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<https://escholarship.org/uc/item/6k54t608>

Journal

JOURNAL OF INVESTMENT MANAGEMENT, 17(2)

ISSN

1545-9144

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Publication Date

2019

Peer reviewed

Automated Financial Management: Diversification and Account Size Flexibility *

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Abstract

We study the value added of automated financial management (AFM) services along two dimensions: diversification and account size flexibility. First, using a company-specific experiment with matched AFM and traditional portfolios, we find AFM portfolios are significantly better diversified. Underdiversified investors are more likely to set up an AFM account, with a 1 standard deviation increase in underdiversification raising the probability of doing so 3 percentage points. Next, we study account size flexibility using an exogenous reduction in minimum account size. The reduction led to a net increase in total deposit inflows and disproportionately raised new account formation by less-wealthy investors.

Keywords: Portfolio Choice, Financial Advice, Household Saving, Financial Innovation

JEL Classification: G11, G23, D14, D18

*We thank John Campbell, Benjamin Friedman, Pedro Gete, Duncan Gilchrist, Jakub Jurek, Matteo Maggiori, Andrei Shleifer, Stanislav Sokolinski, Jeremy Stein, Boris Vallee and seminar participants at Harvard University for comments. The views expressed in this paper are those of the authors and do not necessarily reflect the position of Wealthfront Inc.

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1 Introduction

Automated financial advisors (AFAs), popularly known as “robo advisors”, are firms which practice automated, algorithm-based portfolio management via an online platform based on a passive investment strategy. These firms emerged in 2008, and their subsequent growth was facilitated by a strong U.S. stock market, tighter regulation of financial custodians, and the introduction of the smartphone (Sironi 2016). In response, several traditional advisors have begun offering automated financial management (AFM) services.¹ The demand for AFM services is projected to grow substantially, with common estimates of a 2020 market size ranging between \$2.2 to \$3.7 trillion (Moulliet et al 2016). It is therefore of great practitioner and academic interest to understand the sources of demand for AFM services and their value added.

In this paper we document the value added of AFM along two important dimensions: improved diversification and ability to manage accounts of almost any size. First, because AFM providers often emphasize diversified portfolios over abnormal return, diversification is a natural dimension of value added to study (Malkiel 2015). In addition, AFAs’ reliance on automation means that they can manage small portfolios at little additional cost, providing account size flexibility for clients who would otherwise be constrained by a minimum balance. Notably, while popular images of AFM products often emphasize their low fees, we do not study this as an outcome.² This is because we are interested in the “quantity” of AFM services, measured in terms of diversification or account size flexibility, rather than the “price”, as captured by fees.

However, it is difficult to assess the value added of AFM without information about what a client would otherwise be doing in her outside account. To overcome this challenge, we utilize two company specific experiments by a large U.S. AFA. First, we study a sample of traditional brokerage accounts matched to a counterfactual AFM account. The data were obtained from an online tool which provided portfolio specific advice, and it is our main dataset for studying diversification. Second, we study deposit inflows around an unanticipated reduction in the minimum account balance. This reduction offers a natural experiment through which to

¹Examples include Schwab’s Intelligent Portfolios or Bank of America’s Merrill Edge Guided Investing.

²See, for example, the Wall Street Journal article “Talk Is Cheap: Automation Takes Aim at Financial Advisers and Their Fees” by Jason Zweig, Anne Tergesen, and Andrea Fuller from July 26, 2017.

investigate the effects account size flexibility.

We find that AFM portfolios are substantially more diversified than their traditional counterparts, with an average improvement in Sharpe ratio of 10 percentage points (40%). The difference is especially strong among portfolios comprised primarily of directly held stocks and among non-taxable accounts. It is also interesting given our sample of relatively sophisticated investors who, based on their revealed interest in AFM, presumably attach value to diversification. Indeed, a 1 standard deviation increase in the idiosyncratic variance of an individual's traditional account raises the probability of setting up an AFM account by 3 pp. This holds true after controlling for various demographic characteristics and the difference in fees.

In terms of account size flexibility, we find that a 90% reduction in minimum account size from \$5,000 to \$500 raised new account flow by 56% more from relatively low-wealth individuals than high-wealth individuals. We take this as our estimate of the reduction's effect on new account formation, since other factors potentially coinciding with the reduction (e.g. improved publicity) would likely affect low and high-wealth cohorts equally. Interestingly, despite the leftward shift in the wealth and income distributions of new clients, the reduction still raised total dollar deposit flows by 24%. That is, the intensive margin effect of smaller portfolios per client did not undo the extensive margin effect of a broader client base.

These results are of interest to practitioners seeking to design a profitable AFM platform. Specifically, they show how a well-executed AFM service can substantially improve client diversification relative to a traditional brokerage account, and especially so for non-taxable accounts and accounts consisting primarily of directly held stocks. These gains from diversification are also a significant predictor of account delegation, and thus an effective way to attract clients. Moreover, reducing minimum account size can substantially increase client base, and, to a lesser degree, can raise assets under management on impact.

