On Diseconomies of Scale and Performance Effects in Separate Accounts

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Contents

1 Introduction

1.1 Motivation

While media attention as well as academic research have tended to focus on actively managed mutual funds (MFs) and passively managed exchange traded funds (ETFs), a steadily growing sector within the asset management industry is that of separate accounts (SAs). An increase of 340% in assets under management (AUM) over the 10-year period from 2009-2018, representing now more than $6.5 trillion, exemplifies the growing importance of SAs in the industry.[1]

Although the purpose of actively managed SAs is similar to actively managed MFs – managing and investing money for investors – the organizational structure of these vehicles is quite different. A MF is managed as one homogeneous portfolio in which MF investors own their assets indirectly via fund shares. In contrast, SA investors own an individual account in which they hold their respective assets directly. All individual accounts within a SA are managed independently but follow a common overall strategy. This structure enables investors to customize their portfolio by setting style or risk preferences, which is necessary for many institutional investors such as retirement plans, endowments and foundations to align their investments with self-imposed principles and their own corporate governance.

In recent years, the high increase in AUM and the continuing shift of SAs from being an exclusive investment vehicle for institutional investors and ultra-rich individuals towards becoming an investment alternative for financially less sophisticated, smaller institutional and retail investors, makes it increasingly necessary for regulators to monitor the development of this fast growing market segment. Accordingly, in 2015 the U.S. Securities and Exchange

[1] Money Management Institute and Cerulli Associates (2019).

Commission (SEC) proposed several amendments to Part 1A of Form ADV with the intend to increase reporting requirements, and invited researchers and investment professionals to comment on that proposal.[2] Based on this feedback, the SEC adopted its slightly modified proposal in 2016 with an effective date for the new requirements of October 1, 2017. These amendments require investment advisors with more than $500 million of regulatory AUM (RAUM) attributable to SAs, to disclose additional information annually, including their derivative exposures and the dollar amount of their borrowings. The SEC's declared objective with these stricter reporting requirements is "to enhance our staff's ability to effectively carry out our risk-based examination program and other risk assessment and monitoring activities" with respect to SAs and their investment advisors.[3]

To support this objective, this dissertation aims to increase the general understanding of SAs and thus to benefit research, regulation and various market participants. While many fundamental insights from the academic MF literature can be transferred to SAs, the essential difference in the vehicle structure combined with a lower level of regulatory requirements and the fact that most SA investors are still institutional investors differentiate SAs significantly from MFs.

The first topic addressed in this dissertation is the impact of the unique organizational SA structure on diseconomies of scale, the diminishing effect of size on the risk-adjusted performance known from the MF literature. The topic of diseconomies of scale in general has been in the focus of academic literature since the earliest empirical studies on MFs. Sharpe (1966) proposed and tested the competing hypotheses regarding whether a fund exhibits economies or diseconomies of scale. Since that time, fund size has become a standard control variable in performance regressions (e.g. Grinblatt and Titman, 1989; Carhart, 1997; Sirri and

[2] https://www.sec.gov/rules/proposed/2015/ia-4091.pdf
[3] https://www.govinfo.gov/content/pkg/FR-2016-09-01/pdf/2016-20832.pdf

Tufano, 1998), often with a negative and statistically significant coefficient being interpreted as evidence of diseconomies of scale.

As there is no existing study on diseconomies of scale in SAs to date, Chapters II and III of this dissertation aim to close this research gap. Chapter II examines how the unique organizational structure of SAs affects the phenomenon of diminishing returns to scale. Chapter III takes advantage of the facts that 1) SAs openly disclose their investment approach and 2) quantitative and fundamental investment approaches differ in their underlying nature. These basic differences in their underlying nature suggest potential differences in both channels for diseconomies of scale, the liquidity costs channel and the information processing/hierarchy costs channel.

In large asset management companies, it is common practice to offer developed investment strategies (e.g. "large cap value" or "small cap growth") to different types of investors in parallel through several investment vehicles. A particular investment strategy could be offered to retail investors via a retail MF and to an institutional investor via an institutional MF or a SA. Chapter IV uses a comprehensive sample of these side-by-side managed SA-MF twins to quantify the effect of unobserved investment constraints on risk-adjusted performance. Since this twin setting controls directly for managerial skill, advisor efficiency and investment style, it represents the perfect laboratory to examine how differences with respect to regulation, investor preferences and the organizational vehicle structure affect performance.

One reason for the increasing popularity of SAs is the option of a customized asset management combined with an above average past performance. Previous studies on the performance of SAs show that the SA universe as a whole was able to outperform the MF universe significantly (e.g. Elton, Gruber and Blake, 2014). Building on these results, Chapter V contains a comprehensive performance analysis of SAs answering questions such as whether SA managers are capable of generating value for their investors and what type of investor can benefit from SAs. Furthermore, it distinguishes between luck and skill with respect to the superior past performance of the SA universe.

The last Chapter VI sums up the results and highlights the key contribution of each article. Furthermore, it gives an understanding of how future research might build upon insights provided in this dissertation. In the following, Chapter I contains an overview and brief summaries of the research articles provided in this dissertation.

1.2 Overview over papers included

Paper title	Co-authors	Published?	Journal	Date
On Size Effects in Separate Accounts	Richard Evans Martin Rohleder Marco Wilkens	No[4]	WP, University of Virginia, University of Augsburg	2020
Diseconomies of Scale in Quantitative and Fundamental Investment Styles	Richard Evans Martin Rohleder Marco Wilkens	No[5]	WP, University of Virginia, University of Augsburg	2020
The Effect of Unobserved Constraints on Portfolio Management: Evidence from Separate Account-Mutual Fund Twins	Martin Rohleder René Weh Marco Wilkens	No[6]	WP, University of Augsburg	2020
The Value of Separate Accounts for Different Types of Investors	–	No[7]	WP, University of Augsburg	2020

1.2.1 Article I: On Size Effects in Separate Accounts

The first article of this dissertation focuses on the specific effects of size on the performance of SAs. Based on a large and comprehensive sample of 3,770 US domestic equity SAs over a 26-year sample period from 1990 to 2015, we find that SAs suffer from two major sources of diseconomies of scale: 1) liquidity constraints and market impact costs as well as 2) organizational stress. According to further analyses, the latter is more severe and is caused by

[4] Accepted at the 57th Annual Meeting of the Southern Finance Association 2017, Key West, Florida, the 56th Annual Meeting of the Eastern Finance Association 2018, Philadelphia, Pennsylvania for presentation.
[5] "Revise and Resubmit" at the Journal of Financial and Quantitative Analysis (VHB Ranking A).
[6] Accepted at the Doctoral Student Consortium of the 23th FMA European Conference 2019, Glasgow, Scotland; the 56th Annual Meeting of the Eastern Finance Association 2020, Boston, Massachusetts; the 24th FMA European Conference 2020, Limassol, Cyprus, for presentation.
[7] "Under review" at the Journal of Asset Management (VHB Ranking B).

the fact that SAs have an additional structural layer compared to MFs: separate, customized accounts of individual investors, which increases overall management complexity and diminishes performance. Our results indicate that SA managers reduce portfolio complexity by concentrating on fewer stocks to compensate for this additional complexity in SA structure. Various robustness checks show that these findings are independent of the performance model chosen and they do not result from the low beta anomaly (Frazzini and Pedersen, 2014) or from incubation bias (Evans, 2010; Fama and French, 2010). While scale diseconomies have been extensively studied for MFs (e.g. Indro et al., 1999; Berk and Green, 2004; Chen et al., 2004; Evans et al., 2019; Pastor, Stambaugh and Taylor, 2020), our analyses contribute specific new insights into size effects in SAs, which constitute an economically important and fast growing segment of the institutional asset management industry.

1.2.2 Article II: Diseconomies of Scale in Quantitative and Fundamental Investment Styles

In the second article, we revisit the issue of diseconomies of scale by contrasting two different investment approaches: quantitative and fundamental. Using a database of SAs from 1990 to 2018 as a laboratory, we take advantage of the fact that the two investment approaches differ in their underlying nature, which suggests potential differences in both channels for diseconomies of scale, i.e. the liquidity costs and the information processing/hierarchy costs channel. Even after controlling for other SA characteristics, investment advisor-, investment style-, time-, and SA-fixed effects or controlling for endogeneity using the Zhu (2018) recursive-demeaning approach, we still find that quantitative strategies exhibit statistically and economically significantly lower diseconomies of scale. To enhance our understanding regarding the potential channels through which these two investment styles differ, we follow the framework proposed by Pastor, Stambaugh and Taylor (2020) to examine the liquidity costs channel and follow the method of Cici, Jaspersen and Kempf (2017) to estimate information diffusion, a proxy for information processing speed, to explore the processing/hierarchy costs channel. The results indicate that quantitatively managed SAs exhibit lower costs in both dimensions. Accounting for these differences partially explains the differences in diseconomies of scale.

1.2.3 Article III: The Effect of Unobserved Constraints on Portfolio Management: Evidence from Separate Account-Mutual Fund Twins

In this article, we use a large dataset of 907 side-by-side managed SA-MF twins as a setting to analyze how usually unobserved investment constraints affect the portfolio performance of actively managed investment vehicles. We follow the matching procedure of Evans and Fahlenbrach (2012) to collect the most comprehensive sample of SA-MF twins to date. We apply a modification of Cremers and Petajisto's (2009) active share to these twins to determine a time-series of portfolio differences for each twin pair. Since the twin setting controls directly for managerial skill, advisor efficiency and investment style, we employ a similar argument as Kacperzyk, Sialm and Zheng (2008) and interpret differences in portfolio composition as unobserved investment constraints regarding regulation, investor preferences and organizational structure of the investment vehicle. By controlling for a wide range of twin, firm and portfolio characteristics, i.e. observed constraints, we are able to determine the effect of unobserved constraints on portfolio performance. We find strong and robust evidence that such unobserved constraints lead to a decrease in risk-adjusted performance in both vehicles. Even after controlling for differences in style factor exposures between both vehicles, our results remain economically unchanged.

1.2.4 Article IV: The Value of Separate Accounts for Different Types of Investors

The last article of this dissertation focuses on the performance of SAs. While many recent studies show that over the last few decades the MF industry was on average not able to produce sufficient risk-adjusted returns to cover their costs (e.g. Gruber, 1996; Carhart, 1997; Fama and

French, 2010), several studies find that the SA universe has significantly outperformed the MF universe (e.g. Elton, Gruber and Blake, 2014; Chen et al., 2017). Based on this observation, this study provides new uni- and multivariate evidence for the long-term performance of SAs. Over the period from 1990 to 2017, a comprehensive sample of 3,781 SAs was able to produce an average risk-adjusted Carhart performance of 81 bp before and -11 bp after costs. These numbers are in line with recent SA literature and they are a strong indication for the existence of manager skill in the SA universe. In order to distinguish luck from skill, I apply a bootstrapping methodology from Fama and French (2010) on monthly SA returns and test for the existence of a true nonzero alpha. The results suggest that even in a world in which every SA manager has the ability to generate expected returns to cover their trading costs and commissions, SAs are still able to achieve risk-adjusted gross returns that cannot be explained by pure luck. Furthermore, by dividing the sample into three subsamples based on the SA's product focus, this study is the first to evaluate and differentiate the benefit of SAs as an investment alternative to MFs for different types of investors. In terms of risk-adjusted performance, it is remarkable that institutional and retail SAs show a similar risk-adjusted gross performance, however the significantly higher expense ratios of the retail SAs, result in a significant underperformance after costs while institutional SAs achieve a small but positive risk-adjusted Carhart performance.

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2 Article I: On Size Effects in Separate Accounts

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Abstract. We are the first to investigate specific size effects in separate accounts (SAs). This is important because SAs represent a major investment vehicle for institutional investors. More interestingly, they have an additional structural layer compared to mutual funds for which size effects have been intensively studied. This additional layer – separate, individualized accounts of single investors, which increase overall management complexity – significantly diminishes performance. These structural diseconomies economically outweigh the liquidity and market impact cost related negative effects known from mutual funds. However, comparing SAs and mutual funds, we find that SAs outperform mutual funds on average regardless of structural diseconomies of scale.

JEL Classification: G11, G12

Keywords: Institutional investing, separate accounts, performance, diseconomies of scale, flows

2.1 Introduction

This paper is the first to investigate the specific effects of size on the performance of separate accounts (SAs), i.e. separately managed accounts (SMAs) and collective investment trusts (CITs). This topic is important for two reasons: firstly, SAs have developed into a major investment vehicle for institutional investors, and secondly, they have a distinctive organizational structure, which distinguishes them from mutual funds, for which size effects have been intensively studied. Thus, our analyses contribute specific new insights into size effects in this economically important investment segment and further, they will strengthen the general understanding of institutional asset management. We use a large and comprehensive sample of 3,770 US domestic equity SAs with monthly net and gross returns and a large variety of quarterly SA characteristics over a 26-year sample period from 1990 to 2015 to dig specifically into the effects of SA size on SA performance. Our key finding is that SAs suffer from two major sources of diseconomies of scale: 1) liquidity constraints and market impact costs as well as 2) organizational stress. According to further analyses, the latter is more severe and caused by the fact that SAs have an additional structural layer compared to mutual funds: separate, individualized accounts of single investors, which increases overall management complexity and diminishes performance.

What makes SAs different to mutual funds? Within an SA each investor has an own account via which she directly owns the respective assets instead of owning a fund share like in mutual funds. All individual accounts are managed independently, but based on a common overall strategy. This construction offers the investor the opportunity to deviate from the common overall strategy by restricting or individualizing her portfolio, for example by implementing a tax-harvesting strategy to optimize individual after-tax returns. This special structure makes SAs an investment alternative to mutual funds with unique features like negotiable and comparatively low fees. To be able to offer this combination of low costs and high individual service, SAs usually have high minimum investments between $100,000 and $25 million which makes them only affordable to a limited number of investors, including retirement plans, endowments, foundations and wealthy individuals. Thus, they are predominantly offered to sophisticated investors, who do not need as much customer protection as retail investors. Accordingly, SAs are not registered with the SEC which implies less regulation,[8] lower reporting requirements and, consequently, lower costs. However, low reporting requirements lead to data limitations, which made SAs a challenging area of research in the past. Thus, it is not surprising, that the existing literature regarding SAs is rare compared to mutual funds.[9] A topic that has been explored elaborately in the mutual fund literature, but has not been investigated for SAs in detail so far, is the effect of size on performance.

Regarding mutual funds, the literature seems to agree on the existence of diminishing returns to scale. A first stream of studies traces diseconomies of scale to liquidity constraints and transaction costs (e.g. Berk and Green, 2004; Yan, 2008; Chan et al., 2009). Both are intimately connected to each other. The liquidity explanation is based on a fund's individual level of holdings illiquidity. For example, large small-cap funds have on average a higher illiquidity exposure than large-cap funds with the same size. Stocks with a lower market capitalization are usually more illiquid and in addition, larger funds have a smaller universe of investment opportunities (e.g., Bogle, 2010). The transaction cost explanation focuses on the negative effect of explicit transaction costs and implicit market impact costs on performance.

[8] Strictly speaking, this applies only to SMAs while CITs are regulated by the Office of the Controller of the Currency (Coalition of Collective Investment Trusts, 2015). However, this regulation is much less restrictive and therefore also less costly as the regulation of mutual funds by the SEC.

[9] The existing literature regarding SAs can be grouped into two segments. The studies in the first group use SAs to investigate characteristics of institutional investors, e.g. DelGuerico and Tkac (2002), Heisler et al. (2007) and Goyal and Wahal (2008). The second group studies performance and persistence in SA performance, e.g. Lakonishok et al. (1992), Coggin et al. (1993), Ferson and Khang (2002), Tonks (2005), Busse et al. (2010), Peterson et al. (2011), Elton et al. (2014).

