0.0108*
Portfolio risk	0.0006	0.0126***	0.0060***
RIA*Portfolio risk	−0.0001	0.0039**	0.0026*
R^2	0.001	0.31	0.17
N	1,585	1,151	858
UMA			
Intercept	0.0325***	0.0185***	0.0109***
RIA	−0.0098*	−0.0075*	−0.0081**
Portfolio risk	0.0002	0.0135***	0.0062***
RIA*Portfolio risk	0.0036**	0.0010	0.0021*
R^2	0.017	0.46	0.26
N	1,484	1,163	857
TAMP			
Intercept	0.0414***	0.0063***	0.0051***
RIA	−0.0050*	−0.0058**	−0.0032
Portfolio risk	−0.0028***	0.0157***	0.0076***
RIA*Portfolio risk	0.0043***	0.0030***	0.0021***
R^2	0.035	0.59	0.34
N	3,789	3,132	2,434

Note. Portfolio risk and an interaction term combining RIA and portfolio risk are included in each of the regressions as independent variables.

***$p < 0.001$, **$p < .01$, *$p < .05$.

negatively associated with returns. The natural log of average account size was positive and highly significant in all nine regressions. The interaction variable between RIA and Portfolio Risk continues to be significant and positive in most of the regressions in Table 8.

For the regressions in Table 8 where both the RIA coefficient and the interaction variable coefficient are significant (the three- and five-year AMP time periods, the one-year UMA time period, and all three TAMP time periods), the combined effect of RIAs is positive only for the higher risk categories and not for the lower risk categories. (This combined effect is calculated by using RIA = 1 and Risk Category = 5 and multiplying by the corresponding parameter estimates.) In each of these instances, the Aggressive Growth risk categories shows that RIAs outperform IBDs. In the one-year UMA and all three TAMP time periods, RIAs outperform IBDs in the Growth risk category as well (where Risk Category = 4).

4. Discussion

Our hypothesis states that RIAs will outperform IBDs regardless of the portfolio management approach (AMP, UMA, or TAMP). This hypothesis was formulated based on the theoretical framework that RIAs expend less cognitive energy during the day-to-day activities of a practicing financial advisor due to the lack of the requirement to complete the

Table 7 Differences in mean returns for RIAs and IBDs by risk category

	Differences (RIA-IBD)	Risk category				
		#1 (capital preservation)	#2 (conservative)	#3 (moderate)	#4 (growth)	#5 (aggressive growth)
AMP						
	One-year return	−0.36%	−0.30%	0.45%	−0.59%	−0.07%
	Three-year return	−0.60%	−0.80%**	−0.76%*	−0.70%**	1.19%
	Five-year return	−0.43%	−0.61%	−0.42%	−0.55%	0.71%**
UMA						
	One-year return	−0.91%	0.18%	0.17%	−0.01%	1.00%**
	Three-year return	0.15%	−0.67%*	−0.76%***	−0.43%**	−0.07%
	Five-year return	−0.18%	−0.43%	−0.30%	−0.11%	0.36%
TAMP						
	One-year return	−0.14%	0.75%***	0.05%	0.58%**	1.81% ***
	Three-year return	−0.50%***	0.86%***	0.24%	−0.16%	1.17%***
	Five-year return	−0.33%*	0.47%*	0.15%	0.20%	0.76%**

Note. Significant *t*-test results comparing the differences in the means are indicated with asterisks.
***$p < 0.001$, **$p < .01$, *$p < .05$.

Table 8 Regressions #4 results for each of the portfolio management approaches, where one-, three-, and five-year returns are the dependent variables

	One-year return	Three-year return	Five-year return
AMP			
Intercept	0.0145	−0.0150	−0.0343**
RIA	0.0006	−0.0158**	−0.0115**
Portfolio risk	0.0009	0.0127***	0.0060***
RIA*Portfolio risk	−0.0007	0.0038**	0.0028*
Average advisor fee	−2.5417***	−1.5082***	−1.7469***
Ln (Average account size)	0.0043***	0.0046***	0.0057***
Number of accounts	0.0000001	0.0000004	0.0000005
R^2	0.041	0.35	0.28
N	1,585	1,151	858
UMA			
Intercept	−0.0381**	−0.0241**	−0.0388***
RIA	−0.0095*	−0.0072*	−0.0073*
Portfolio risk	−0.0002	0.0132***	0.0059***
RIA*Portfolio risk	0.0031**	0.0007	0.0014
Average advisor fee	−0.8754*	−0.5646	−0.6910*
Ln (Average account size)	0.0063***	0.0038***	0.0054***
Number of accounts	0.0000027***	0.0000032***	0.0000027**
R^2	0.074	0.48	0.34
N	1,484	1,163	857
TAMP			
Intercept	−0.0566***	−0.0478***	−0.0613***
RIA	−0.0076**	−0.0077***	−0.0056**
Portfolio risk	−0.0027***	0.0156***	0.0075***
RIA*Portfolio risk	0.0043***	0.0031***	0.0023***
Average advisor fee	−0.9896**	−0.6072**	−0.5024*
Ln (Average account size)	0.0089***	0.0050***	0.0059***
Number of accounts	0.0000002	0.0000004	0.0000005
R^2	0.109	0.62	0.40
N	3,789	3,132	2,434

Note. All the control variables are included as independent variables.
***$p < 0.001$, **$p < .01$, *$p < .05$.

Compensation Puzzle. The absence of this mental calculus, that IBDs must perform for every client, frees working memory capacity to potentially utilize in investment management.

Our analysis confirmed that risk is an important aspect to consider when evaluating the relative performance of RIAs and IBDs. Overall, RIAs may not outperform IBDs; however, when considering the risk category of the portfolio, our findings provide qualified support for our hypothesis that RIAs tend to outperform IBDs for portfolios in higher risk categories.