In terms of contribution to the literature, our paper is one of a few to study AFM services directly and, to the authors' best knowledge, the first to use data from a leading U.S. AFA in its analysis. In that respect, it is most similar to D'Acunto, Prabhala, and Rossi (2017), who study an AFM service provided by a brokerage house in India. They study the effects of the AFM service on behavioral biases like return chasing and the disposition effect and, consistent

with this paper’s results, find that AFM portfolios feature greater diversification on average and especially for portfolios concentrated in a few stocks. We are also similar to Fisch and Turner (2017), who study AFAs from a legal perspective.

This research also relates to fundamental questions about households’ financial decisions and their relationships with advisors.³ Broadly, our results connect with studies that have documented household underdiversification using more representative datasets (e.g. Calvet, Campbell, and Sodini 2007, 2009a; Badarinsa, Campbell, and Ramadorai 2016). There is also a separate and very large literature focusing on the incentives and behavioral biases of financial advisors.⁴ We relate to that literature by studying a new form of financial advice which, due to its reliance on automation, is designed to attenuate such biases.

The rest of the paper is organized as follows. Section 2 describes the source of our data. Section 3 studies diversification. Section 4 studies account size flexibility. Section 5 concludes. The appendix describes our methodology in greater detail.

2 Data Description

Our analysis is based on two core datasets described below, as well as auxiliary information on security returns from the Center for Research in Security Prices (CRSP). Both datasets were generated by company specific initiatives by Wealthfront Inc., an automated financial advisor (AFA), whom we refer to as the “data provider”.⁵

³See Guiso and Sodini (2013) for a recent survey of the household finance literature.

⁴A partial list includes Linnainmaa, Melzer, and Previtero (2017), Celerier and Vallee (2017), Christoffersen, Evans, and Musto (2013), Mullainathan, Noeth, and Schoar (2012), and French (2008).

⁵Briefly, Wealthfront’s business model offers many services including tax loss harvesting, long term financial planning, and portfolio lines of credit. Its most basic product, which is most relevant for this paper, is a portfolio of 10 ETFs across 10 asset classes that is automatically rebalanced. The portfolio weights are determined by a questionnaire which asks the client several questions about her financial situation and risk tolerance. More details can be found on Wealthfront’s website.

2.1 Matched Portfolio Holdings

The first core dataset contains snapshots of individuals' portfolio holdings in an outside, traditional brokerage account. This information is paired with the portfolio holdings of the individual's counterfactual automated financial management (AFM) account with our data provider, along with basic demographic information about the individual's age, annual income, and financial wealth (i.e. liquid net worth).⁶ We also observe each portfolio's advisory fees and tax status. The dataset was generated by a free online tool through which our data provider gave financial advice to candidate clients about their outside portfolio holdings.

Specifically, candidate clients would provide their log-in credentials for their outside brokerage account. Then, our data provider would take a snapshot of the account holdings and run an advice-generating algorithm on it. This produces a set of snapshots of individuals' non-AFM accounts. While the advice algorithm ran, our data provider would ask the individual to answer its standard questionnaire meant to gauge risk preferences, which is the source of our three demographic variables. Finally, at the conclusion of the report, our data provider would tell the individual the portfolio she would receive as a client, and give her the option to transfer. This produces a matched, counterfactual AFM portfolio for each individual in the sample.⁷ The tool was launched in January 2016, and our sample contains 2,654 snapshots taken between January 2016 and November 2016. We merge this dataset with security level information from CRSP to produce a cross sectional dataset of individuals' brokerage and counterfactual AFM portfolios. We use this dataset when studying diversification in Section 3.

2.2 Account Openings

The second core dataset contains a time series of individual client deposits in 2015. We observe the date and size of the deposit, an indicator for whether the deposit represents an account opening with our data provider, and basic demographic information about the individual's age,

⁶Liquid net worth includes cash, savings accounts, certificates of deposit, mutual funds, IRAs, 401(k)s, and public stocks.

⁷Portfolios are matched based on tax status and the client's risk preferences according to their answers to the questionnaire. Also, given this paper's research question, we are interested in this tool insofar as it provides information about non-AFM account holdings, and we do not focus on the nature of the advice received.

annual income, and financial wealth. We aggregate the data to the weekly frequency. The result is a panel dataset of weekly deposits for clients of our data provider from January 2015 through December 2015. We use this dataset when studying account size flexibility in Section 4. Importantly, this dataset covers a broader set of individuals than the matched portfolio data. Specifically, the individuals in this dataset do not need to have an outside brokerage account, and their median AFM account size is relatively modest at \$25,000.

3 Diversification

In this section, we study the gains from diversification provided by an AFM portfolio. After first briefly describing our methodology, we quantify these gains within our sample and estimate their effect on AFM usage.

3.1 Measuring Portfolio Returns

Since we are interested in diversification, we focus on estimating the expected excess return and volatility of the portfolios in our sample. Given the difficulties in measuring expected return, we follow Calvet, Campbell, and Sodini (2007) and propose an asset pricing model to estimate the mean and variance of return for the securities in our sample. Specifically, for each security i , we estimate

$$R_{it} - R_t^f = \beta_i^F F_t + \epsilon_{it}^F, \tag{1}$$

where F_t denotes a column vector of pricing factors in month t , β_i^F denotes the respective row vector of loadings, and R_{it} denotes the monthly return on security i , net of expense ratio, and R_t^f denotes the 1-month Treasury yield. As standard, ϵ_{it}^F is an idiosyncratic, zero-mean shock to security i with standard deviation σ_i^F .