Both depend on trade volume, and thus indirectly on fund size. Due to higher market impact costs and a longer time span to trade larger positions Beckers and Vaughan (2001) argue that managers are not able to implement their optimal trading strategies. Hence, they lose the flexibility they need to achieve positive risk-adjusted returns. This stream of literature is also closely related to the research of flow effects on mutual fund performance as funds' trading on flows leads to liquidity constraints and market impact costs which are also more pronounced for larger and for small-cap funds (e.g., Edelen, 1999; Alexander et al., 2007; Pollet and Wilson, 2008).

A second stream of size related mutual fund literature focuses on structural differences between large and small organizations. Indro et al. (1999) argue that a growing company needs more employees, which leads to administrative stress and results in diminishing returns to scale. Chen et al. (2004) provide a similar explanation for structural size effects. They adopt Stein's (2002) theory of hierarchy costs on mutual funds and call them organizational diseconomies. The larger a fund, the higher the inefficient effort managers need to convince others to implement their ideas. Based on different proxies for hierarchy costs, they show that larger funds have higher hierarchy costs. On firm level, there barely occur structural diseconomies, because different funds within a firm are usually managed separately. Thus, the second explanation is based on coordination problems resulting from an increasing complexity within a growing fund. In a very recent paper, Evans et al. (2017) find that diseconomies of scope, i.e. of managing multiple funds or even multiple fund objectives side by side, diminish the performance of mutual fund managers.

Although there is no existing study with the main focus on size effects in SAs, a few studies provide brief comments as side-effects of their main findings. None of these studies, however, go on to analyze such size effects in detail. Busse et al. (2010) study performance persistence in quarterly SA returns. One of their results is a higher risk-adjusted performance when they use equally-weighted instead of value-weighted SA portfolio returns. This indicates a superior performance from smaller SAs, which is in line with the presented mutual fund literature. Furthermore, in their cross-sectional analyses, Peterson et al. (2011) and Elton et al. (2014) identify factors that explain risk-adjusted SA performance and amongst others, they use SA and family size as control variables, respectively. The latter do not find any significant explanatory power for performance differences between SAs in neither logarithmized size nor logarithmized firm size. Peterson et al. (2011) find a negative impact of size on risk-adjusted performance, which supports Busse et al.'s (2010) finding. As an additional SA-specific variable, Peterson et al. (2011) include the number of different accounts into their model. The results suggest a negative impact on risk-adjusted performance. However, it is not significant. Nevertheless, the authors' believe that there should be a negative correlation and conjecture that mostly extreme values for the number of accounts matter.

From an economical point of view, this is a reasonable consideration. In contrast to a mutual fund investor, every SA investor has her own account with her own assets. From an investor's perspective, this organizational structure has several advantages including higher transparency, multiple client services such as individual tax optimization and the opportunity to demand a certain degree of portfolio individualization. Lakonishok et al. (1992) state that especially institutional investors demand many individual services, that make their job more convenient. However, for the SA management, this construction is time-consuming, implies higher coordination effort and higher complexity in its investment decisions. SA managers have to manage several accounts at the same time, each with a certain demand for individualization, which they need to consider in their investment decision. The higher the number of accounts is, the lower the manager's attention span per investor can be. Furthermore, the complexity within the SA increases with every additional investor. On the one hand, an SA manager needs to combine individual portfolio requirements, on the other hand, the individual returns should not deviate too far from the overall SA return. To be able to offer high-quality service to meet each investor's demand in spite of managers' limited attention span (e.g., Kacperczyk et al., 2016; Gupta-Mukherjee and Pareek, 2016), SAs with more accounts potentially need more staff compared to mutual funds of the same size. However, it is known from the mutual fund literature that more staff causes administrative stress (Indro et al., 1999) and hierarchy costs (Chen et al., 2004), which both have a negative impact on performance. Thus, with a growing number of different accounts, an SA faces an additional layer in its organizational structure that does not exist in mutual funds and which potentially amplifies diminishing returns to scale.

Therefore, we derive the following expectations regarding size effects in SAs. First, like mutual funds, we expect SAs to suffer from diminishing returns to scale in the dimension of total assets, i.e. due to liquidity constraints and market impact costs. Second, due to their additional organizational layer, in which every investor has her own account, SAs should be even more prone to structural size effects. Thus, we also expect SAs to suffer from diminishing returns to scale in the dimension of number of accounts. Third, we expect both size effects to exist side by side.

Our results indicate that SAs indeed suffer from two dimensions of diseconomies of scale. The first is directly related to size and caused by similar reasons as in mutual funds. The more important dimension, however, is related to the specific structure of SAs as an increasing number of individual investor accounts within an SA severely hurts performance. This diminishing effect on performance is explained by a limited manager attention span stemming from an increasing overall management complexity. Furthermore, due to the specific structure of SAs, we find no relevant negative effects of flows on the performance of SAs. This is contrary to numerous findings in the mutual fund literature. This may be explained by better communication between SA managers and investors and by the fact that individual investor accounts within SAs are on average below the critical size for market impact costs.

The remainder of the paper is organized as follows. Section 2 introduces the data. Section 3 describes the methodology and reports the results of our main empirical analysis. Section 4 provides specific further analyses to tackle the reasons of size effects in SAs. Section 5 comments on robustness and Section 6 concludes.

2.2 Data and sample description

As indicated above, each SA investor directly owns an account which is managed in conjunction with other accounts following a common overall strategy (e.g. “small-value” or “large-neutral”). Therefore, to maintain customer anonymity, they are reported on a pooled basis as one SA, which is our unit of analysis. Thus, the reported returns are composite returns, i.e. weighted averages of the realized returns of the different accounts within an SA. The data stems from Morningstar Direct from which we select the whole universe of U.S. equity SMAs and CITs with seamless monthly return series. This dataset initially includes 5,322 SAs with 750,199 SA-months managed by 1,007 different asset management firms between January 1990 and December 2015. It contains monthly returns and quarterly SA characteristics. Compared to prior studies, which predominately use quarterly returns, monthly return data reduces interim trading bias (e.g. Ferson and Khang, 2002) and allows for more precise performance measurement. We eliminate all SAs for which net returns exceed gross returns (48 SAs) and which have less than 36 monthly return observations (434). Furthermore, we exclude all index (360) or specialty (710) SAs.[10] The final dataset consists of 3,770 U.S. equity SAs with 580,165 SA-months and is thus one of the largest and the most comprehensive dataset used in the SA literature to date. Table 1 contains summary statistics for the whole sample. Panel A shows summary statistics by SA and Panel B reports pooled summary statistics.

[10] We define as “specialty SAs” also all SAs with an average systematic market beta below 0.2 from the 24-month rolling window regressions.

[Insert Table 1 here]

Average SA total assets (TA) are about 519 million US dollar. The number of accounts, which is the number of different investors within an SA, is 243 on average. The average account size (avAS), which we compute following Eq. (1), provides us with more detailed information about the average investor.

$$avAS_{i,t} = \frac{TA_{i,t}}{Number\ of\ accounts_{i,t}} \tag{1}$$

The fact that the average number of accounts times the average account size does not roughly equal the average TA shows the impact of different levels of positive skewness.[11] In general, all variables seem to be right skewed, which illustrates the high heterogeneity between the SAs. However, for the number of accounts, the relative difference between mean and median is particularly high. Hence, some SAs have an extremely high number of accounts.

The expense ratio, which is the difference between reported gross and net returns, has an average of 0.86% which is lower than comparable numbers for US domestic equity mutual funds (e.g, 1.20% p.a., Rohleder et al., 2016). The comparatively low costs can partly be attributed to the high average minimum investment of 7.24 million US dollar and to the relatively low annual turnover of 70.15% which is distinctively lower than that of US domestic equity mutual funds where annual turnover is on average around 85% (e.g., Pastor et al., 2016). On average, SAs have 89 different holdings and 33.79% of their assets are invested in their top 10 holdings. In the period from 1990 to 2015, SAs have experienced substantial annual implied percentage net flow of 14.45%. We calculate quarterly implied percentage net flow (hereafter "flow") from quarterly TA and quarterly returns as in Sirri and Tufano (1998) following Eq. (2).

[11] Keep in mind that data availability differs between the variables so that the numbers may not be directly combined (e.g., mean average account size ≠ mean number of accounts / mean total assets).

$$flow_{i,q} = \frac{TA_{i,t} - TA_{i,q\text{-}1}\ (1+R_{i,q})}{TA_{i,q\text{-}1}} \tag{2}$$

The positive average flow attests to the growing importance of SAs over these 26 years. To calculate an individualization score, we use sixteen questions asked by Morningstar regarding the range of services offered (e.g. an individual tax-optimization) to investors. These question can be answered with "proactive", "by request only" or "no", which we evaluate with 2, 1 or 0 points. The individualization score is then calculated as the sum of these points. Thus, the maximum an SA can achieve is 32 points. The average number of managers, which can take values between 1 and 4, is 2.1.

The dataset consist of surviving- and non-surviving separate accounts, which eliminates a potential survivorship bias. However, due to weaker reporting requirements than for mutual funds, the data is self-reported which means it is more prone to further biases, like an upward-bias through self-selection or the opportunity to report data with a lag of up to six months. Elton et al. (2014), who used the same data provider in their SA study, have tested the existence of these biases in the Morningstar Direct Database. They do not find any serious bias and argue that the costs of not being included in the database are comparable to costs of revealing some month of bad performance. Furthermore, they argue that a possible upward bias will be equalized by many bad managers, who do not report at all. That argument also applies to the best performing managers, who do not report to protect their investment strategy or who have already exceeded their maximum AUM that they can handle without suffering seriously from diseconomies of scale.

2.3 Empirical analysis of size effects in SAs

2.3.1 SA performance

Our basic performance model is Carhart's (1997) four-factor model, as it is the most commonly accepted model in modern mutual fund literature. The model is based on the following regression (Eq. 3):[12]

$$ER_{i,t} = \alpha_i^{4F} + \beta_i^{Mkt}\, ER_{Mkt,t} + \beta_i^{SMB}\, SMB_t + \beta_i^{HML}\, HML_t + \beta_i^{UMD}\, UMD_t + \varepsilon_{i,t} \qquad (3)$$

where $ER_{i,t}$ is the return of SA i in month t in excess of the 1-month T-Bill rate, α_i^{4F} is stock i's risk-adjusted performance, $ER_{Mkt,t}$ is the monthly market excess return, SMB_t is the monthly size factor, HML_t is the monthly value factor (Fama and French, 1993), and UMD_t is the monthly momentum factor (Carhart, 1997).

To get a time-series of risk-adjusted SA performance, we follow Sharpe (1992) and calculate the out-of-sample performance for each SA in each month t using a 24-month rolling window Carhart regression from t–25 to t–1:[13]

$$Style\ return_{i,t}^{4F} = \beta_{i,t\text{-}1}^{Mkt}\, ER_{Mkt,t} + \beta_{i,t\text{-}1}^{SMB}\, SMB_t + \beta_{i,t\text{-}1}^{HML}\, HML_t + \beta_{i,t\text{-}1}^{UMD}\, UMD_t \qquad (4a)$$

$$\alpha_{i,t}^{ooS\text{-}4F} = ER_{i,t} - (\beta_{i,t\text{-}1}^{Mkt}\, ER_{Mkt,t} + \beta_{i,t\text{-}1}^{SMB}\, SMB_t + \beta_{i,t\text{-}1}^{HML}\, HML_t + \beta_{i,t\text{-}1}^{UMD}\, UMD_t) \qquad (4b)$$

Eq. (4a) shows how the monthly style return for SA i in month t is calculated by multiplying its estimated factor sensitivities from the prior 24 months with the return of the corresponding risk factors in month t. It represents an individually constructed benchmark with the same style as the SA. Eq. (4b) illustrates the calculation of the monthly out-of-sample performance (henceforth simply "Carhart performance" unless otherwise qualified). It is the difference between the actual return of SA i in month t and its style return in this month. Notice that it

[12] We thank Kenneth French for providing the corresponding risk-factors on: http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html.
[13] Alternative window lengths of 12 and 36 months yield economically similar results.

differs from the residuum of a simple regression, which is an in-sample value. Furthermore, the Carhart performance is winsorized at the 1% and 99% percentiles to control for outliers.

In our analysis, we focus on Carhart's (1997) four-factor model. Nevertheless, Table 2 reports SA performance and corresponding factor loadings for various factor models, including models we are going to use as robustness checks. Panel A shows the results for net returns and Panel B for gross returns, both equally-weighted (EW) and value-weighted (VW).

[Insert Table 2 here]

The annualized equally-weighted Carhart net performance of -0.348% is slightly lower than the measured performance in the existing studies of Busse et al. (2010) or Elton et al. (2014). Our results suggest, that SA managers are on average not able to generate an additional value over a passive benchmark investment. Remarkable is the difference between the equally- and the value-weighted results which is distinctively lower. This is in line with the finding of Busse et al. (2010) and indicates a superior performance for smaller SAs.

2.3.2 Sorted portfolio analysis of size effects

To start our analysis, we sort SAs each quarter into quintiles based on their size, their number of accounts and their average account size. Afterward we calculate the summary statistics for the most important SA characteristics. Table 3 provides the results. Panel A shows the sorting by TA, Panel B the sorting by number of accounts and Panel C the sorting by average account size.

[Insert Table 3 here]

Regarding our first expectation formulated in Section 2.2, Panel A shows some systematic trends like an enormous spread in TA between the quintiles. The SAs in the smallest quintile have average TA of $11 million, whereas the SAs in the biggest quintile have an average of $2.53 billion. It is obvious, that the average account size needs to increase as well, because the average account size cannot be larger than the average SA in a certain quintile. Beyond that, it is reasonable that also the average number of accounts within an SA increases with its size. However, this trend is not as strong as the growing account size. Regarding the performance in Panel A, we see the expected size effects. SAs have decreasing returns to scale and on average increasing market risk. This could be based on the fact that bigger SAs invest in stocks with a higher market capitalization. These stocks typically make a higher fraction of the market return, which explains the higher market sensitivity of larger SAs (e.g. Chan et al., 2009). Generally, Panel A supports our first expectation of the existence of diseconomies of scale in the dimension of size.

To get a first impression regarding our second expectation, Panel B shows SAs sorted by their number of accounts. Here, we find an even stronger trend regarding Carhart performance and market risk. We have a difference of 1.54% in annualized Carhart performance. This means that a higher number of different investors reduces the average risk-adjusted performance, which can be explained by a higher level of organizational stress. This confirms our second expectation, the existence of diseconomies of scale in the dimension of number of different investors.

In contrast to that, the sorting by average account size in Panel C does not show a clear pattern regarding performance. Only quintile 1 has an inferior risk-adjusted performance compared to other quintiles. The major reason is probably the high average number of accounts. The SAs in quintile 2 to 5 perform similarly. For these quintiles, both prior described size effects seem to offset each other. E.g. in quintile 2, the positive effect of a small size is equalized by the negative effect of a high number of accounts. In quintile 5, it is the other way around. However, regarding the market risk, the quintiles differ more clearly and even stronger than in the two previous sortings. Generally, it seems reasonable that SAs with smaller accounts deviate stronger from the market. Another interesting point is the expense ratio. In Section 1, we have already explained that expenses are individually negotiated between the investor and the management firm. Here, we see that the larger the initial investment is, the lower the average expenses are.

With regard to our third expectation that both effects exist side by side, we compare the number of accounts and the TA over the different quintiles between Panels A and B. Considering the differences between mean and median, it seems that all five size quintiles in Panel A contain some SAs with a very high number of accounts. In Panel B, these SAs are probably included in quintile 5, the worst performing quintile. Similarly, every number of accounts quintile in Panel B seems to contain some large funds, which are likely included in quintiles 4 or 5, the bad performing quintiles, in Panel B. This means, we have two mostly independent classifications that both show a systematic trend in performance.