RIAs outperforming at higher risk categories can be explained through the theoretical framework and the equity risk premium, or the excess return above the risk-free rate provided to investors for taking on the additional risk of equity investments. Based on data from 1928 to 2018, the geometric average annual equity risk premium is 6.11% over 3-Month Treasury Bills and 4.66% over the 10-Year Treasury Bond (Damodaran, 2019). However, to achieve this equity risk premium one must also assume increased risk. Over the same time period, from 1928 to 2018, the S&P 500 (including dividends) had a standard deviation of 19.58%, while the 3-Month Treasury Bill had a standard deviation of only 3.04%, and the 10-Year Treasury Bond had a standard deviation of 7.70%.

With a higher variance of returns and a higher expected average return, equities can be considered a more difficult asset class to effectively value than fixed income. When valuing a bond, the primary concern is whether the issuing company has enough capital to honor the interest and principal repayments. Although corporate profits are used to fund the capital requirements necessary to honor the covenants of a bond, the magnitude of corporate profits is not material in valuing a bond. Bonds held to maturity also receive a fixed return, making valuations rather straight-forward. Conversely, to properly value stocks, one must estimate future cash flows and discount those cash flows to the present. If a company does better than expected, equity shareholders could potentially be rewarded with increased dividends or improved share prices. Bond holders, however, are not entitled to any additional compensation beyond the bond covenants. Because equities are more difficult to value than fixed income instruments, they naturally require more cognitive load to analyze and evaluate. Because advisors at RIAs can devote more working memory capacity toward the task of investment management (due to fewer extraneous cognitive load detractors such as the Compensation Puzzle), our study provides evidence that advisors at RIAs who focus more on equity-heavy portfolios are able to outperform their IBD counterparts.

Implications from these findings apply to both clients and advisors. Clients with higher risk tolerance who wish to invest more in equities may be better served by employing advisors at RIAs rather than IBDs. Conversely, advisors may want to consider their competitive advantage as a financial professional. Advisors at IBDs, for example, may provide more benefit to clients with more conservative portfolios, while advisors at RIAs may have a competitive advantage on portfolios with more equity investments.

4.1. Limitations

We note that our study is not without limitations. For example, risk performance measures were not reported due to data limitations. While returns are key determinants of portfolio success, risk-adjusted returns would provide a more robust measurement of investment performance. In addition, individual account level data were not available, so firm level data were analyzed instead. Because firms served as our unit of analysis, we made no attempt to measure the experience level of the advisors at the firms. Experience could play a role in an advisor's ability to manage investments that could influence the affect created by the business model.

We also recognize that we have limited information about the advisors at the RIAs and IBDs in our study and their clients. For example, details about the attitudes, skills, preferences, and beliefs of the advisors of the firms in our study would have enhanced our analysis. Additional information about the clients of these firms would also have allowed for an analysis of potentially unobserved heterogeneity among client groups.

We also recognize that the performance windows that were analyzed were rather small and at a single point in time, July 31, 2019. As such, the results of this study are heavily reliant on the capital market performance during the time periods preceding that date. In addition, the single point in time data limits the ability to analyze potential changes over time. For example, an account with a five-year track record could have seen its account size grow to the point where the advisor fee was decreased; however, the fee and size of the account were reported only as of the ending date, and changes in account sizes and fees were not observed.

Most importantly, we recognize that our results are correlational and do not indicate a direction of effect. Although our results provide evidence that advisors at RIAs may perform differently than advisors at IBDs because they have a different compensation motivation, it is also possible that each business model attracts different types of advisors. Due to data limitations, we are not able to disentangle these possible explanations.

4.2. Future research

Regulators continue to evaluate the role of advisor compensation in providing professional financial advice, as seen in the Department of Labor's Fiduciary Rule and the Security and Exchange Commission's Regulation Best Interest. In this discussion, one must also consider the role that business models play on portfolio performance. Future research in this area that can include demographic information about advisors (e.g., education, age, gender, years in the profession, advanced designations, and disciplinary actions) would provide a better understanding of the effects business models have on advisor managed portfolio performance. In addition, analyzing performance over longer time periods, such as seven or even ten years, would provide greater insight into the long-term effects of business models on investor returns.

4.3. Conclusion

Ample evidence both condemns professional financial advice (e.g., see Bergstresser et al., 2009; Del Guercio et al., 2010; Desai & Jain, 1995; French, 2008; Gil-Bazo & Ruiz-Verdú, 2009; Gruber, 1996; Jensen, 1968; Malkiel, 1995; Reuter, 2015), and praising it (Hackethal et al., 2012; Gennaioli et al., 2015; Kinniry et al., 2016; Warshcuer & Sciglimpaglia, 2012). However, the literature is scant regarding advantages or disadvantages provided to clients through the different business models available to advisors. This study sought to determine whether business models had an association with investment portfolio performance.

The theoretical framework suggests that advisors at RIAs can eliminate the extraneous cognitive load created by the Compensation Puzzle and would be able to potentially redirect freed working memory capacity toward the difficult task of investment management. By virtue of having more working memory capacity to apply to the intrinsic cognitive load of investment management, we hypothesize that RIAs could outperform IBDs regardless of the chosen portfolio management approach (AMP, UMA, or TAMP) and regardless of risk category. Our findings, however, provide qualified support of RIAs outperforming IBDs through UMA and TAMP portfolios at higher risk categories but not at lower risk categories.

While evidence is mixed regarding the efficacy of professional financial advice, this study provides qualified support for the hypothesis that business models have an association with investment performance. Qualified support exists in favor of RIAs producing higher net investment results through AMP, UMA, and TAMP portfolios in higher risk categories when compared with IBDs.

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