While imposing a model improves the efficiency of the estimates relative to directly measuring them from historical returns, it leads to some bias due to an imperfect depiction of the

return structure. Since the choice of model is somewhat arbitrary and the degree of bias will depend on the characteristics of the portfolio in question, we estimate (1) separately for five common models indexed by factor vector F . As described in the appendix, these five models are: the standard capital asset pricing model (CAPM), the “market model”, the Fama and French three-factor model, a five-factor model augmenting the Fama and French model with global and U.S. bond returns, and a two-factor model based on Vanguard’s total equity and bond ETFs.

Given the estimated loadings $\hat{\beta}_i^F$ and idiosyncratic volatilities $\hat{\sigma}_i^F$ from estimating (1) for model F , it is straightforward to compute some statistic θ_p^F (e.g. expected excess return, volatility, Sharpe ratio, etc.) for portfolio p .⁸ We then take the average value of θ_p^F across the five asset pricing models, which we denote by θ_p . To avoid overweighting any particular model, we always use the average statistic θ_p in our analysis.

3.2 Gains from Diversification

Our first exercise is to measure the gap in diversification between candidate clients’ outside brokerage and counterfactual AFM accounts. Importantly, we measure this gap both for individuals who eventually became clients and for those who did not. Thus, our estimates have the interpretation of an average treatment effect, and are therefore not biased by self-selection into an AFM portfolio.⁹ Also, recall that our data consists of one snapshot per brokerage account, so that what we measure is the gap in diversification at a given point in time.

Table 1 summarizes brokerage and AFM portfolios according to the following statistics: expected excess return, volatility, Sharpe ratio, idiosyncratic variance as a percent of total variance, and total fees.¹⁰ The third column of the table shows the average matched-portfolio difference for each statistic.¹¹ For each statistic, there is a statistically significant difference

⁸See the appendix for details. We multiply the mean and variance of all returns by 12 to obtain approximate annual values.

⁹There is, however, self-selection into the decision to use our data provider’s advice tool. This is therefore an average treatment effect conditional on using the tool.

¹⁰By idiosyncratic variance, we mean the variance of $\epsilon_{i,t}^F$ in (1). This is distinct from the variance of the factors F_t , which is priced according to β_i^F and thus comes with a higher expected return.

¹¹Observations are weighted by brokerage account size to avoid overstating the volatility of small accounts,

between the brokerage account and the AFM match. In particular, the average AFM portfolio has a 0.6 percentage point (pp) higher expected excess return and a 5.6 pp lower volatility. Reduced idiosyncratic variance is a key driver of this lower volatility, since the average AFM portfolio's variance is only 15.6% idiosyncratic, and therefore uncompensated, compared to 48.5% for the average brokerage portfolio. Taken together, these differences give rise to a 10.4 pp (40.4%) higher average Sharpe ratio for AFM portfolios.¹² Finally, AFM portfolios have 11.6 basis point (bp) lower total fees than their brokerage match which, while statistically significant, is economically small. This is interesting because it suggests diversification is a stronger contribution than fees to AFM portfolios' value added, despite popular emphasis on low fees charged by many AFAs. It may also reflect how the individuals in our sample, by virtue of participating in our data provider's online tool, may be relatively fee-conscious.

Table 1: Gains from Diversification

	Brokerage	AFM	Difference
Expected Excess Return	4.47 (1.18)	5.11 (0.58)	0.642*** (0.052)
Volatility	19.64 (9.63)	14.09 (1.21)	-5.551*** (0.370)
Sharpe Ratio	25.86 (7.80)	36.30 (5.35)	10.442*** (0.379)
Idiosyncratic Variance	44.48 (24.15)	15.57 (2.43)	-28.914*** (0.948)
Total Fees (bps)	48.84 (51.46)	37.22 (1.18)	-11.622*** (2.123)
Observations	2,654		