Therefore, we next double-sort the monthly Carhart (1997) performance in 5x5 portfolios by their lagged size and lagged number of accounts and by their lagged size and lagged average account size, respectively. Hereby, we use a conditional sorting approach where we first sort SAs in each month by their lagged size and then within each size-quintile we further sort SAs into quintiles by their lagged number of accounts or by their lagged average account size. The results for the sorting by size and number of accounts are displayed in Table 4. Panel A shows a distinctive pattern of decreasing net performance from the upper left corner of small SAs with few accounts (+0.902% p.a.) to the lower right corner with large SAs with many accounts (-1.319% p.a.). This pattern is driven both by size and by the number of accounts as indicated by the respective single sortings ("all"). Moreover, the high-low difference portfolios are statistically significant in all rows and columns. A similar pattern is displayed in Panel B for the gross performance of SAs, however with an upward shift of around 0.8% p.a. consistent with the average expense ratio displayed in Table 1. To make sure that these findings on the side-by-side existence of the two size effects are not driven by differences in systematic risk, Panel C shows results for the in-sample 24-month rolling Carhart (1997) market beta. However, there is a weak decreasing pattern from the lower left corner to the upper right corner which is not in accordance with the performance pattern.

[Insert Table 4 here]

Table 5 shows the results for 5x5 sortings based on size and average account size. They are very similar in that there is a decreasing pattern from the right upper corner of small SAs with large investor accounts (0.595% p.a.) to the lower left corner of large SAs with small investor accounts (-1.427% p.a.). However, the highest performing portfolio is the portfolio of small SAs with medium (3) average account size (0.900% p.a.). Otherwise, the results using average account size are consistent with the results in Table 4 for the number of accounts.

[Insert Table 5 here]

2.3.3 Panel regression analysis of size effects

The sorted portfolio analysis shows the side by side existence of diseconomies of scale in the two dimensions of TA and number of accounts and average account size, respectively. To further examine their negative effect on the annualized Carhart performance and to control for further SA characteristics, we run the following panel regressions (Eq. 5):

$$\alpha_{i,q+1}^{ooS\text{-}4F} = \varphi_0 + \varphi_1 \, Log\ TA_{i,q} + \varphi_2 \, Log\ \#Accs_{i,q} + \sum_{m=3}^{M} \varphi_m \, Control_{i,q}^{m} + \eta_{i,q} \tag{5a}$$

$$\alpha_{i,q+1}^{ooS\text{-}4F} = \varphi_0 + \varphi_1 \, Log\ TA_{i,q} + \varphi_2 \, Log\ avAS_{i,q} + \sum_{m=3}^{M} \varphi_m \, Control_{i,q}^{m} + \eta_{i,q} \tag{5b}$$

The dependent variable is future Carhart performance, calculated for monthly 24-month rolling window regressions and aggregated on a quarterly basis ($q+1$).[14] This is necessary because most SAs report their characteristics only on a quarterly basis. Besides, the independent variables are

[14] $\alpha_{i,q+1}^{ooS\text{-}4F} = \sum_{m=1}^{3} \alpha_{i,t+m}^{ooS\text{-}4F}$

log size (*Log* $TA_{i,t}$), log number of accounts (*Log* $\#Accs_{i,t}$), log average account size (*Log* $avAS_{i,t}$), and the usual control variables. Further, we control for style-fixed effects by style-wise demeaning and for time-fixed effects by quarter-wise demeaning (within transformation).[15] This type of regression allows inferences on the effect of cross-sectional differences in characteristics on cross-sectional differences in future performance while controlling for overall influences like the business cycle. We standardize all variables to mean zero and unit standard deviation to ease comparisons between independent variables. Following Peterson (2009), standard errors are two-dimensionally clustered by SA and quarter to consider heteroscedasticity, time-series and cross-sectional correlation. Table 6 provides the results for net and gross returns. M1 refers to Eq. (5a) and M2 to Eq. (5b), respectively. This differentiation enables a detailed view on the relationship between the overall size of the SA and the number of different investors.

[Insert Table 6 here]

As expected, size has a significantly negative effect on the future Carhart performance in both models. This is in line with the existing mutual fund literature. The number of accounts is the most interesting variable for this analysis. It accounts for the structural difference between mutual funds and SAs as it considers an effect that does not exist in mutual funds. As expected from the prior results, it has a negative influence on Carhart performance. Comparing the effects of TA and number of accounts by their standardized coefficients, an increase of one standard deviation in the log number of accounts is more detrimental to performance as a one standard deviation increase in log size.

[15] Further model specifications also include SA fixed-effects. The results are economically the same. Results are available upon request.

Thus, with a higher number of individual investors with potentially competing elements of individualizations either the attention span of SA managers per investor goes down which is detrimental to performance (e.g., Kacperczyk et al., 2016) or SAs must hire more staff which causes administrative stress and hierarchy costs, consistent with Chen et al.'s (2004). Both explanation approaches belong to the structural size effects and as a result of their different organizational structure, these occur in SAs differently than in mutual funds.

To be able to completely understand the relation between TA and the number of accounts, we alternatively consider average account size in M2. It shows a significantly positive impact on future performance. Thus large SAs can reduce their diseconomies of scale by managing only a small number of larger single investor accounts, thereby mitigating the negative effects of administrative stress and hierarchy costs.

Overall, the results in this section clearly show that SAs suffer from diseconomies of scale. Moreover, the specific structure of SAs which makes them different from widely studied mutual funds is the more important reason for such negative size effects. Therefore, in the following, we analyze in more detail how the number of accounts influences management behavior and the performance of SAs.

2.4 Further tests of the sources of diseconomies of scale in SAs

2.4.1 Structural diseconomies of scale, limited attention and diversification

To disentangle the reasons for diseconomies of scale in SAs, we go into more detail on SA behavior and the multidimensional relation between size and performance. Therefore, we perform further 5x5 sortings on subsamples of SA months for which we have respective additional information. Table 7 shows conditional double sortings where SAs are first sorted into quintiles by lagged TA and then by lagged number of accounts.[16] Panel A shows TA and the number of accounts to document the orginial sorting variables. Panel B shows the degree of individualization offered to investors (individualization score), Panel C shows the number of managers running the SA, and Panel D shows the number of different holdings. Keep in mind that using the same sorting algorithm in Table 4, SA performance shows a decreasing pattern from the upper left corner of small SAs with few accounts to the lower right corner of large SAs with many accounts.

[Insert Table 7 here]

In Panel A, the upper figure represents the average TA (in million USD) of the SAs in the portfolio while the lower figure in parentheses represents the average number of accounts. Interestingly, the average number of accounts in the “Low” column is between 1 and 7, which makes many of these SAs closely resemble the organizational structure of mutual funds, which should create high “classic” diseconomies of scale but no relevant structural diseconomies. On the other hand, the SAs in the “High” column show very high numbers of accounts of up to 1,181 for the largest SAs. This suggests very high structural diseconomies of scale. Panel B shows that the individualization score increases from the lower left corner to the upper right corner indicating that SAs with more accounts offer more individualization. This could be due to retail accounts as they usually offer tax optimization services, which are not necessary for institutional investors. Furthermore, the results indicate that smaller SAs offer higher individualization. A possible explanation is that over the last 26 years, many new SAs have been launched creating a very competitive environment, also vis-à-vis mutual funds, in which new (and therefore smaller) SAs try to attract investors by offering more individual services.

[16] Similar double sortings using average account size yield economically consistent results and are available upon request.

At the same time, the number of managers in Panel C increases only slightly with SA size from 2.04 on average for the smallest quintile to 2.43 in the largest quintile. From the standpoint of management fee revenues, which are usually a percentage of TA, this makes sense because more managers can be employed. However, it is puzzling that there is no relevant difference in the number of managers between SAs with many and few individual accounts. In three of five size quintiles, the number of managers is even smaller for SAs with more accounts given they have approximately the same size. From the standpoint of efforts necessary to manage several hundreds of accounts at the same time, each with a higher degree of individualization on average, we would have expected relatively more managers in SAs with more accounts.

The number of holdings displayed in Panel D thus reveals how SAs handle the higher managing effort with more or less the same number of managers. They hold significantly fewer different stocks, i.e. they scale rather than diversify. Specifically, while the number of stocks generally increases with size, as also shown by Pollet and Wilson (2008) for mutual funds, it decreases dramatically with the number of accounts. This suggests that, to cope with the organizational effort necessary to manage a large SA that has many accounts and a high level of individualization with roughly the same number of managers, they must reduce complexity by concentrating on a smaller number of stocks. This is also in line with the literature on mutual fund manager attention (e.g., Kacperczyk et al., 2016; Gupta-Mukherjee and Pareek, 2016).

Overall, the results in this section deliver valuable new insights into the behavior of SA managers. Specifically, they show in which way SA managers faced with the task of providing high quality, individualized service to a large number of investors compensate for their limited attention span. Interestingly, they reduce portfolio complexity by concentrating on fewer different stocks.

2.4.2 Investor flow, liquidity constraints and price impact costs

As mentioned in Section 1, the effects of size on mutual fund performance are also connected to the effects caused by flows, i.e. by changes of size (e.g., Edelen, 1999; Alexander et al., 2007; Pollet and Wilson, 2008). The reason is that flows either cause liquidity constraints and price impact costs or – by mitigating these effects – keep managers from following their optimal portfolio strategy. Both mechanisms are detrimental to performance. Looking at the descriptive statistics in Table 1 reveals that flows to SAs have been substantial during these 26 years. However, the coefficients of flow on SA performance displayed in Table 6 are insignificant indicating no relevant relation, which is puzzling from the standpoint of the mutual fund literature.

Therefore, in Table 8, we analyze annualized flows in more detail by perfoming another double-sorting based on lagged TA and lagged number of accounts. Furthermore, in Table 9, we run piecewise linear panel regressions where the coefficient for flow may be different for small, medium (quintile 2-4), and large SAs following Eq. (6a), and for SAs with few, medium (quintile 2-4), and many accounts following Eq. (6b). To account for the specific structure of SAs vis-à-vis mutual funds, we additionally condition the flow-interaction variables on situations where flows occur without a change in the number of accounts, where flows occur in combination with an increase in the number of accounts, and where flows occur in combination with a decrease in the number of accounts, separately for inflows and outflows, respectively.[17] As above, we use 2-dimensionally clustered standard errors (Petersen, 2009).

[17] Using gross performance as dependent variable yields economically consistent results. The same applies for panel regressions using average account size (*avAS*) instead of the number of accounts (#*Accs*) and conditioning the coefficients of flow on large, medium, and small averge account size. The results are available upon request.

$$\alpha_{i,q+1}^{ooS\text{-}4F} = \varphi_0 + \varphi_1\, Log\ TA_{i,q} + \varphi_2\, Log\ \#Accs_{i,q} + \varphi_{3a}\, Flow_{i,q}\text{: } Large_{i,q} \tag{6a}$$
$$+\varphi_{3b}\, Flow_{i,q}\text{: } Medium_{i,q} + \varphi_{3c}\, Flow_{i,q}\text{: } Small_{i,q} + \sum_{m=4}^{M} \varphi_m\, Control_{i,q}^{m} + \eta_{i,q}$$

$$\alpha_{i,q+1}^{ooS\text{-}4F} = \varphi_0 + \varphi_1\, Log\ TA_{i,q} + \varphi_2\, Log\ \#Accs_{i,q} + \varphi_{3a}\, Flow_{i,q}\text{: } Many\ Accs_{i,q} \tag{6b}$$
$$+\varphi_{3b}\, Flow_{i,q}\text{: } Medium\ Accs_{i,q} + \varphi_{3c}\, Flow_{i,q}\text{: } Few\ Accs_{i,q} + \sum_{m=4}^{M} \varphi_m\, Control_{i,q}^{m} + \eta_{i,q}$$

The results for the conditional double-sorting in Table 8 display a clear pattern that small SAs experienced very high inflows while large SAs experienced outflows on average, which is in line with the related literature (e.g., Del Guercio and Tkac, 2002; Heisler et al., 2007).

[Insert Table 8 and Table 9 here]

All results from the piecewise linear panel regressions in Table 9 show the expected relations regarding log size and log number of accounts as both have a significantly negative impact on SA performance. In situations where flows occur without a change in the number of accounts, inflows display significantly positive relations to the performance of small- and medium-sized SAs. As possible explanation, one could suspect that the SA management maintains a close communication with investors (e.g., Del Guercio and Tkac, 2002), so that new inflows may be anticipated quite well and are used to make valuation-motivated purchases (e.g., Alexander et al., 2007; Rohleder et al., 2017). Similarly, we also find high positive coefficients of inflows in SAs with few and medium accounts, but only significant for the latter. For outflows, we only find a significant negative effect on performance for SAs with few accounts. This negative coefficient may be explained by the fact that these accounts have on average a relatively large average account size (see Table 3, Panel B), so that these outflows may cause some price impact. In situations where flows occur with an increase or a decrease in the number of accounts the results display no significant effect at all.

It is remarkable that we do not find stronger negative effects of flows on performance as documented regularly for mutual funds. This could be explained by the fact that both account closings and inflow may be anticipated quite well due to close investor communication and the inflow to some accounts may be partly matched by the necessary sells for the closed accounts. This mitigates outside transaction costs and price impact. Moreover, the size of individual accounts may be below the critical level to cause price impact costs. This once more underlines that structural size effects caused by a high number of individual investor accounts are more important for SAs than classic size effects such as liquidity constraints and market impact costs.

2.4.3 Propensity score matching

In the previous section, we have established that SAs, like mutual funds, suffer from diseconomies of scale. Moreover, we identify an additional layer of diseconomies of scale vis-à-vis mutual funds which is the number of individual investor accounts. To get a more comprehensive view on such structural differences between SAs and mutual funds, we run a matched comparison analysis based on a propensity score (e.g. Evans and Fahlenbrach, 2012)[18] between SAs and single mutual funds. Specifically, we identify for each SA at each point in time five neighbor mutual funds which are closest in character regarding the size, as well as further control variables used in previous analyses including the investment style and the risk characteristics. This way, an SA and the matched mutual funds are very similar in character except only for the number of accounts of the particular SA.

Like the SA data, also the mutual fund data stems from Morningstar Direct from which we select the whole universe of U.S. equity open-end mutual fund share classes with seamless monthly return series.[19] This dataset includes 13,006 mutual fund share classes with 1,43 mio. monthly obversations between January 1990 and December 2015.

[18] The authors use a similar matching algorithm to match retail mutual funds with an institutional twin (either SA or institutional mutual fund) to retail mutual funds without an institutional twin to assess the effects of monitoring by institutional investors on fund governance.

[19] For the matching, we use share class level expense ratios, to capture the different fee structures of mutual fund share classes, and fund level size.

For our analysis, we sort SAs with their matched mutual funds into quintiles according to the number of individual accounts and calculate the average Carhart alpha for each group and the difference in performance between the SAs and mutual funds. The results are presented in Table 10 where Panel A matches SAs and mutual funds on controls and investment style and Panel B matches them on controls and risk.

[Insert Table 10 here]

The results on the left for net returns clearly show that SAs overall outperform mutual funds, which is in line with previous research (e.g. Elton et al., 2014). The results for gross returns additionally show that the outperformance is not entirely due to differences in fees. More importantly the results show that while the performance of mutual funds is stable over all quintiles, the performance of SAs is monotonically decreasing with a growing number of accounts as could be expected from previous analyses. The stable performance of the matched mutual funds further supports our presumption, that it is no other portfolio characteristic which is able to systematically explain the decreasing trend in SA performance, but the increasing organizational stress stemming from a growing number of accounts. Another impressive result is that also those SAs with the highest number of accounts still outperform their mutual fund counterparts. Thus, we conclude that the additional structural layer in SAs severely hurts the performance of SAs, however not to an extent sufficient to dive it below that of mutual funds with similar characteristics.