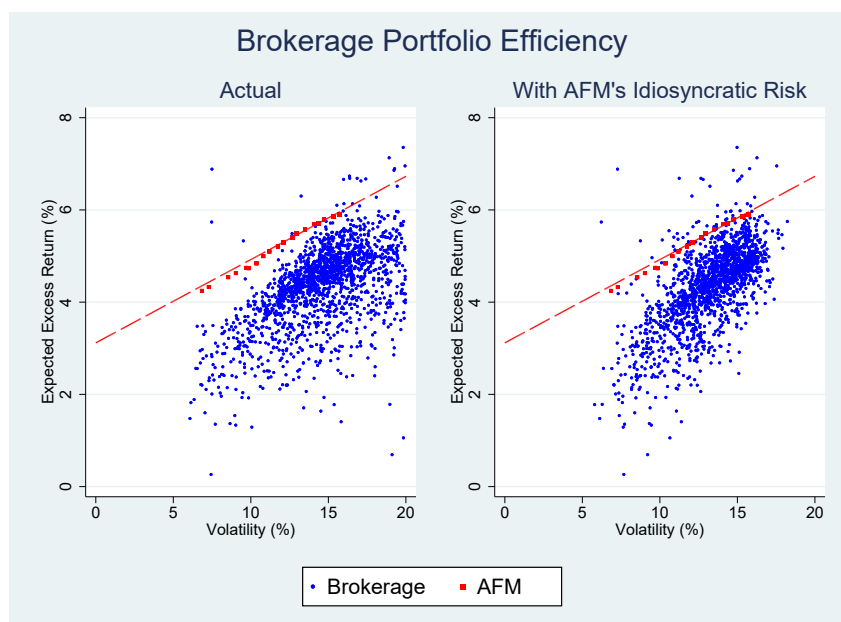
Note: The first two columns of this table show averages for brokerage and their matched AFM portfolios, with standard deviations in parentheses. The third column shows the average difference, with robust standard errors in parentheses. All variables are based on an average of five asset pricing models and are annualized. Idiosyncratic variance is expressed as a percent of total variance. All units are in percentage points except for Fees which are in basis points. Expected return is in excess of risk free rate. Total fees include advisory fees and expense ratios. Observations are weighted by account value. The notation ***, **, and * denote p-values less than 0.01, 0.05, and 0.10 respectively.

which frequently consist of a single stock. Thus, the estimated gaps in volatility, Sharpe ratio, and idiosyncratic variance in Table 1 are conservative.

¹²To maintain consistency with the other statistics, we express the Sharpe ratio as a percentage: 100 times the ratio of expected excess return to volatility.

Figure 1 illustrates the gains from diversification by plotting the expected excess return and volatility for portfolios in our sample. The smaller blue points correspond to brokerage accounts, and the larger red points represent the matched AFM portfolios.¹³ The red dashed line traces a linear approximation to the AFA's mean-volatility frontier. On the left side, the figure shows the actual distribution of excess return and volatility. On the right side, the figure replaces each brokerage portfolio's idiosyncratic variance with that of its matched AFM portfolio, and it then plots the counterfactual distribution. Notice how the distribution of brokerage portfolios shifts to the left in the counterfactual exercise: investors can receive the same expected return with the AFA while taking much less risk.¹⁴

Figure 1: Expected Portfolio Returns and Volatility, Actual and Counterfactual



Note: This figure plots the expected excess return and volatility for brokerage portfolios in our sample (smaller blue) and their AFM match (larger red). The red dashed line is a linear approximation to the mean-volatility frontier for AFM portfolios. On the left, we plot the actual data. On the right, we replace each brokerage portfolio's share of idiosyncratic variance with that of its AFM match, and plot the counterfactual data.

¹³The reason there are only 40 AFM points compared to over 2,000 brokerage points is because our data provider's benchmark service assigns clients one of 40 portfolios based on tax status and risk preference.

¹⁴One could produce a very similar figure holding total volatility constant, but scaling the brokerage portfolio's expected return according to the AFM portfolio's Sharpe ratio. The result would be an upward shift of the distribution: investors receive a higher expected return for the same level of risk.

Next, to test for heterogeneous effects, we partition observations into various subsamples and study the difference in log Sharpe ratio between brokerage and AFM portfolios.¹⁵ We consider two partitions: portfolios with a majority of their value in directly held stocks versus those without, and taxable accounts versus non-taxable accounts.¹⁶ Table 2 shows the average improvement in log Sharpe ratio for each subsample, defined as the log Sharpe ratio for AFM portfolios minus that for their matched brokerage portfolio. In the third column, it tests for a difference in this improvement between subsamples.

Table 2: Heterogeneous Effects

Outcome: Log Sharpe Ratio Improvement			
	No	Yes	Difference
Stocks > 50%	27.40 (29.92)	52.62 (37.52)	25.221*** (2.757)
Non-Taxable	27.11 (34.74)	46.33 (34.04)	19.221*** (2.714)
Observations	2,651		

Note: The first two columns of this table shows the average gap in log Sharpe ratio between AFM and brokerage portfolios for different subsamples in log points, with standard deviations in parentheses. The leftmost column describes how the sample is partitioned, and the subsample in question is indicated by “Yes” or “No” in the top row. The third column shows the average difference in this gap, with robust standard errors in parentheses. Stocks > 50% indicates whether the portfolio has over 50% of its value in directly held stocks. Non-Taxable indicates whether the portfolio is non-taxable. The Sharpe ratio is based on an average of five asset pricing models and is annualized. Observations are weighted by account value. The notation ***, **, and * denote p-values less than 0.01, 0.05, and 0.10 respectively.

Focusing on the first row of Table 2, there is an improvement in log Sharpe ratio both for portfolios with over half their value in directly held stocks and those without. Perhaps as expected, the improvement is 25.2 log points higher for the former group, which is statistically significant. In the second row of the table, we partition according to the portfolio’s tax status. Interestingly, the improvement in log Sharpe ratio is 19.2 log points higher for non-taxable accounts than for taxable ones, and is again statistically significant. This suggests that AFM can

¹⁵Calvet, Campbell, and Sodini (2007) show how the log Sharpe ratio gap approximates the welfare gains from diversification.

¹⁶Non-taxable accounts are individual retirement accounts (IRAs), Roth IRAs, or 401k plans that have been transferred to our data provider.

offer greater value added among non-taxable portfolios, where individuals are less diversified. That non-taxable accounts are less diversified is consistent with Waggle and Englis (2000), who find that a majority of IRA accounts hold only a single asset category, and with the idea that tax-motivated sales in December can help overcome the disposition effect in taxable accounts (Odean 1998).

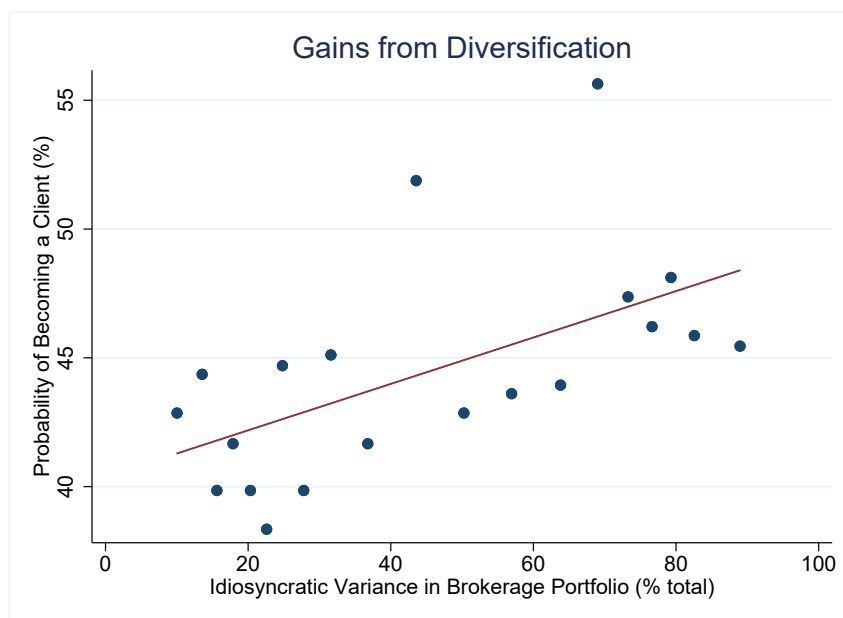
3.3 Account Delegation

An important follow-up question is which individuals realize these gains from diversification by creating an AFM account. Specifically, we now study the cross-sectional differences between AFA clients (i.e. those who delegated an account to our data provider) and non-clients.¹⁷

As a first pass, Figure 2 plots the probability of account delegation based on the percent of brokerage portfolio variance that is idiosyncratic and therefore uncompensated. As illustrated by the figure, idiosyncratic variance has a positive impact on the probability of setting up an AFM account. The relationship is statistically significant, with a 1 standard deviation (25.8 pp) increase in idiosyncratic variance raising the probability of delegation by 2.3 pp.

¹⁷Because individuals self-select into using our data provider's advice tool, we do not address whether the tool itself had a causal effect on account delegation.

Figure 2: Gains from Diversification and Probability of Becoming a Client



Note: This figure plots the probability an individual becomes a client of our data provider against the share of idiosyncratic variance in her brokerage account. The estimated slope is 0.09 (0.04).

Table 3 tests the intuition of Figure 2 more rigorously by regressing the probability of account delegation on an individual's age, financial wealth, income, the fraction of brokerage portfolio variance that is idiosyncratic, and the total fees in that portfolio.¹⁸ Consistent with Figure 2, individuals whose brokerage accounts are less diversified are more likely to set up an AFM account. To interpret the magnitude, a one standard deviation (25.8 pp) increase in idiosyncratic variance raises the probability of account delegation by 2.8 pp. Turning to the other variables in the table, younger and higher-income individuals are more likely to delegate to an AFA, consistent with the popular appeal of AFM services among young professionals. Interestingly, fees do not have a significant effect, again suggesting that diversification is a stronger source of value added.

¹⁸The results are very similar if instead we used the gap in idiosyncratic variance between the individual's brokerage and AFM portfolios and the analogous gap in fees.

Table 3: Account Delegation and Clientele Effects

Outcome: Account Delegation	
Idiosyncratic Variance	0.114*** (0.037)
Fees	-0.022 (0.021)
Log Income	0.010 (0.010)
Log Financial Wealth	0.016** (0.007)
Age	-0.009*** (0.001)
R-squared	0.052
Number of Observations	2,638

Note: The outcome is whether the individual becomes a client of our data provider. Each observation is a brokerage portfolio. Fees are in basis points. Idiosyncratic variance is expressed as a percentage of total variance. Observations are weighted by account value. Robust standard errors are in parentheses. The notation ***, **, and * denote p-values less than 0.01, 0.05, and 0.10 respectively.