2.5 Robustness tests

As described in the beginning of Section 4, our baseline model is Carhart's (1997) four-factor model. To rule out that the choice of the Carhart (1997) model drives our results, we alternatively use the CAPM (Jensen, 1968) and the Fama and French (1993) model for robustness. Moreover, following Elton et al. (2014) we use the fund's particular best-fit benchmark which we identify by the maximum R^2 from running regressions of SAs on a large variety of stock indices. For overall performance results using these models, see Table 2. Moreover, despite the fact that the SAs in our sample are mostly invested in US domestic equity, they may also invest some percentage of their TA in bonds or non-US equity. Therefore, in further alternative models, we augment the Carhart (1997) model with an US aggregate bond index, and with the MSCI World Ex US index, respectively. For all of the mentioned alternative performance models, we run our main analyses presented in Sections 4.2 and 4.3. The results remain robust. Moreover, for the construction of the panel regression dataset, we run all of these models for monthly rolling windows of 12, 24 and 36 months. The results are similar and from an economical point of view they stay the same.

As an alternative to the conditional double sorting which first sorts SAs into quintiles by size and then within the quintiles further by the number of accounts or average account size, we also use unconditional double sortings. The major difference is that with this independent sorting it is possible that some extreme portfolios remain vacant. For example, this is intuitively the case for very small accounts (size quintile 1) with a very high overall number of accounts (#accs quintile 5). Other than that, the economic patterns displayed in the conditional sortings are also observable in the unconditional sorting and thus robust.

2.6 Conclusion

Is there something new to learn from the structural differences between SAs and mutual funds regarding the effects of size on performance in professional asset management? We contribute to this question by providing the first in-depth investigation of the specific effects of size on the performance of SAs. We show that SAs suffer from two sources of diseconomies of scale. First, like mutual funds, SAs suffer from diminishing returns to scale in the dimension of TA, i.e. liquidity constraints and market impact costs. Second, due to their additional structural layer compared to mutual funds, which increases their overall management complexity, SAs particularly suffer from organizational stress. To compensate this additional complexity in SA structure, SA managers reduce portfolio complexity by concentrating on fewer different stocks. Further, we do not find a relevant negative effect of flow on the performance of SAs, which is contrary to numerous findings in the mutual fund literature. This can be explained by a close investor communication, which enables SA managers to anticitpate new flows quiet well. Finally, we show that SAs outperform mutual funds with similar characteristics, even those SAs with the highest number of accounts.

Our key takeaways are thus that: 1) Small SAs outperform large SAs, 2) SAs with few accounts outperform their counterparts with many accounts, and 3) SAs outperform mututal funds with similar characteristics. Overall smaller SAs with a low number of individual accounts are able to provide a high quality and individual service at low costs with a reasonable level of diversification which makes them the best performing SAs in our sample.

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Tables

Table 1
Summary statistics

Variable	N	Mean	Standard Deviation	Percentile 10th	25th	50th	75th	90th	Skewness
Panel A: Summary statistics by SA									
Total assets (mio. $)	3,671	519.00	1020.00	5.38	28.60	128.00	499.00	1470.00	3.99
Number of accounts (#)	3,370	243	1484	2	4	15	72	305	13.19
Avg. account size (mio. $)	3,281	72.70	239.00	0.27	0.79	9.56	52.20	169.00	12.74
Expense ratio (% p.a.)	3,770	0.86	0.60	0.31	0.55	0.75	0.97	1.34	2.06
Min. investment (mio. $)	3,377	7.24	10.90	0.10	0.25	2.00	10.00	25.00	2.30
Turnover (% p.a.)	2,981	70.15	63.72	18.69	29.76	52.45	88.41	140.70	3.25
Number of holdings (#)	3,650	89	151	27	39	57	93	154	10.71
Assets in top10 hold. (%)	3,401	33.79	17.33	17.33	23.36	30.52	38.97	51.85	1.84
Flow (% p.a.)	3,483	14.45	32.32	-13.53	-2.59	10.66	27.39	47.68	1.46
Individualization score	1,279	8.13	8.41	0.00	0.00	6.00	15.00	21.00	0.73
Number of managers (#)	3,466	2.10	1.01	1.00	1.00	2.00	3.00	3.83	0.51
Panel B: Pooled summary statistics									
Total assets (mio. $)	469,324	640.00	1360.00	4.00	23.80	134.00	582.00	1730.00	4.05
Number of accounts (#)	386,306	231	1865	1	3	13	51	224	21.49
Avg. account size (mio. $)	344,432	78.80	268.00	0.26	1.00	11.70	54.80	175.00	12.95
Expense ratio (% p.a.)	574,377	0.86	0.81	0.00	0.36	0.72	0.96	2.04	1.62
Min. investment (mio. $)	530,328	7.92	11.40	0.10	0.50	3.00	10.00	25.00	2.18
Turnover (% p.a.)	189,211	66.11	61.37	16.00	28.00	50.00	85.00	131.00	3.57
Number of holdings (#)	246,929	87	144	29	40	58	92	147	12.88
Assets in top10 hold. (%)	91,687	33.33	17.13	16.54	22.94	30.49	38.79	50.81	1.85
Flow (% p.a.)	417,314	12.78	89.07	-45.68	-15.04	-0.30	17.40	76.53	2.26
Individualization score	230,689	7.96	8.28	0.00	0.00	6.00	15.00	21.00	0.75
Number of managers (#)	479,235	2.14	1.12	1.00	1.00	2.00	3.00	4.00	0.50

This table shows summary statistics for a sample of actively managed U.S. domestic equity Separate Accounts (SAs) from 1990/01 to 2015/12. The unit of obsersvation is the SA in Panel A and the SA-month in Panel B. The average account size of SA i in period t is the quotient of total assets and the number of accounts in period t. The expense ratio is calculated as the difference between gross and net return. Min. investment is minimum initial investment an investor has to make to open an account within a particular SA. The net flow of SA i in period t is calculated as the change in total assets from period t-1 to period t less value changes due to net returns on assets. For the individualization score, we use sixteen questions asked by Morningstar regarding the range of services offered (e.g. an individual tax-optimization) to investors. These question can be answered with "proactive", "by request only", or "no", which we evaluate with 2, 1, or 0 points. The individualization score is calculated as the sum of these points.

Table 2
Separate account performance

	CAPM		Best-fit		Fama-French		Carhart	
	EW	VW	EW	VW	EW	VW	EW	VW
Panel A: Net returns								
Performance	0.198	-0.425	0.072	-0.342	-0.332	-0.762***	-0.348	-0.733**
(% p.a.)	(0.71)	(0.30)	(0.80)	(0.23)	(0.30)	(0.01)	(0.28)	(0.01)
Market	1.005***	1.012***			0.968***	0.991***	0.969***	0.988***
	(0.00)	(0.00)			(0.00)	(0.00)	(0.00)	(0.00)
Best-fit index			0.934***	0.956***				
			(0.00)	(0.00)				
SMB					0.230***	0.145***	0.220***	0.138***
					(0.00)	(0.00)	(0.00)	(0.00)
HML					0.043***	0.020***	0.040***	0.016***
					(0.00)	(0.00)	(0.00)	(0.00)
MOM							0.026***	0.013***
							(0.00)	(0.00)
Adj. R^2	0.80	0.84	0.87	0.90	0.87	0.90	0.88	0.91
Panel B: Gross returns								
Performance	1.119**	0.376	0.992***	0.453	0.588*	0.037	0.571*	0.065
(% p.a.)	(0.04)	(0.36)	(0.00)	(0.11)	(0.07)	(0.90)	(0.08)	(0.58)
Market	1.005***	1.012***			0.968***	0.991***	0.970***	0.988***
	(0.00)	(0.00)			(0.00)	(0.00)	(0.00)	(0.00)
Best-fit index			0.934***	0.956***				
			(0.00)	(0.00)				
SMB					0.229***	0.145***	0.219***	0.138***
					(0.00)	(0.00)	(0.00)	(0.00)
HML					0.043***	0.020***	0.040***	0.016***
					(0.00)	(0.00)	(0.00)	(0.01)
MOM							0.025***	0.013***
							(0.00)	(0.00)
Adj. R^2	0.80	0.84	0.87	0.90	0.87	0.90	0.88	0.91

This table presents annualized SA performance and factor sensitivities from a sample of actively managed U.S. domestic equity SAs from 1990/01 to 2015/12. The performance for SA i in month t is the difference between its actual return and a style return, which is calculated using a 24-month rolling window regression and multiplying its estimated factor sensitivities from the prior 24 months with the values of the corresponding risk-factors in month t. All further factor sensitivities are measured using the Carhart (1997) four-factor model in 24-month rolling window regressions. Panel A displays the results for net returns and Panel B for gross returns. ***, **, and * denote significance at the 1%, 5%, or 10% level, respectively. P-values are given in parentheses.

Table 3

SA characteristics, sorted by total assets, number of accounts and average account size

	Total Assets (Mio. $)		Number of Accounts (#)		avAS (Mio. $)		Net Flow (% p.a.)		Expense Ratio (% p.a.)		Carhart model (% p.a.)	
Q	Mean	Med.	Mean	Med.	Mean	Med.	Mean	Med.	Mean	Med.	Performance	Market
Panel A: Sorted by total assets												
1	11	5	54	5	4.2	0.7	38.86	2.18	0.96	0.78	0.40	0.94
2	47	39	78	11	12.5	4.9	18.70	0.49	0.87	0.75	0.02	0.96
3	155	141	136	13	35.0	13.3	7.70	-0.97	0.86	0.75	-0.34	0.97
4	479	441	196	16	76	29	1.49	-2.68	0.81	0.73	-0.55	0.99
5	2528	1743	401	24	248	248	-2.89	-4.02	0.77	0.71	-0.73	0.99
5-1	2517	1739	348	19	244	87	-41.74	-6.19	-0.19	-0.07	-1.14	0.05
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Panel B: Sorted by number of accounts												
1	286	51	3	2	169.3	30.4	20.42	0.31	0.78	0.72	0.49	0.99
2	594	160	6	5	112.9	29.7	12.55	-0.72	0.81	0.73	-0.12	0.99
3	737	241	15	14	56.6	18.4	8.54	-1.61	0.85	0.75	-0.61	0.99
4	1049	347	47	39	31	10	6.88	-1.73	0.85	0.72	-0.73	0.97
5	916	247	1081	241	6	6	5.32	-1.71	1.01	0.75	-1.10	0.95
5-1	628	197	1077	239	-164	-29	-14.61	-1.97	0.23	0.03	-1.54	-0.05
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Panel C: Sorted by average account size												
1	127	18	675	72	1.1	0.3	24.08	1.71	1.10	0.82	-0.64	0.93
2	227	52	153	28	4.1	2.5	18.13	0.50	0.89	0.76	-0.18	0.96
3	406	139	44	13	14.4	12.1	9.79	-0.80	0.81	0.73	-0.41	0.99
4	847	389	23	10	45	40	2.29	-2.03	0.75	0.72	-0.48	1.00
5	1867	1100	13	5	326	326	0.47	-3.10	0.71	0.71	-0.30	1.00
5-1	1739	1082	-663	-67	325	175	-23.59	-4.80	-0.39	-0.11	0.35	0.07
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.10)	(0.00)

This table shows summary statistics for a sample of actively managed U.S. domestic equity Separate Accounts (SAs) from 1990/01 to 2015/12. The SAs are quarterly sorted into quintiles by their lagged total assets in Panel A, by their lagged number of accounts in Panel B, and by their lagged average account size in Panel C. The expense ratio is calculated as the difference between gross and net return. The net flow of SA i in period t is calculated as the change in total assets from period t-1 to period t less value changes due to net returns on assets. The average account size of SA i in period t is the ratio of total assets and the number of accounts in period t. Carhart performance of SA i in month t is the difference between its actual return and a style return, which is calculated using a 24-month rolling window regression and multiplying its estimated factor sensitivities from the prior 24 months with the values of the corresponding risk-factors in month t. Market risk is the market sensitivity of SA i in the prior 24 months.

Table 4
Conditional double-sorting of performance based on lagged size and lagged number of accounts

	Number of accounts$_{t-1}$						
Total assets$_{t-1}$	Low	2	3	4	High	All	High-low
Panel A: Carhart performance using net returns							
Low	0.902**	0.635	0.180	-0.108	-0.784**	0.196	-1.653***
	(0.04)	(0.17)	(0.65)	(0.78)	(0.04)	(0.59)	(0.00)
2	0.467	-0.016	-0.316	-0.773**	-1.209***	-0.336	-1.662***
	(0.32)	(0.97)	(0.46)	(0.04)	(0.00)	(0.37)	(0.00)
3	-0.016	-0.400	-0.766*	-0.583	-1.396***	-0.611*	-1.401***
	(0.97)	(0.37)	(0.07)	(0.14)	(0.00)	(0.09)	(0.00)
4	-0.201	-0.514	-0.906**	-0.488	-1.098***	-0.633*	-0.878***
	(0.64)	(0.23)	(0.04)	(0.25)	(0.00)	(0.09)	(0.01)
High	-0.175	-1.046***	-0.808**	-1.002***	-1.319***	-0.860***	-1.146***
	(0.61)	(0.01)	(0.03)	(0.00)	(0.00)	(0.00)	(0.00)
All	0.253	-0.340	-0.533	-0.592*	-1.160***	-0.448	-1.390***
	(0.51)	(0.38)	(0.15)	(0.08)	(0.00)	(0.19)	(0.00)
High-low	-1.072***	-1.588***	-0.960***	-0.919***	-0.538*	-1.054***	
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	
Panel B: Carhart performance using gross returns							
Low	1.772***	1.635***	1.242***	1.066***	0.430	1.243***	-1.315***
	(0.00)	(0.00)	(0.00)	(0.01)	(0.26)	(0.00)	(0.00)
2	1.255***	0.794*	0.581	0.213	0.010	0.600	-1.233***
	(0.01)	(0.07)	(0.17)	(0.58)	(0.98)	(0.11)	(0.00)
3	0.735*	0.366	0.111	0.295	-0.284	0.263	-1.041***
	(0.06)	(0.41)	(0.79)	(0.46)	(0.41)	(0.46)	(0.00)
4	0.526	0.216	-0.011	0.372	-0.005	0.226	-0.515
	(0.22)	(0.61)	(0.98)	(0.38)	(0.99)	(0.54)	(0.12)
High	0.538	-0.297	-0.025	-0.260	-0.354	-0.070	-0.895***
	(0.11)	(0.43)	(0.95)	(0.43)	(0.22)	(0.81)	(0.00)
All	1.029***	0.460	0.367	0.336	-0.040	0.452	-1.048***
	(0.01)	(0.23)	(0.32)	(0.32)	(0.89)	(0.18)	(0.00)
High-low	-1.234***	-1.824***	-1.229***	-1.353***	-0.787**	-1.312***	
	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)	(0.00)	

Table 4 cont'd.

	Number of accounts$_{t-1}$						
Total assets$_{t-1}$	Low	2	3	4	High	All	High-low
Panel C: Carhart market beta							
Low	0.976***	0.968***	0.947***	0.940***	0.931***	0.951***	-0.046***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
2	1.006***	0.991***	0.976***	0.945***	0.922***	0.969***	-0.085***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
3	0.997***	0.998***	0.997***	0.969***	0.945***	0.981***	-0.051***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
4	1.013***	1.006***	0.998***	0.990***	0.954***	0.993***	-0.060***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
High	0.989***	1.002***	1.006***	0.991***	0.963***	0.990***	-0.026***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
All	0.996***	0.991***	0.985***	0.967***	0.943***	0.977***	-0.053***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
High-low	0.012***	0.046***	0.061***	0.051***	0.032***	0.039***	
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	

This table presents annualized portfolio Carhart performance and market risk for 5x5 portfolios using monthly returns from a sample of actively managed U.S. domestic equity SAs from 1990/01 to 2015/12. Portfolios are formed by sorting all SAs each quarter in quintiles by their lagged total assets and within these quintiles the SA are sorted into quintiles by their lagged number of accounts. Panel A and B show net and gross Carhart performance of SA i in month t, which is the difference between its actual return and a style return, which is calculated using a 24-month rolling window regression and multiplying its estimated factor sensitivities from the prior 24 months with the values of the corresponding risk-factors in month t. Market risk, shown in Panel C, is the market sensitivity of SA i in the prior 24 months. ***, **, and * denote significance at the 1%, 5%, or 10% level, respectively. P-values are given in parentheses.