Before concluding this section, one should recognize that the individuals in our sample are not representative of most U.S. households. For example, Biliias, Georgarakos, and Haliassos (2010) estimate that under a fifth of U.S. households have a brokerage account. Moreover, the median brokerage account size in our sample exceeds \$400,000 for both participants and non-participants, which is well above most Americans' financial wealth.¹⁹ That said, the individuals in our sample are also fairly young, with a median age of 34. They are thus an important group to study, given that the early thirties is when most individuals begin participating in risky asset markets (Fagereng, Gottlieb, and Guiso 2017).

4 Account Size Flexibility

In this section, we study the gains from AFM account size flexibility. Specifically, automation allows AFAs to manage portfolios of almost any size with little additional cost per portfolio. By contrast, it is infeasible for traditional advisors to manage portfolios below a certain size.

¹⁹To be clear, this is the median size of the individual's traditional, non-AFM account.

Account size flexibility is a subtle yet potentially far reaching margin of AFA value added, since advisors can more easily attract clients with high future earnings during the wealth building stage of their lives. In a frictionless world, such individuals who seek financial management could set up an account of arbitrary size. In reality, they are unable to do so because most financial advisors require a minimum account balance.

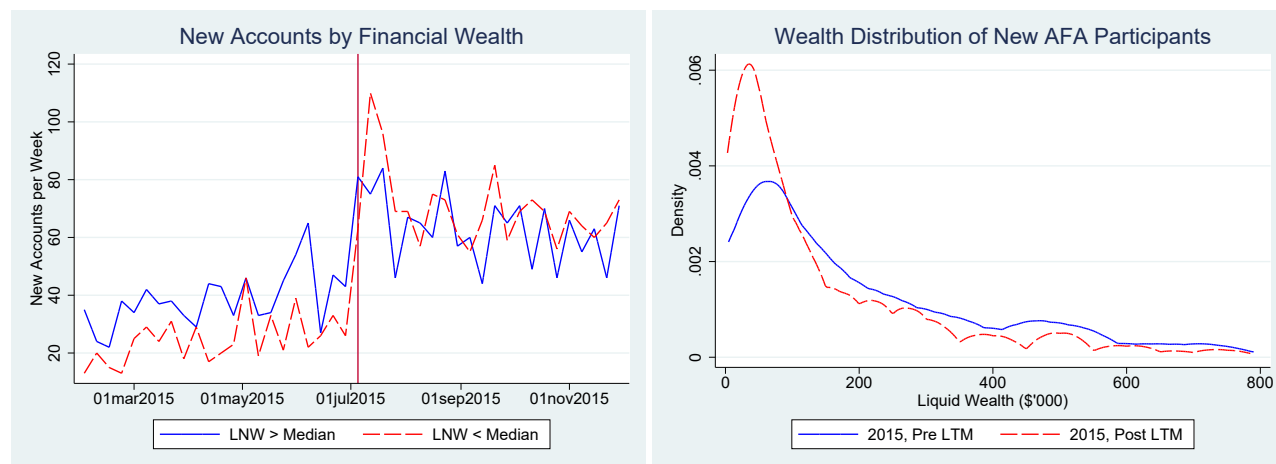
We utilize a company specific shock to study the effect of minimum account size on account delegation. On July 5, 2015, our data provider unexpectedly lowered its minimum account size by 90% from \$5,000 to \$500. In theory, the effect of this reduction on an individual's propensity to set up an AFM account should be decreasing in financial wealth, since for lower-wealth individuals the minimum account size is a more binding constraint. Consequently, one should expect to see relatively greater new account formation by lower-wealth cohorts following the reduction. To be clear, the dataset used in this analysis is broader than that from Section 3. In particular, the individuals in this dataset do not necessarily have an outside brokerage account, and the median AFM portfolio size is \$25,000. Thus, a reduction in minimum account size from \$5,000 to \$500 is meaningful for many individuals in the data.

Figure 3 provides stylized evidence consistent with this hypothesis. In panel (a) of the figure, it plots the number of new accounts set up per week set up by individuals in comparatively high and low wealth cohorts. The blue solid line corresponds to individuals in the upper half of the financial wealth distribution, among clients of our data provider, and the red dashed line corresponds to those in the lower half.²⁰ Around the reduction date, indicated by the vertical red line, there is a spike in new account flow from both cohorts.²¹ This may reflect the attractiveness of setting up an account of almost arbitrary size even when the account minimum is non-binding. Or, it may capture any positive publicity generated by the reduction. However, notice that new account flow by the lower-wealth cohort was generally less than the higher-wealth cohort before the reduction date, but after the reduction this relationship was frequently reversed.

²⁰The median financial wealth among clients of our data provider is \$107,500.

²¹Since the data are weekly, the vertical line corresponds to the week of July 5, 2015.

Figure 3: New Clients and Minimum Account Size Reduction



(a) New Account Flow

(b) Wealth Distribution

Note: Panel (a) plots the number of new accounts opened per week for individuals with above-median financial wealth (blue solid line) and below-median financial wealth (red dashed line). The red vertical line corresponds to the week of the minimum account size reduction. The median financial wealth in our sample is \$107,500. Panel (b) plots the empirical probability density function for the financial wealth of new accountholders in 2015. The blue solid line corresponds to the distribution before the reduction in minimum account size (LTM), and the red dashed line corresponds to the distribution afterwards. The density is based on a Epanechnikov kernel. The Kolmogorov-Smirnov D-statistic for the difference in distributions is 0.155 ($p < 0.001$).

Panel (b) of Figure 3 plots the wealth distribution of new clients based on a kernel density and conveys a similar message.²² The blue solid line corresponds to the distribution in 2015 before the reduction, which was called LTM (i.e. “lower-the-min”). The red dashed line corresponds to the distribution in 2015 after the reduction. There is a clear increase in the skewness of the wealth distribution after the reduction.²³

To quantify the intuition of Figure 3, we partition the sample into a lower-wealth and a higher-wealth cohort based on the sample median. Our parameter of interest is the effect of the reduction in minimum account size on new account formation. For reasons discussed above, it is

²²The density is based on a Epanechnikov kernel. The figure is qualitatively the same when plotted with a simple histogram.

²³The Kolmogorov-Smirnov D-statistic for the difference in distribution is 0.155 ($p < 0.001$). Also, since one might be concerned that financial wealth is only measured with substantial error, a version of Figure 3 in terms of the income distribution of new clients is qualitatively very similar.

likely that the reduction coincided with other factors (e.g. improved publicity) that would raise inflows for separate reasons than minimum account size. However, in theory a lower minimum account size should disproportionately raise new account formation for the lower-wealth cohort, while it is unlikely that the effects of additional factors like publicity should differ by financial wealth. Therefore, we estimate the following difference-in-difference specification

$$\log(\text{New Accounts}_{j,t}) = \alpha_t + \beta_0 \text{Low Wealth}_j + \beta_1 (\text{Post}_t \times \text{Low Wealth}_j) + u_{j,t}, \quad (2)$$

where j indexes cohort and t indexes week. Low Wealth_j is an indicator for whether cohort j is the lower-wealth cohort, Post_t is an indicator for whether week t equals or is after the week of July 5, 2015, and α_t represents a vector of week fixed effects.²⁴ Our parameter of interest in (2) is β_1 , which captures the additional effect of the account reduction on lower-wealth individuals. The week fixed effects α_t subsume any time varying factor (e.g. publicity) that affects account delegation equally across wealth cohorts. We estimate (2) over the period January 1, 2015 through December 1, 2015.

Table 4 has the estimates of (2). Focusing on the first column, the estimate for β_1 , the coefficient on $\text{Post}_t \times \text{Low Wealth}_j$, is 0.56 and is statistically significant. This suggests the reduction in minimum account size raised weekly new account flow by 56%.²⁵ This is consistent with the intuition of Figure 3 that reducing minimum account sizes can have a substantial effect on new account formation.

²⁴By estimating (2) at the cohort as opposed to individual level, we attenuate any bias due to the fact that our sample consists of individuals who eventually set up an AFM account. That is, since we estimate (2) on this sample, the estimate of β_1 has the interpretation of the effect of minimum account size conditional on eventually delegating to our data provider. This would be an inconsistent estimate for the unconditional effect if an individual's unobserved preference for AFM portfolios is growing over time and thus correlated with Post_t . Aggregating to the cohort level reduces the impact of such idiosyncratic taste shocks, and thus limits the degree of any such bias.

²⁵Strictly speaking, the interpretation of the estimate is that weekly new account flow increased by 56% more for the lower-wealth than the higher-wealth cohorts after the reduction in minimum account size. Under our identification assumption, this equals the effect of the reduction on new account flow.

Table 4: Difference-in-Difference: New Accounts by Wealth Cohort

Outcome:	Log New Accounts $_{j,t}$	Log New Deposits $_{j,t}$
Post LTM $_t \times$ Low Wealth $_j$	0.575*** (0.057)	0.237** (0.119)
Low Wealth $_j$	-0.458*** (0.049)	-1.771*** (0.079)
Week FE	Yes	Yes
R-squared	0.611	0.900
Number of Observations	88	88

Note: Low Wealth $_j$ indicates the cohort with financial wealth under \$107,500, the median in our sample. Each observation is a cohort-week. The outcome in the first column is log number of new accounts by cohort j in week t . The outcome in the second column is the log value of deposits in new accounts by cohort j in week t . The sample period is January 1, 2015 through December 1, 2015. Robust standard errors are in parentheses. The notation ***, **, and * denote p-values less than 0.01, 0.05, and 0.10 respectively.

Given our interest in how lowering minimum account thresholds can attract clientele, we study new account formation as our primary outcome. However, this measure cannot capture the effect of account size reductions on dollar deposit flows, and thus the initial impact on assets under management. For example, it is possible that newly formed accounts are sufficiently small that deposit flows do not rise significantly after a reduction in minimum account size. That is, reducing the minimum account size has both an intensive and an extensive margin effect, and the effect on new deposit flows will reflect their product. To study this alternative channel, the second column of Table 4 replaces the outcome with the log of total dollar deposits by cohort j in week t . The statistically significant point estimate of 0.24 suggests that the reduction in minimum account size raised total deposit flows by 24%. Interestingly, the magnitude is smaller than in the first column, consistent with competing extensive and intensive margin effects.