Table 5
Conditional double-sorting of performance based on lagged size and lagged average account size

	Average account size$_{t-1}$						
Total assets$_{t-1}$	Low	2	3	4	High	All	High-low
Panel A: Carhart performance using net returns							
Low	-0.667	-0.307	0.900**	0.543	0.595	0.206	1.281***
	(0.10)	(0.42)	(0.02)	(0.20)	(0.17)	(0.57)	(0.00)
2	-0.998***	-0.841**	-0.545	0.180	0.496	-0.345	1.510***
	(0.01)	(0.03)	(0.20)	(0.69)	(0.27)	(0.35)	(0.00)
3	-1.363***	-0.649*	-0.684	-0.392	0.041	-0.612*	1.414***
	(0.00)	(0.10)	(0.12)	(0.35)	(0.92)	(0.09)	(0.00)
4	-1.072***	-0.566	-1.011**	-0.355	-0.130	-0.629*	0.947***
	(0.00)	(0.17)	(0.02)	(0.40)	(0.76)	(0.09)	(0.00)
High	-1.427***	-0.852**	-0.988***	-0.688**	-0.358	-0.864***	1.064***
	(0.00)	(0.02)	(0.01)	(0.02)	(0.32)	(0.00)	(0.00)
All	-1.106***	-0.645*	-0.465	-0.142	0.130	-0.449	1.244***
	(0.00)	(0.05)	(0.21)	(0.70)	(0.73)	(0.19)	(0.00)
High-low	-0.762**	-0.537	-1.878***	-1.235***	-0.956***	-1.068***	
	(0.03)	(0.13)	(0.00)	(0.00)	(0.00)	(0.00)	
Panel B: Carhart performance using gross returns							
Low	0.689*	0.814**	1.904***	1.476***	1.429***	1.257***	0.759**
	(0.09)	(0.03)	(0.00)	(0.00)	(0.00)	(0.00)	(0.02)
2	0.213	0.144	0.345	0.984**	1.283***	0.592	1.084***
	(0.55)	(0.71)	(0.42)	(0.03)	(0.00)	(0.11)	(0.00)
3	-0.251	0.228	0.166	0.388	0.787*	0.262	1.047***
	(0.46)	(0.56)	(0.71)	(0.35)	(0.05)	(0.47)	(0.00)
4	0.011	0.312	-0.131	0.365	0.593	0.228	0.585*
	(0.97)	(0.45)	(0.77)	(0.38)	(0.16)	(0.54)	(0.06)
High	-0.446	-0.087	-0.263	0.078	0.350	-0.075	0.791***
	(0.16)	(0.81)	(0.48)	(0.80)	(0.33)	(0.80)	(0.00)
All	0.042	0.281	0.405	0.658*	0.890**	0.453	0.853***
	(0.89)	(0.40)	(0.28)	(0.08)	(0.02)	(0.18)	(0.00)
High-low	-1.136***	-0.895**	-2.157***	-1.402***	-1.081***	-1.330***	
	(0.00)	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)	

Table 5 cont'd.

	Average account size$_{t-1}$						
Total assets$_{t-1}$	Low	2	3	4	High	All	High-low
Panel C: Carhart market beta							
Low	0.937***	0.941***	0.944***	0.965***	0.981***	0.954***	0.044***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
2	0.924***	0.940***	0.978***	1.002***	1.002***	0.969***	0.077***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
3	0.942***	0.972***	0.997***	0.998***	0.998***	0.981***	0.056***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
4	0.957***	0.987***	1.002***	1.006***	1.011***	0.993***	0.054***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
High	0.966***	0.996***	1.005***	0.992***	0.990***	0.990***	0.024***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
All	0.945***	0.967***	0.985***	0.993***	0.996***	0.977***	0.051***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
High-low	0.029***	0.056***	0.061***	0.027***	0.009***	0.036***	
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	

This table presents annualized portfolio Carhart performance and market risk for 5x5 portfolios using monthly returns from a sample of actively managed U.S. domestic equity SAs from 1990/01 to 2015/12. Portfolios are formed by sorting all SAs each quarter in quintiles by their lagged total assets and within these quintiles the SA are sorted into quintiles by their lagged average account size. Panel A and B show net and gross Carhart performance for SA i in month t, which is the difference between its actual return and a style return, which is calculated using a 24-month rolling window regression and multiplying its estimated factor sensitivities from the prior 24 months with the values of the corresponding risk-factors in month t. Market risk, shown in Panel C, is the market sensitivity of SA i in the prior 24 months. ***, **, and * denote significance at the 1%, 5%, or 10% level, respectively. P-values are given in parentheses.

Table 6
Panel regressions of SA performance

	Future net performance		Future gross performance	
	M1	M2	M1	M2
Log TA	-0.236***	-0.636***	-0.241***	-0.638***
	(0.01)	(0.00)	(0.01)	(0.00)
Log Number of accounts	-0.344***		-0.341***	
	(0.00)		(0.00)	
Log Avas		0.458***		0.453***
		(0.00)		(0.00)
Log FirmTA	-0.009	-0.009	-0.007	-0.007
	(0.91)	(0.91)	(0.93)	(0.93)
Lagged Alpha (1year)	-0.178	-0.178	-0.199	-0.199
	(0.61)	(0.61)	(0.57)	(0.57)
Expense ratio (% TA p.a.)	-0.416***	-0.416***	0.114	0.114
	(0.00)	(0.00)	(0.11)	(0.11)
Log Min. investment	-0.003	-0.003	-0.006	-0.006
	(0.97)	(0.97)	(0.94)	(0.94)
Net flow	0.058	0.058	0.053	0.053
	(0.27)	(0.27)	(0.32)	(0.32)
Age	0.019	0.019	0.022	0.022
	(0.75)	(0.75)	(0.71)	(0.71)
Retail Dummy	-0.285	-0.285	-0.193	-0.193
	(0.24)	(0.24)	(0.43)	(0.43)
CIT Dummy	0.434	0.434	0.447*	0.447*
	(0.11)	(0.11)	(0.10)	(0.10)
Time FE	Yes	Yes	Yes	Yes
Style FE	Yes	Yes	Yes	Yes
Adjusted R^2	0.06	0.06	0.06	0.06
N	77,151	77,151	77,151	77,151

This table reports panel regressions of Separate account (SA) performance on SA size, number of accounts, and average account size. The sample consists of actively managed U.S. domestic equity SAs from 1990/01 to 2015/12. Carhart performance of SA *i* in month *t* is the difference between its actual return and a style return, which is calculated using a 24-month rolling window regression and multiplying its estimated factor sensitivities from the prior 24 months with the values of the corresponding risk-factors in month *t*. Style and time fixed effects (FE) are considered using style- and quarterly demeaned variables, respectively (within transformation). All variables are standardized to mean zero and unit standard deviation. ***, **, and * denote significance at the 1%, 5%, or 10% level, respectively. P-values are given in parentheses. Standard errors are 2-dimensionally clustered by SA and quarter to be consistent with regard to heteroscedasticity, time series correlation, and cross-sectional correlation.

Table 7

Conditional double-sorting of SA characteristics based on lagged size and lagged number of accounts

	Number of accounts$_{t-1}$						
Total assets$_{t-1}$	Low	2	3	4	High	All	High-low
Panel A: Total assets and number of accounts							
Low	14	14	13	13	21	15	8
	(1)	(4)	(8)	(21)	(295)	(63)	(293)
2	67	73	71	66	72	70	5
	(2)	(6)	(17)	(60)	(444)	(103)	(441)
3	203	211	216	211	205	209	3
	(3)	(8)	(17)	(71)	(637)	(144)	(635)
4	591	603	602	633	600	605	10
	(3)	(9)	(20)	(63)	(1181)	(250)	(118)
High	2406	2653	2757	3121	3191	2819	793
	(7)	(15)	(27)	(66)	(1985)	(411)	(1977)
All	602	768	746	809	818	743	217
	(3)	(9)	(18)	(56)	(914)	(195)	(910)
High-low	2388	2641	2747	3108	3173	2805	
	(6)	(11)	(19)	(45)	(1690)	(349)	
Panel B: Individualization score							
Low	7.07***	8.96***	9.50***	11.86***	11.73***	9.96***	4.70***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
2	6.61***	7.08***	7.68***	10.63***	11.76***	8.82***	4.94***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
3	5.79***	5.92***	6.30***	8.07***	11.02***	7.68***	5.00***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
4	3.61***	4.48***	5.77***	6.68***	11.01***	6.66***	7.44***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
High	4.90***	4.47***	3.92***	4.83***	9.19***	5.74***	4.24***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
All	5.68***	6.02***	6.56***	8.27***	10.86***	7.73***	5.05***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
High-low	-2.22***	-4.35***	-5.74***	-7.03***	-2.57***	-4.25***	
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	

Table 7 cont'd.

	Number of accounts$_{t-1}$						
Total assets$_{t-1}$	Low	2	3	4	High	All	High-low
Panel C: Number of managers							
Low	2.10***	2.07***	1.99***	1.97***	2.08***	2.04***	-0.03*
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.08)
2	2.34***	2.15***	2.09***	2.14***	2.36***	2.22***	0.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.64)
3	2.42***	2.28***	2.18***	2.27***	2.25***	2.28***	-0.17***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
4	2.42***	2.34***	2.30***	2.36***	2.37***	2.36***	-0.03**
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)
High	2.30***	2.52***	2.33***	2.51***	2.48***	2.43***	0.21***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
All	2.30***	2.28***	2.18***	2.25***	2.31***	2.27***	0.01
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.34)
High-low	0.15***	0.47***	0.33***	0.53***	0.39***	0.37***	
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	
Panel D: Number of holdings							
Low	91.76***	72.72***	62.10***	55.42***	82.71***	74.17***	-10.86***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)
2	119.51***	86.87***	76.54***	61.19***	54.79***	80.15***	-65.02***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
3	140.37***	92.70***	74.51***	58.23***	57.06***	84.93***	-83.56***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
4	140.18***	108.26***	93.50***	75.69***	58.27***	93.95***	-80.70***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
High	145.91***	102.99***	105.82***	86.94***	54.85***	97.39***	-89.92***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
All	126.01***	93.55***	82.68***	67.92***	60.48***	86.37***	-65.58***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
High-low	52.79***	29.93***	43.11***	31.21***	-25.33***	23.46***	
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	

This table presents summary statistics for 5x5 portfolios from a sample of actively managed U.S. domestic equity SAs from 1990/01 to 2015/12. Portfolios are formed by sorting all SAs each quarter in quintiles by their lagged total assets and within these quintiles, the SA are sorted into quintiles by their lagged number of accounts. Panel A shows the total assets and the corresponding number of accounts in parentheses, Panel B the individualization score, Panel C the number of managers and Panel D the number of holdings. ***, **, and * denote significance at the 1%, 5%, or 10% level, respectively. For the Panels B to E, p-values are given in parentheses.

Table 8
Conditional double-sorting of flow based on lagged size and lagged number of accounts

	Number of accounts$_{t-1}$						
Total assets$_{t-1}$	Low	2	3	4	High	All	High-low
Low	27.99***	30.45***	30.03***	24.80***	22.04***	26.69***	-5.50***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
2	12.73***	14.38***	11.81***	12.17***	10.54***	12.25***	-1.78
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.18)
3	1.17	3.19***	2.68**	3.98***	2.68***	2.64***	1.59
	(0.16)	(0.00)	(0.02)	(0.00)	(0.00)	(0.00)	(0.13)
4	2.73***	-3.94***	-2.97***	0.26	-0.55	-0.86*	-3.19***
	(0.00)	(0.00)	(0.00)	(0.69)	(0.48)	(0.07)	(0.00)
High	-1.08**	-3.34***	-4.95***	-4.81***	-3.66***	-3.51***	-2.36***
	(0.02)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
All	9.54***	6.60***	6.98***	7.14***	6.12***	7.35***	-3.22***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
High-low	-28.98***	-32.25***	-35.13***	-29.11***	-25.73***	-30.13***	
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	

This table presents yearly net flows for 5x5 portfolios from a sample of actively managed U.S. domestic equity SAs from 1990/01 to 2015/12. Portfolios are formed by sorting all SAs each quarter in quintiles by their lagged total assets and within these quintiles, the SA are sorted into quintiles by their lagged number of accounts. The net flow of SA i in period t is calculated as the change in total assets from period t-1 to period t less value changes due to net returns on assets. ***, **, and * denote significance at the 1%, 5%, or 10% level, respectively. P-values are given in parentheses.

Table 9

Piecewise linear panel regressions of SA future net performance

	Inflows						Outflows					
	No change in #accs		Increase in #accs		Decrease in #accs		No change in #accs		Increase in #accs		Decrease in #accs	
Log TA	-0.223**	-0.231***	-0.218**	-0.230***	-0.233***	-0.235***	-0.241***	-0.233***	-0.236***	-0.234***	-0.232***	-0.240***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.00)
Log #accs	-0.348***	-0.350***	-0.368***	-0.370***	-0.365***	-0.359***	-0.352***	-0.342***	-0.367***	-0.368***	-0.358***	-0.355***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Flow : Small	0.106**		0.064		-0.030		-0.019		0.003		0.007	
	(0.01)		(0.22)		(0.63)		(0.73)		(0.95)		(0.91)	
Flow : Medium	0.086**		0.012		-0.015		-0.045		-0.040		-0.001	
	(0.04)		(0.78)		(0.76)		(0.40)		(0.35)		(0.99)	
Flow : Large	0.014		-0.039		-0.006		-0.051		0.002		0.053	
	(0.72)		(0.34)		(0.88)		(0.13)		(0.96)		(0.25)	
Flow : Few accs		0.076		-0.028		-0.025		-0.124***		-0.016		-0.009
		(0.17)		(0.50)		(0.71)		(0.01)		(0.73)		(0.88)
Flow : Med accs		0.099**		0.039		0.026		0.019		-0.012		0.014
		(0.01)		(0.40)		(0.60)		(0.68)		(0.79)		(0.80)
Flow : Many accs		0.032		0.005		-0.057		-0.060*		-0.029		0.031
		(0.61)		(0.91)		(0.27)		(0.09)		(0.53)		(0.65)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Style FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.06	0.06	0.06	0.06	0.06	0.06	0.06	0.06	0.06	0.06	0.06	0.06
N	75,119	75,119	75,119	75,119	75,119	75,119	75,119	75,119	75,119	75,119	75,119	75,119

This table reports piecewise linear panel regressions of Separate account (SA) performance on net flows. The sample consists of actively managed U.S. domestic equity SAs from 1990/01 to 2015/12. In this analysis, we allow the coefficients of flow to be different for small SAs (quintile 1), medium SAs (quintiles 2-4), and large SAs (quintile 5) and for SAs with few accounts (quintile 1), medium accounts (quintiles 2-4), and many accounts (quintile 5), respectively. Furthermore, the variables are conditioned on situations where flows occur without a change in number of accounts, with an increase or a decrease in number of accounts. Style and time fixed effects (FE) are considered using style- and quarterly demeaned variables, respectively (within transformation). All variables are standardized to mean zero and unit standard deviation. ***, **, and * denote significance at the 1%, 5%, or 10% level, respectively. P-values are given in parentheses. Standard errors are 2-dimensionally clustered by SA and quarter to be consistent with regard to heteroscedasticity, time series correlation, and cross-sectional correlation.

Table 10
Separate Accounts vs. Mutual Funds

Panel A: Control variables plus Morningstar investment style

	Net					Gross				
	Number of accounts$_{t-1}$					*Number of accounts$_{t-1}$*				
	Low	2	3	4	High	Low	2	3	4	High
SA	0.43	-0.10	-0.50	-0.67	-1.19	1.21	0.71	0.36	0.21	-0.13
MF	-1.74	-1.74	-1.60	-1.64	-1.64	-0.74	-0.73	-0.57	-0.61	-0.56
SA - MF	2.17***	1.65***	1.10***	0.98***	0.44***	1.95***	1.43***	0.93***	0.82***	0.43***

Panel B: Control variables plus Carhart sensitivities

	Net					Gross				
	Number of accounts$_{t-1}$					*Number of accounts$_{t-1}$*				
	Low	2	3	4	High	Low	2	3	4	High
SA	0.43	-0.10	-0.50	-0.67	-1.19	1.21	0.71	0.36	0.21	-0.13
MF	-1.42	-1.43	-1.38	-1.42	-1.36	-0.42	-0.41	-0.36	-0.39	-0.30
SA - MF	1.87***	1.33***	0.87***	0.74***	0.21**	1.65***	1.11***	0.69***	0.59***	0.20**

This table reports the results from a matched sample comparison test between separate accounts (SA) and mutual fund share classes (MF). The sample consists of actively managed U.S. domestic equity SAs and MFs from 1990/01 to 2015/12. In Panel A, we identify for each SA at each point in time five neighbor MFs which are closest in character based on a propensity score matching technique that considers all SA and MF control variables (total assets, expense ratio, netflow, age) as well as the investmentstyles reported in the Morningstar database. In Panel B, the propensitiy score considers all SA and MF control variables as well as the sensitivities to the four Carhart (1997) factors. For the comparison, SAs are sorted into quintiles according to their number of accounts in the previous quarter t-1. Then, the average Carhart (1997) alpha in quarter *t* is compared to the average alpha of the matched MFs. The difference (SA – MF) represents the result of a two-sample comparison t-test. ***, **, and * indicate statistical significance on the 1%, 5%, and 10% level, respectively. We do not report significance for the single measures for the sake of clarity.

3 Article II: Diseconomies of Scale in Quantitative and Fundamental Investment Styles

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Abstract. We examine diseconomies of scale for two different investment approaches: quantitative and fundamental. Using separate account (SA) data where the investment approach is specified, we find that fundamental SAs exhibit greater diseconomies of scale than quantitative SAs. Looking at characteristics of the underlying investment strategies, we find that fundamental SAs hold more concentrated portfolios of lower liquidity stocks, while quantitative SAs trade more frequently. We also find that consistent with lower information processing/hierarchy costs, the speed of information diffusion is higher for quant SAs. Accounting for these differences partially explains the differences in diseconomies of scale.

JEL Classification: G11, G12, L11, L23, L25

Keywords: Diseconomies of scale, quantitative, fundamental, performance, flows, trading costs, hierarchy costs, information processing, separate accounts, institutional investing

3.1 Introduction

The question of whether or not the asset management industry exhibits economies or diseconomies of scale has received increased attention in the academic literature as of late, but it is a question that dates back to the earliest papers on mutual funds. Sharpe (1966) proposes and tests the competing hypotheses, ultimately concluding that there is no relationship between size and performance.[20] Since that time, fund size has become a standard control variable in performance regressions[21] often with a negative and statistically significant coefficient being interpreted as evidence of diseconomies of scale. Additionally, the widely referenced Berk and Green (2004) model depends on the assumption of scale diseconomies. Recent papers, however have questioned these results noting the endogeneous relationship between fund size and performance. Alternative approaches to address this endogeneity, like recursive demeaning (Pastor, Stambaugh and Taylor, 2015 and Zhu, 2018) and regression discontinuity (Reuter and Zitzewitz, 2015), either fail to find diseconomies of scale at all, or find a much less economically significant relationship between size and performance than identified previously.

While these papers highlight econometric concerns with the prior literature, they also highlight the crude nature of the proxy used for scale. While fund size is easily measured, it does not differentiate between the possible mechanisms for diseconomies of scale including liquidity – the increased trading and price impact costs associated with investing a larger pool of assets[22], information processing – the increased difficulty of timely identifying an increasing

[20] "A fund with substantial assets can obtain a given level of security analysis by spending a smaller percentage of its income than can a smaller fund; alternatively, by spending the same percentage it can obtain more (and/or better) analysis. On the other hand, more analysis may be required for a large fund than for a small one. In any event, both influences should be considered.", Sharpe (1966), p. 131.

[21] Sharpe (1966), Grinblatt and Titman (1989), Carhart (1997), Sirri and Tufano (1998), Chen, Hong, Huang and Kubik (2004).

[22] Pollet and Wilson (2008), for example, examine how managers respond to increases in fund size through analyzing their investment decisions. They find that the average manager responds to fund growth by increasing the size of their existing positions as opposed to identifying and investing in new securities, even though this behavior results in decreased performance. This finding suggests liquidity constraints on the scalability of fund portfolios is a contributing factor to diseconomies of scale in asset management. Further, Pastor, Stambaugh and Taylor (2018) acknowledge an important tradeoff between fund size on the one hand and the liquidity of the portfolio on the other hand (among other tradeoffs).

number of profitable investment strategies, and hierarchy costs – the cost or delay of communicating soft information throughout a larger firm as more people with more diverse functions and specializations are involved in the investment process.

In this paper, we revisit the issue of diseconomies of scale, but contrasting two different investment approaches: quantitative and fundamental. Using a database of separate accounts (SAs) from 1991 to 2018 as a laboratory, we test for differences in diseconomies of scale across the two approaches. The advantage of using SA data is the disclosure of the investment approach, quantitative or fundamental, by the manager, which is not available for other investment vehicles like mutual funds. While managers using these two different approaches may oversee funds of similar size investing in similar securities, the underlying nature of the two approaches suggests potential differences in both information processing/hierarchy costs and liquidity cost channels. Because fundamental analysis relies on soft information production and communication between investment professionals in the firm (e.g. stock pitch from analyst to manager) to a greater degree than quantitative analysis, we expect both the information processing/hierarchy cost and the associated liquidity impact of increasing fund size to be greater for fundamental analysis.

To illustrate why fundamental strategies may exhibit different information processing/hierarchy and liquidity costs, consider the two investment strategy descriptions below. First, *Ariel Investments, LLC, Small Cap Value SA*, a fundamentally managed SA, describe their investment strategy as follows:

> *"Once we identify a new idea for the possible inclusion in our portfolio, the portfolio managers…conduct further research and investigation by examining: 1.) Basic financial ratios…and 2.) Qualitative factors — company's position in the market, new product potential, quality of management, stock ownership by senior management and stakeholders, turnaround or takeover potential…. Once it is clear that a candidate meets our criteria…the portfolio managers and industry analyst evaluate which methodology is most useful in determining whether the security can be purchased with a margin of safety. There are no rigid criteria to our analytical*

> *process nor is the same decision-making process applied to each prospective investment for the strategy. Rather, we are simply looking to uncover each company's intrinsic value. After the appropriate analysis is conducted, the final decision on whether to purchase …the security is made by the lead portfolio manager."*[23]

This description from Ariel suggests both a high degree of soft information analysis and multiple feedback loops between different investment professionals at the firm before a decision is made to invest in a security. These potential information processing and hierarchy costs may also give rise to increased liquidity costs. Because the security selection process in a fundamental strategy is more time consuming, the investment response to sudden flows is more likely to scale existing holdings as opposed to diversifying into new positions (e.g., Pollet and Wilson, 2008).

This stands in stark contrast to the description by the *Amalgamated Bank LongView LC Quant SA* of their quantitative investment process:

> *"Investment ideas are generated through the application of a stock screening algorithm to a database of financial statistics for a stock universe. (…) We look to add value to the Fund's portfolio through a highly controlled process that utilizes quantitative analysis of portfolio behavior, as well as other methods of statistical analysis incorporating sophisticated computer technology."*[24]

The quantitative investment process described by Amalgamated involves an automated analysis with no person-to-person communication. With primary dependence on hard information and little or no communication or feedback loops required between different investment professionals at the firm, these lower hierarchy and information processing costs are more likely to translate into lower liquidity costs as well as a larger number of potential investments may be covered by the algorithm.

[23] Source: Morningstar Direct.
[24] Source: Morningstar Direct.

To begin our empirical analysis, we first examine diseconomies of scale across quant and fundamental SAs. Sorting SAs by the quintile of their total invested assets, we find a monotonically decreasing risk-adjusted performance for fundamental SAs with a statistically and economically significant alpha difference of -1.15% annualized. Sorting quant SAs by size, however, generates a flat relationship between size and risk-adjusted performance with an insignificant difference of -0.06% between the largest and smallest size quintiles.

Given the importance of controlling for other covariates like family size, in measuring diseconomies of scale, we repeat the analysis in a panel regression framework. Even after controlling for other SA, investment advisor, investment style, time, and SA-fixed effects or controlling for endogeneity using the Zhu (2018) recursive-demeaning approach, we still find a statistically and economically significant difference in scale diseconomies between fundamental and quantitative strategies. While in over half of the regression specifications, quantitative SAs exhibit no statistically significant diseconomies of scale, the standardized point estimate for fundamental SAs is 2.7 times larger, on average, than the point estimate for quantitative SAs across the various regression specifications.

Because both the quantitative and fundamental SAs are investing in similar securities[25], the difference in diseconomies of scale is striking. To better understand the potential channels through which these two investment styles differ on this dimension, we first explore the liquidity channel and then the information processing/hierarchy cost channel. To examine the liquidity channel, we use the framework proposed by Pastor, Stambaugh and Taylor (2020 – hereafter PST) who show that fund size may affect performance as part of a system of interrelated investment constraints, i.e. “mutual fund tradeoffs”, across fund size, turnover, fees, and portfolio liquidity. They further decompose portfolio liquidity into stock liquidity (i.e. the

[25] Over the sample period, quant and fundamental SAs have approximately 96% of their holdings in common on a value-weighted basis.

costs of trading a given stock) and diversification (i.e. the coverage or number of stocks in a portfolio and balance, the weight in those given stocks).

We examine the differences in turnover, fees, and portfolio liquidity for fundamental and quantitative SAs. In terms of turnover and fund fees, we find that quantitative SAs have higher turnover and lower expense ratios. Consistent with the equilibrium suggested in PST, this higher turnover/lower fee combination for quantitative separate accounts is also accompanied by higher portfolio liquidity relative to fundamental SAs. The higher portfolio liquidity of quantitative SAs is accomplished through both holding higher liquidity stocks and more diverse portfolios. Decomposing portfolio diversification into its two components – coverage and balance – we find that quantitative SAs have both more extensive coverage (i.e. hold a greater total number of stocks) and have greater balance (i.e. less concentration in any given stock) than fundamental SAs.

While on average quantitative SAs exhibit much greater portfolio liquidity, we also examine how portfolio liquidity changes as SA size increases for both quantitative and fundamental SAs. We find that while diversification increases with increased size in a similar fashion for both investment strategies, stock liquidity declines at a faster rate for quantitative SAs relative to fundamental. Given the much higher average stock liquidity for quantitative SAs to begin with, however, it would take a nearly two standard deviation increase in quantitative SA size to equalize the stock liquidity between the two.

While analyzing quant and fundamental SAs through the PST framework provides direct evidence of differences in portfolio liquidity between the two strategies, they do not give much insight into the underlying economic rationale behind these liquidity differences. The two strategy descriptions above, however, provide one plausible explanation, namely the difference in information processing and hierarchy costs inherent in the strategy. For example, the fundamental strategy description highlighted both a high degree of soft information analysis (causing high information processing costs) and multiple feedback loops between different investment professionals at the firm (high hierarchy costs). In contrast, the quant strategy description suggests a primary dependence on hard information (low information processing costs) and an automated analysis with no person-to-person communication (low hierarchy costs).

The PST liquidity analysis provides indirect evidence of the role of hierarchy and information processing costs. The lower coverage and balance of fundamental SAs relative to quant SAs is consistent with higher information processing costs. Similarly, the higher portfolio turnover of quant strategies is consistent with lower hierarchy costs.

While the liquidity channel has been the subject of a number of previous studies,[26] the literature's sparse treatment of the information processing and hierarchy cost mechanisms attests to the difficulty in measuring these two dimensions directly. The industrial organization literature, however, provides some insight into how to potentially test these mechanisms. Radner and Van Zandt (1992), Radner (1993), Bolton and Dewatripont (1994) and Stein (2002) all model different aspects of the information processing problem in firms. These papers point to the efficient transfer of information through a firm as a key outcome of low information processing/hierarchy costs in a firm. Empirically, we attempt to measure the efficient transfer of information in two ways.

First, we look at the speed of information diffusion within SA firms as a proxy for low hierarchy and information processing costs. We estimate information diffusion following the method of Cici, Jaspersen and Kempf (2017).[27] If quant SA firms use hard information to a higher degree and their investment decision process involves fewer or even no feedback loops,

[26] E.g., Pollet and Wilson (2008), Pastor, Stambaugh and Taylor (2018).

[27] Specifically, we identify the purchase of a new security not held by other separate accounts of the investment advisor as an information acquisition event. The information event is assumed to continue until the initiating account decreases its position in the security. We then measure the time elapsed until other SAs of the same investment advisor purchase the security as well during the time period associated with the information event.

we would expect information to diffuse faster through quant firms than through fundamental ones. Using detailed portfolio holdings information of quant and fundamental SAs, our test confirms this expectation in that information diffusion speed is higher at quant firms, consistent with lower information processing costs. Moreover, while the overall lower information diffusion speed is rather constant in firm size for fundamental firms, we observe a reverse U-shape for quant firms. When quant firms increase, they initially achieve economies of scale (e.g., Indro et al., 1999) as SAs share more investments and the respective information. However, with further increase information diffusion speed decreases, consistent with quant firms diversifying strategies rather than increasing diversification within SAs (e.g., Pollet and Wilson, 2008) such that SAs cease sharing investments and the respective information. This, again shows the interconnectedness of the liquidity and information processing/hierarchy channels.

Second, we look at the hard vs. soft information content of the investment decisions made by quantitative vs. fundamental asset managers through a factor analysis of their performance. If the performance of a given fund is better captured by the systematic return factors identified in the literature (e.g. market, SMB, HML and MOM), this proxies for the greater use of systematic or hard information by the manager. Across all four models we employ (CAPM, CAPM using the manager preferred benchmark "MPB", Fama-French, and Carhart), the average adjusted R^2 of the quantitative SAs is between 4.5% and 7.6% higher than of fundamental SAs. Moreover, we analyze the change in factor loadings and adjusted R^2 in reaction to changes in the portfolio management using a difference-in-differences approach and find a statistically significantly lower change in the strategy as measured by these variables from the old manager to the new manager for the quantitative investment strategies, also consistent with greater use of hard information and lower hierarchy costs, as the model largely determines the investment decision.

We then repeat our risk-adjusted performance analysis, accounting for manager ability through fixed effects, the differential liquidity costs associated with quant and fundamental strategies as well as broad proxies for information processing/hierarchy costs (i.e. the aggregate size of quant/fundamental strategies and the number of quant/fundamental SAs at an advisor). While our manager fixed effect baseline regression still shows evidence of higher diseconomies of scale for fundamental SAs, controlling for the PST liquidity proxies and the broad proxies for information processing/hierarchy costs both help to explain the difference in diseconomies of scale between the two.

Two recent papers analyze the performance of quantitative vs. fundamental investment strategies. Harvey, Rattray, Sinclair, and Van Hemert (2017) examine the performance of discretionary (fundamental) vs. systematic (quantitative) hedge funds from 1996 to 2014. They find that discretionary equity hedge funds do outperform systematic equity, but they take more risk and have higher factor exposures. After controlling for this risk, both systematic equity and macro strategies outperform their discretionary counterparts. Abis (2017) models the equilibrium outcomes for quant and discretionary funds, assuming quant funds have superior information processing skills, but less flexible investment strategies, both consistent with our findings. The model predicts that quantitative funds will hold more stocks, have pro-cyclical performance, and hold positions that are more likely to suffer from overcrowding. She then classifies a sample of mutual funds as following quantitative or discretionary investment strategies using machine learning and empirically confirms these predictions of her model.