5 Conclusion

This paper documented the value added of automated financial management (AFM) services in terms of improved diversification and account size flexibility. Compared to traditional accounts, AFM portfolios feature significantly higher Sharpe ratios, which is predominantly due to less

idiosyncratic risk. The gains from diversification are especially pronounced among non-taxable accounts and those with a high share of directly held stocks. Individuals with underdiversified portfolios are also more likely to delegate their account to an automated financial advisor (AFA). In addition, when an AFA provided more account size flexibility by lowering the minimum balance threshold, new account formation increased substantially. This led to increased deposit flow, despite the fact that the reduction disproportionately increased new account formation by relatively less wealthy individuals.

These results are of practical interest given recent growth in the demand for AFAs and traditional advisors offering AFM services. In particular, they show how advisors with a well-designed AFM service can attract clientele through reduced idiosyncratic risk and constraints on account size. There are many other dimensions along which AFM services can provide value, such as tax efficient allocation and rebalancing algorithms, portfolio lines of credit, or financial education and planning. We leave these as topics for future research.

To date, there has been relatively little research on the real effects of AFM. Our paper provides evidence that AFM can increase household investment in financial markets and improve the diversification of these investments. However, many interesting and important questions remain unanswered, such as the effects of AFM on particular behavioral biases or stock market participation.

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A Estimating Portfolio Returns

Given the estimated loadings $\hat{\beta}_i^F$ and idiosyncratic volatilities $\hat{\sigma}_i^F$ from estimating (1) for model F , we compute the estimated mean μ_p^F and variance $(\sigma_p^F)^2$ of excess returns on portfolio p as

$$\mu_p^F = \left(\sum_i w_{i,p} \hat{\beta}_i^F \right) \mu^F \quad (3)$$

$$(\sigma_p^F)^2 = \sum_i (w_{i,p} \hat{\sigma}_i^F)^2 + \left(\sum_i w_{i,p} \hat{\beta}_i^F \right) \Sigma^F \left(\sum_i w_{i,p} \hat{\beta}_i^F \right)', \quad (4)$$

where μ^F is the expected value of F_t , Σ^F is the covariance matrix of F_t , and $w_{i,p}$ is the weight of security i in portfolio p . The weights $w_{i,p}$ are based on the subportfolio consisting of stocks, mutual funds, and exchange traded funds (ETFs). This is because bonds and options are held by few portfolios in our sample, and, as pointed out by Calvet, Campbell, and Sodini (2007), pricing them is less straightforward.

We estimate (1) for the following five asset pricing models,

$$F_t^{CAPM} = \left[R_t^m - R_t^f \right]', \quad (5)$$

$$F_t^{MKT} = \left[R_t^m - R_t^f, \quad 1 \right]', \quad (6)$$

$$F_t^{FF} = \left[R_t^m - R_t^f, \quad R_t^{HML}, \quad R_t^{SMB} \right]', \quad (7)$$

$$F_t^{FF+} = \left[R_t^m - R_t^f, \quad R_t^{HML}, \quad R_t^{SMB}, \quad R_t^{USB} - R_t^f, \quad R_t^{GLB} - R_t^f \right]', \quad (8)$$

$$F_t^{VAN} = \left[R_t^{VT} - R_t^f, \quad R_t^{BND} - R_t^f \right]', \quad (9)$$

$$(10)$$

where R_t^m is the monthly market return based on the global Morgan Stanley Capital International Index (MSCII), R_t^f is the one month Treasury yield, R_t^{HML} is the monthly return between high book-to-market stocks and low book-to-market stocks, R_t^{SMB} denotes the spread in monthly return between stocks with a small market capitalization and a big market capitalization, R_t^{USB} is the monthly return on the Barclays Aggregate U.S. Bond Index Unhedged, R_t^{GLB} is the monthly return on the Barclays Global Aggregate Bond Index Unhedged, R_t^{VT} is

the monthly return on Vanguard's total stock market ETF (VT), and R_t^{BND} denotes the return on Vanguard's total bond market ETF (BND).

In words, (5)-(9) are: the standard capital asset pricing model (CAPM), the "market model", the Fama and French three-factor model, a five-factor model augmenting the Fama and French model with global and U.S. bond returns, and a two-factor model based on Vanguard's total equity and bond ETFs. Our data on monthly returns come from the Center for Research in Security Prices (CRSP) and Kenneth French's website. We use the sample mean and covariance matrices to calibrate the moments of the factors. For the CAPM, these are $\mu^{CAPM} = 0.068$ and $\Sigma^{CAPM} = 0.170$. To obtain annualized estimates, we multiply the estimated mean and variance from (3)-(4) by 12.

In terms of data cleaning, we winsorize the sample according to the estimated moments from (3)-(4) by 2.5% on both sides. We also drop brokerage portfolios under \$100 in value. We use the longest available time series of monthly returns for each security $R_{i,t}$ and factor F_t dating back to January 1975.