Relative to the previous literature, our contribution is threefold. First, we document underperformance of quantitative strategies relative to fundamental strategies with respect to classic factor models but not relative to the manager-preferred benchmark in a sample of institutional separate accounts. Second, we directly test for differences in diseconomies of scale between the two investment strategies and find quantitative SAs exhibit statistically and economically significantly lower diseconomies of scale. Third using proxies for liquidity costs and hierarchy/information processing costs, we show that quantitatively managed SAs exhibit low costs on both dimensions.

The paper proceeds as follows. Section 2 introduces our dataset, explains how we measure performance and presents summary statistics. Section 3 examines performance and diseconomies of scale differences between quant and fundamental SAs. Section 4 tests two possible channels for these differences, liquidity costs and hierarchy/information processing costs. Section 5 concludes.

3.2 Data and Performance measurement

3.2.1 Data and sample construction

We obtain survivorship bias-free data on actively managed US domestic equity separate accounts (SAs) over the period 1990 to 2018 from Morningstar Direct.[28] We recognize as "SAs" all separately managed accounts (SMAs) and collective investment trusts (CITs) following Elton, Gruber and Blake (2014). Management firms report as an SA the pool of individual customer accounts managed by the same management team and following the same strategy (e.g. "small value"). The returns and SA characteristics are thus customer account-weighted composite measures. We exclude those SAs with reported net returns exceeding gross returns and those with less than 36 monthly return observations. Following Elton, Gruber and Blake (2014) we exclude index SAs both by their names and by an R^2 above 99% from a performance regression against the SA's "best-fit benchmark", which we identify by regressions of the SAs against a wide range of stock market indices.[29] We exclude "specialty" SAs both by their names and by stock market betas below 0.2 from the performance regression. Because our analysis

[28] Elton, Gruber and Blake (2014), who use a similar dataset from 2000 to 2010, test for potential further biases arising from low reporting requirements compared to, e.g., mutual funds, and conclude that the data is unbiased.
[29] Appendix A shows the list of managers' self-stated or "manager preferred benchmarks" (MPB). We use the indices on this list to determine the SAs "best-fit benchmarks".

focuses on the differences between SAs with pure quantitative (hereafter, quants) and fundamental investment strategies (hereafter, fundamentals), we exclude those SAs, as self-categorized by the SAs and reported conveniently by Morningstar, whose investment strategy does not focus solely on one strategy or the other.[30] The final sample contains 1,780 SAs of which 363 are quantitative and 1,417 are fundamental strategies. For those, we obtain quarterly SA characteristics as well as investment advisor level data including firm. We also obtain quarterly SA level portfolio holdings in the sub-period from 2001 to 2018 for the majority of our sample SAs.

[Insert Table 1 here]

Table 1 presents summary statistics on SA characteristics separately for quants (Panel A) and fundamentals (Panel B). Quants have lower total assets (TA) on average ($386m vs. $740m) and their annual expense ratio, calculated as the difference between reported gross and net returns, is lower than for fundamentals (0.73% vs. 0.93%). The average annual turnover of 110.33% for quants is twice as high as the turnover of fundamentals (53.71%). At the same time, quants are less concentrated, with 155 different holdings on average and 29% of TA in the top 10 holdings. Fundamentals are more concentrated, with only 62 different holdings on average and 34% of TA in the top 10. Quants are younger with an average age of 7.66 years compared to 9.51 years on average for fundamentals. A slightly higher fraction of quants have an institutional focus (24.2% to 21.8%) and only half as many quants have a retail focus (5.0% vs. 10.2%).

SAs of both investment strategies have experienced substantial annual implied percentage net flow with 9.93% for quants and 11.37% for fundamentals. We calculate quarterly implied percentage net flow (hereafter "flow") from quarterly TA and quarterly

[30] This excludes 470 SAs following a combination of quantitative and fundamental investment decision approaches. Further, it excludes 484 SAs following a purely "technical" approach.

returns as in Sirri and Tufano (1998) following Eq. (2). This positive average flow attests to the growing economic importance of SAs over the past 29 years.

$$flow_{i,q} = \frac{TA_{i,t} - TA_{i,q\text{-}1}\,(1+R_{i,q})}{TA_{i,q\text{-}1}} \tag{1}$$

Panel C of Table 1 shows by-year market value-weighted summary statistics on the stock holdings common to quant and fundamental SAs. The numbers show that the investment universes of quant and fundamental SAs overlap by 95.99% on average, with a minimum of 90.75% in 2001 and a maximum of 99.25% in 2015. Thus, both investment approaches hold virtually the same stock universe.

3.2.2 Performance

To measure risk-adjusted SA performance, we use the CAPM (Jensen, 1968), the CAPM vis-à-vis the manager-preferred benchmark (MPB; e.g., Elton, Gruber and Blake, 2014), the Fama/French (1993) model and the Carhart (1997) model. The models are based on the following regressions (Eq. 2, 3, 4 and 5).

$$ER_{i,t} = \alpha_i^{CAPM} + \beta_i^{Mkt}\, ER_{Mkt,t} + \varepsilon_{i,t} \tag{2}$$

$$ER_{i,t} = \alpha_i^{MPB} + \beta_i^{MPB}\, ER_{MPB,t} + \varepsilon_{i,t} \tag{3}$$

$$ER_{i,t} = \alpha_i^{FamaFrench} + \beta_i^{Mkt}\, ER_{Mkt,t} + \beta_i^{SMB}\, SMB_t + \beta_i^{HML}\, HML_t + \varepsilon_{i,t} \tag{4}$$

$$ER_{i,t} = \alpha_i^{Carhart} + \beta_i^{Mkt}\, ER_{Mkt,t} + \beta_i^{SMB}\, SMB_t + \beta_i^{HML}\, HML_t + \beta_i^{UMD}\, MOM_t + \varepsilon_{i,t} \tag{5}$$

$ER_{i,t}$ is the return of SA *i* in month *t* in excess of the 1-month T-Bill rate, $\alpha_i^{Carhart}$ is SA *i*'s risk-adjusted performance, $ER_{Mkt,t}$ is the monthly market excess return, β_i^{Mkt} is the SA's sensitivity to the market, $ER_{MPB,t}$ is the monthly excess return of the manager-preferred benchmark index, SMB_t is the monthly size factor return, HML_t is the monthly value factor return and MOM_t is the monthly momentum factor return. $\varepsilon_{i,t}$ is a mean zero error term.

For the CAPM, the Fama/French and the Carhart model, we use the common risk factors provided via Kenneth R. French's data library.[31] As MPBs, we use 74 different self-stated benchmarks indices for which we obtain monthly returns from Morningstar Direct.[32] Using the MBP implicitly accounts for the fact that sophisticated investors may chose SAs specifically for their stated investment style and therefore manager compensation/motivation may depend on their MBP-performance rather than on the performance vis-à-vis the "academic benchmark".

To obtain monthly estimates of risk-adjusted SA performance for the panel regressions, we follow Sharpe (1992) and calculate the out-of-sample performance, $\alpha_{i,t}^{ooS}$, for each SA i in each month t. Specifically, the style benchmark return (Eq. 6a) is defined as the sum of the SA's loadings to the respective risk factors $k = 1, \ldots, K$ during the 24-month "in sample" rolling window from t–25 to t–1 ($\beta_{i,t-1}^{k}$) times the risk factor (excess) returns in month t ($f_{k,t}$).[33] The SAs out-of-sample performance in month t is the difference between the SAs excess return ($ER_{i,t}$) and the style benchmark return (Eq. 6b). To account for outliers and estimation errors in the rolling regressions, we winsorize the out-of-sample performance at the 1st and 99th percentiles.

$$Style\ return_{i.t} = \sum_{k=1}^{K} \beta_{i,t-1}^{k}\, f_{k,t} \tag{6a}$$

$$\alpha_{i,t}^{ooS} = ER_{i,t} - Style\ return_{i,t} \tag{6b}$$

Table 2 reports annualized average out-of-sample alphas as well as in-sample risk-factor loadings and R^2 statistics for all four models, separately for quants (Panel A) and fundamentals (Panel B). "EW" denotes equal-weighted and "VW" denotes size-weighted results across

[31] http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html. We thank Kenneth French for providing the data.
[32] See Appendix A for a list of the 74 MPBs.
[33] Repeating the analysis with alternative sample window lengths of 12 and 36 months yields economically similar results.

SAs.[34] Looking first at the single index MPB results, we see that both the quant and fundamental SAs have EW alpha point estimates above zero and slightly negative VW alpha point estimates, but neither are statistically different from zero. With the CAPM, both EW and VW alphas are negative albeit insignificant for quant and fundament SAs, with the respective VW results being lower. With the Fama-French and Carhart alphas, however, there are two interesting patterns. First, the fundamental SA alphas are consistently higher than the quant SA alphas. Second, while there is little or no difference between the EW and VW alphas for the quantitative SAs, indicative of little or no decrease in performance for larger portfolio sizes, there is a marked difference in the EW and VW alphas for fundamental SAs. The much lower VW alphas suggests that for fundamental SAs, the larger portfolios underperform the smaller portfolios, a first indication that diseconomies of scale may play a more important role for fundamentals than for quants.

[Insert Table 2 here]

Regarding risk factor loadings, the market risk betas are near one for all measures and for both SA groups, however slightly lower for fundamentals. Fundamentals have higher average SMB betas while quants have higher HML betas on average. Fundamentals have no significant exposure to the momentum factor while quants have a significant exposure, consistent with momentum being a quant strategy rather than a fundamental one. Lastly, with respect to the model fit, quants show consistently higher R^2 statistics than fundamentals with differences between 4.5% and 7.6% depending on the model and weighting scheme. In the rest of the analysis, we focus on the MPB and Carhart models as the most relevant models from investor and academic standpoints, respectively.[35]

[34] Similar regressions for gross-returns are qualitatively the same, however, on a higher level. Further, due to the difference in the total expense ratio displayed in Table 1, the difference between quants and fundamentals is smaller.
[35] Repeating the analysis with the CAPM and the Fama/French model risk-adjusted performance yields qualitatively similar results.

Table 3 presents hypothesis tests of the differences in monthly out-of-sample alphas, in-sample risk factor sensitivities and R^2 statistics between quant and fundamental strategies. The first three columns report statistics for quants, the next three for fundamentals and the three rightmost columns report the respective differences. Quants have significantly lower mean and median Carhart alpha than fundamentals. They have higher market risk, lower exposure to SMB, higher exposures to HML and momentum, and they have higher adjusted R^2s. The table also reports standard deviations of the alpha, beta and adjusted R^2 estimates. Almost all of the statistics are significantly more stable through time for quants compared to fundamentals as indicated by the negative and significant differences in standard deviations.

[Insert Table 3 here]

3.3 Differences in the Impact of Size on Performance

3.3.1 Portfolio Sorting by SA Size

In a first step to analyzing the differences in diseconomies of scale between quant and fundamental investment strategies, we follow the classic method of Chen et al. (2004) and calculate the average performance of quarterly rebalanced size-quintile portfolios. Table 4 reports the results for all SAs (left columns) and separately for quant (middle columns) and fundamental SAs (right columns). For all SAs, the risk-adjusted performance of the "Low" size quintile is positive but statistically insignificant at +0.19% p.a. for the Carhart model and statistically significant at +0.97% p.a. for the MPB model, respectively. The performance of the "High" size quintile is negative but only statistically significant for the Carhart model risk-adjusted performance. The "High-Low" difference is negative and statistically significant, consistent with the general existence of diseconomies of scale in SAs.

However, looking at quant and fundamental SAs separately reveals that this finding is driven by the decline in performance as size increases for fundamental SAs. Specifically, the

"High-Low" difference in Carhart alpha for quants is close to zero and statistically insignificant and all size quintiles show very similar performance at around –1.00% p.a. The "High-Low" difference in MPB alpha is relatively small and only weakly statistically significant. Conversely, especially for the Carhart model fundamental SAs show highly negative and statistically significant "High-Low" differences and almost monotonically decreasing performance from the significant "Low" size quintile (0.54% p.a) to the significant "High" quintile (–0.61% p.a.). This is a first indication that diseconomies of scale differ across quant and fundamental SAs.

[Insert Table 4 here]

3.3.2 Panel Regressions of Future Performance

While the quintile sorting in Table 4 is compelling because an accordingly structured hypothetical investment strategy would earn positive risk-adjusted returns, it cannot be ruled out that this univariate result stems from other sources than differences in size. Therefore, Table 5 reports a wide range of panel regression approaches, where we explain quarterly future net Carhart model risk-adjusted performance ($a_{t+1,\, t+3}^{ooS,\, Carhart}$) with lagged SA size (Log TA), fundamental and quant group fixed effects[36] and various other SA and firm control variables (Eq. 7a). Further, to separate the effects of size on performance for quant and fundamental SAs, we include interaction terms between Log TA and indicator variables for quant and fundamental SAs (Eq. 7b). The different panel regressions include pooled regressions (M1, M2), style-fixed effects regressions (M3, M4), style- and time-fixed effects regressions (M5, M6), SA-fixed effects regressions (M7, M8)[37] and Zhu (2018) recursive demeaning two-stage least squares regressions to control for the endogeneity between size and performance (M9, M10). All variables are standardized to a unit standard deviation to ease comparisons between the

[36] To include both dummies without imposing multicollinearity, we run the regressions without a global constant.
[37] We consider fixed effects via within group demeaning.

coefficients. Standard errors are two-dimensionally clustered by SA and date to consider time-series and cross-sectional correlations.

$$a_{t+1,\ t+3}^{ooS,\ Carhart} = \varphi_1\ Ln\ TA_t + \varphi_2\ D^{Fundamental} + \varphi_3\ D^{Quant} + \varphi_4\ Net\ flow_t + \varphi_5\ a_{t-11,\ t}^{ooS,\ Carhart} + \varphi_6\ Expense\ ratio_t + \varphi_7\ Log\ Minimum\ Investment + \varphi_8\ Ln\ Firm\ TA_t + \varphi_9\ Age_t + \varphi_{10}\ D^{Retail} + \varphi_{11}\ D^{CIT} + \eta_{t+1,t+3} \tag{7a}$$

$$a_{t+1,\ t+3}^{ooS,\ Carhart} = \varphi_{1a}\ Ln\ TA_t : D^{Fundamental} + \varphi_{1b}\ Ln\ TA_t : D^{Quant} + \varphi_2\ D^{Fundamental} + \varphi_3\ D^{Quant} + \varphi_4\ Net\ flow_t + \varphi_5\ a_{t-11,\ t}^{ooS,\ Carhart} + \varphi_6\ Expense\ ratio_t + \varphi_7\ Log\ Minimum\ Investment + \varphi_8\ Ln\ Firm\ TA_t + \varphi_9\ Age_t + \varphi_{10}\ D^{Retail} + \varphi_{11}\ D^{CIT} + \eta_{t+1,t+3} \tag{7b}$$

The first column (M1) reports an overall negative effect of Log TA on future performance, in line with the univariate sorting for all SAs in Table 4. As for the most important control variables, the fundamentally managed SA indicator variable has a positive effect on performance, consistent with the higher average performance in Tables 2 and 3. Higher expense ratios are associated with lower future performance, in line with the previous literature.[38] Higher minimum investment amounts are associated with higher future SA performance while a retail investor focus is associated with lower SA performance, both consistent with better monitoring by more sophisticated and institutional investors (Evans and Fahlenbrach, 2012).

[Insert Table 5 here]

[38] Similar panel regressions using future gross returns as dependent variable yields economically similar coefficients.

The second column (M2) shows separate coefficients on Log TA for quant and fundamental SAs. Consistent with our previous result on the separate size quintile sorting in Table 4, the coefficient for fundamental SAs is negative and statistically and economically significant. A one standard deviation increase in Log TA is associated with a decrease of future Carhart alpha of 0.341% per quarter. In contrast, the coefficient for quant SAs is statistically insignificant and the point estimate is close to zero (0.094%). The effects are significantly different from each other as indicated by the difference in coefficient p-values reported directly below the coefficients. Repeating the regressions with various fixed effects to control for systematic differences between styles or structural differences over time (M3 – M6) does not change this finding materially. Considering constant cross-sectional differences (M7, M8)[39] and recursively demeaned cross-sectional differences between SAs (M9, M10)[40], which may include manager talent and skill, reveals that quant SAs also show diseconomies of scale but significantly weaker so than fundamental SAs. Overall, this evidence is consistent with the existence of diseconomies of scale in active management, which is significantly stronger in the fundamental investment process than the quant investment process.

3.4 Diseconomies of Scale Channels

3.4.1 Liquidity Costs

As elaborated in the introduction, there are two channels frequently put forward to rationalize the existence of diseconomies of scale in active investment management: higher liquidity costs and higher hierarchy and information processing costs. In this subsection, we intensively test

[39] Note that quant dummy, fundamental dummy, minimum investment amount, retail focus dummy, and CIT dummy are constant within SAs and therefore absorbed by the SA fixed effect.
[40] Note that while SA fixed effects consider constant cross-sectional differences between SAs, the recursive demeaning method also considers potentially endogenous changes of such differences over time, thereby mitigating bias by blunt application of fixed effects (Pastor, Stambaugh, and Taylor, 2015). Variables, which are constant within the SA (quant, fundamental, minimum investment amount, retail focus and CIT) are therefore included in the regressions in their un-demeaned form. All other variables are recursively demeaned following the instructions in Zhu (2018). The first stage results of the 2SLS regression approach are reported in Appendix B.

whether the differences in diseconomies of scale between the quant and fundamental investment processes is driven by differences in liquidity costs. Therefore, we extend the equilibrium model provided by Berk and Green (2004) and further developed by Pastor, Stambaugh, and Taylor (2020, hereafter PST) to separately consider the "separate account tradeoffs" of quant and fundamental SAs. Such tradeoffs exist between liquidity, turnover, and expense ratio, which are at the discretion of the management, and size, which is (for the most part) externally determined by investor decisions.

Specifically, we exactly follow the methodology laid out in PST to construct the quantity "portfolio liquidity" as well as its components "stock liquidity" and "diversification", with sub-components "balance" and "coverage". Therefore, we use the quarterly holdings of our sample SAs and the Vanguard Total Stock Market Index fund.[41] Further, to be consistent with PST, we also construct the quantity "turnover" following their definition as the "dollar amount traded divided by [TA]", which deviates from the SEC's definition (minimum of sales and purchases divided by TA).

Panel A of Table 6 mirrors PST's Table 1 by explaining portfolio liquidity with the other tradeoff variables. In addition, we explain portfolio liquidity with its components and with the quant and fundamental dummies. Most importantly, we interact all of the tradeoff variables with these dummies, to capture differences between the different investment processes. Panel B mirrors PST's Table 4 by explaining the components of portfolio liquidity. Panel C reports regressions of the other tradeoff variables, expense ratio and turnover ratio, against the liquidity components. Like PST, we use quarter-style fixed effects and cluster by SA. All variables are standardized to unit standard deviation.

[41] We obtain quarterly (1992–2013) respectively monthly holdings (2014–2018) of the Vanguard Total Stock Market Index fund from Morningstar Direct.

Fundamental SAs have lower portfolio liquidity on average, indicated by the significantly negative coefficient on the respective dummy variable (Panel A). This is due to lower diversification, lower coverage, lower balance, and the fact that quants show higher stock liquidity (Panel B). This general difference may be a first indication, that the liquidity channel affects fundamentals more strongly. Then, as SAs grow, fundamentals increase portfolio liquidity (Panel A). This is consistent with the tradeoff hypothesized by PST, as larger funds have to make larger trades, which is easier with more liquid stocks. This is, however, not the case for quants, which seem not to face this tradeoff, probably due to the already high average portfolio liquidity. Panel B thus reveals that both quants and fundamentals increase diversification in reaction to growth, consistent with PST. Quants do this mainly by increasing coverage while fundamentals equally increase coverage and balance. In contrast to PST, growing quants decrease stock liquidity as their widened coverage must be achieved by investing in less liquid stocks. However, given the much higher average stock liquidity for quant SAs to begin with (+0.710) it would take a nearly two standard deviation increase in quant size (–0.355) to equalize the stock liquidity between the two. Moreover, the fact that the increase in coverage counteracts the decrease in stock liquidity explains the insignificant coefficient of quant size in Panel A. This tradeoff between stock liquidity and diversification can also be seen in the opposing signs of "Stock Liquidity : D^Q" in explaining diversification and its components in Panel B. Growing fundamentals keep stock liquidity constant, such that the increase in diversification explains the overall increase in portfolio liquidity. Also, the negative but small coefficient on "Diversification : D^F" on stock liquidity confirms the tradeoff hypothesized by PST, however not for quants. Thus, there are strong "within portfolio liquidity tradeoffs" in quants, while fundamentals show strong "outside tradeoffs" between portfolio liquidity and the other tradeoff variables. This difference may explain differences in scale diseconomies.

[Insert Table 6 here]

With respect to the other tradeoff variables, quants have lower expense ratios on average (Panel C), consistent with the summary statistics in Table 1. Both quant and fundamentals become cheaper as they grow, consistent with correlations between the variables shown in Table 6 of PST, with quants becoming cheaper at a slightly higher pace. Further, more liquid quants are significantly cheaper, consistent with PSTs hypothesized tradeoff (Panel A). This is mainly due to higher diversification and especially higher coverage (Panel B). The PST tradeoff, however, does not hold for fundamentals, which show no or a weakly positive relation between portfolio liquidity, and here especially stock liquidity, and expenses. Panel C explains this by showing that more expensive fundamentals increase stock liquidity but at the same time decrease diversification, trading off the two components of portfolio liquidity.

With respect to turnover, quants have significantly higher turnover than fundamentals (Panel C), consistent with the summary statistics in Table 1. Further, quants decrease turnover as they grow (consistent with PST's Table 6), while fundamental turnover is unrelated to size. Consistent with PST, more expensive quants increase their turnover. Fundamentals show no relation between turnover and expenses. With respect to portfolio liquidity, Panels A and B show no relevant relations while Panel C reveals that fundamentals holding more liquid stocks also trade more, consistent with PST's hypothesized tradeoff that it is easier and less costly to trade liquid stocks.

In summary, explicitly controlling for differences between the investment processes concerning the tradeoffs between size, fees, and turnover, we show that quants and fundamentals react to changes in size quite differently with respect to portfolio liquidity and its components. This may explain the differences in diseconomies of scale between the competing strategies. Thus, if liquidity costs were the dominant channel, explicitly considering PST portfolio liquidity and its components in the performance regressions would narrow the gap between coefficients of size on performance for quants and fundamentals.

3.4.2 Hierarchy and information processing costs

To examine whether differences in hierarchy and information processing costs determine the differences in diseconomies of scale is not a trivial exercise. As laid out in the introduction, there have not been any empirical tests of the channel, which is mainly due to the lack of measurable quantities representing hierarchy and information processing.

As a first analysis of differences in hierarchy and information processing costs between quant and fundamental SAs, we follow a method proposed by Cici, Jaspersen and Kempf (2017) to measure the "speed of information diffusion" (ID) in mutual fund advisory firms. Intuitively, information may travel faster through an organization if physical and hierarchical distances between individuals are smaller and if the information is processed faster at intermediate stations, which depends on the nature of the information and the technology used. Therefore, we expect that higher ID may proxy for lower hierarchy and information processing costs, i.e. lower costs and delay in communicating relevant information.

Specifically, identifying "initial buys" of stocks by any SA within the SA firm, i.e. the buy of a stock not held by any other SA at the time, [42] ID speed measures how long it takes for the other SAs of the firm to buy the same stock, i.e. to obtain and use the information. If all SAs buy the stock within the same quarter, then the ID speed of the firm for this particular initial buy equals one. If no other SA buys the stock until the initial buyer sells the stock, indicating there is new information, the ID speed of the firm for this particular initial buy is zero. Summarizing the ID speeds of all initial buys of an SA firm may therefore proxy for the firm's hierarchy and information processing costs with higher ID speed indicating lower costs. Equation 8 shows how ID speed is calculated for each initial buy[43].

[42] For the determination of ID, we use the holdings of all SAs available to us via Morningstar, not only those of pure quant or fundamental SAs. In total, we use the holdings of 3,338 SAs managed by 897 firms.
[43] Eq. (1) from Cici, Jaspersen, Kempf (2017), pg. 151.

$$ID_{f,s,q} = \frac{I_{f,s,q} - 1}{I_{f,s.q} + J_{f,s,q} - 1} \tag{8}$$

$I_{f,s,q}$ is the number of SAs managed by investment advisor *f*, which buy stock *s* in quarter *q* (initial buy) and $J_{f,s,q}$ is the number of SAs managed by that same investment advisor that follow suit during the information interval. This interval ends when the investment advisor's assessment or valuation of the stock changes as demonstrated by the initial buyer selling the position.

Table 7 reports statistics for ID speed where Panel A shows mean ID speed separately for majority quant and majority fundamental firms.[44] Panel B shows separate results for firms where the identified initial buys are majorly performed by quants (fundamentals), i.e. where majorly quant (fundamental) SAs are the entry points of the information. Panel C shows separate results for firms where the identified "following buys" are majorly performed by quants (fundamentals), i.e. where the intermediate information processors are majorly quants (fundamentals). In all three panels, the ID speed reported for quants is significantly higher than that of fundamentals, indicating that quant firms – and by extension quant SAs – have lower hierarchy and information processing costs.

[Insert Table 7 here]

The rows of the table show results for selections of firms with respect to the number of SAs. Assuming that firm size increases with the number of SAs managed, the overall lower ID speed is rather constant in size for fundamental firms. However, we observe a reverse U-Shape for quant firms. As very small quant firms increase, their ID speed increases indicating economies of scale (e.g., Indro et al., 1999). This is consistent with SAs sharing more investments and the respective information. As quant firms further increase, however, ID speed decreases,

[44] Quant (fundamental) majority means that more than 50% of the firm's SAs identify as quants (fundamentals).

consistent with diversifying strategies rather than single SAs (e.g., Pollet and Wilson, 2008). This is consistent with SAs ceasing to share investments and the respective information.

Another way to look at information processing costs is to examine the nature of the information processed by quants and fundamentals. While both quant and fundamental SAs can be expected to process quantitative data, i.e. hard or systematic information, in their investment process, only fundamentals additionally process qualitative data, i.e. soft information. Compared to hard information, which can be automatically processed by IT in large quantities at high speeds, soft information must be processed, interpreted, and communicated by people, sometimes including multiple feedback loops between individuals on different hierarchical levels, as indicated by the investment process description by *Ariel Investments, LLC, Small Cap Value SA* (see Introduction). One may expect that the differential use of hard and soft information between quants and fundamentals may also show in their investment strategy outcomes. Specifically, we expect that quant investment strategies, which are based on systematic signals only, show higher consistency in their style and risk factor loadings compared to fundamental strategies. The latter additionally rely on qualitative signals, which may not show as systematic signals in quant data. In addition, we expect that, for the same reasons, quant strategies stay closer to their benchmarks.

A first indication of this being true may be seen in Table 3, which shows higher performance model R^2 statistics and lower factor beta standard deviations for quants than for fundamentals. However, to control for endogeneity in such descriptive statistics, Table 8 takes a specific look at changes in the management teams of the SAs in a difference-in-differences analysis. If the managers of fundamental SAs process more soft information, the investment strategy is likely to change with a new investment team introducing new views, opinions and approaches to valuation. For quant SAs, however, if the investment strategy relies primarily on hard information processing via the team's algorithm, the investment strategy should exhibit less deviation after a change in the individuals managing the SA. To test if this is the case, we therefore look at changes in the factor exposures of the two different strategies across a manager change event. Using Morningstar Direct data to identify SA manager names over time, we identify those SA-date observations where there is a change in the SA management team.[45] For each of these management changes (t=0), we analyze the absolute differences in factor exposures, tracking error relative to the factor model and the factor model adjusted R^2 between the year prior to the change (months t–12 to t–1) and the year after the change (months t+1 to t+12). Table 5 reports these differences for all SAs and separately for quant and fundamental, as well as the difference-in-differences between the two groups.

As measures of consistency in the investment strategy, we first look at differences in performance regression betas and document that changes in the four Carhart (1997) factor betas around manager changes are significantly larger in fundamental SAs than in quant SAs. The difference-in-differences with respect to the MPB market beta is also negative but only weakly significant. The overall investment strategies of quant SAs are less affected by manager changes than those of fundamental SAs, suggesting more stable investment process relying more on hard information, which is less costly to process and communicate.

[Insert Table 8 here]

We also look at differences in fit and active risk as measures of potential changes in investment strategy across the manager changes. We calculate differences in the tracking error (TrE) vis-à-vis the Carhart model and the MPB index (e.g., Cremers and Petajisto, 2009) as well as the R^2 statistics from both performance regression models (e.g., Amihud and Goyenko, 2013). Again, the differences are higher for fundamentals than for quants as indicated by negative differences-in-differences, but statistically significant only in the case of R^2. Overall, the results

[45] We obtain detailed information on the names and terms of all members of the SAs management teams from Morningstar Direct. We focus on manager exit and not the addition of a new manager, because it is unclear how much immediate influence a new manager has on the SA's production function while it is clear that the immediate influence of a manager leaving directly drops to zero.

in Table 8 are consistent with the hypothesis that quant SAs rely more on hard information, indicative of lower information processing costs.

3.4.3 Diseconomies of Scale Controlling for Channels

Given the evidence that both channels, liquidity costs and information processing/hierarchy costs affect quantitative and fundamental strategies and firms differently, we revisit our examination of the diseconomies of scale between quant and fundamental SAs controlling for these differences. We repeat our panel regressions of performance accounting for the components of PST's portfolio liquidity as well as broad proxies for information processing and hierarchy costs. Recognizing that manager ability is also related to fund size (e.g. Berk and Green (2004)), we include manager fixed effects. Since SAs may have multiple managers, we reconfigure the panel regression data to manager-SA-date observations but then weight the observations by the inverse of the number of managers. All variables are standardized to unit standard deviation to ease coefficient comparisons. Standard errors are clustered on the dimensions of dimensions of firm and date. The results are presented in Table 9.

[Insert Table 9 here]

The first column (M1) repeats the basic regression with manager fixed effects, but without channel variables as reference. Consistent with the results from M8 and M10 in Table 5, both quant and fundamental strategies exhibit diseconomies of scale, but the difference is significantly higher in fundamentals. The coefficient differences is 0.135.

In the second column (M2), we include the PST tradeoff variables turnover, stock liquidity, balance, and coverage but not allowing for the quant and fundamental strategies to differ. We see that higher turnover decreases alpha, consistent with higher transaction costs, and higher coverage increases alpha, consistent with the benefit of diversification shown by Pollet and Wilson (2008). However, stock liquidity and balance show coefficients near zero and the inclusion of the PST variables does not materially affect the difference in diseconomies of scale across the two strategies.

Recognizing the important insight from PST that different funds/strategies may arrive at different equilibria regarding the tradeoffs between fund size, liquidity, turnover and expenses, we repeat the analysis in specification M3, but allow for the quant and fundamental strategies to weight differently on these four dimensions. Consistent with different equilibria, we see that quant performance increases strongly with stock liquidity and coverage while slightly decreasing with balance. Fundamental performance, on the other hand, increases in balance while being unrelated to the other two components. We also see that allowing for different quant and fundamental coefficients on the PST components reduces the difference in diseconomies of scale to a statistically insignificant 0.103.

Finally, in the last column (M4), we add broad proxies for information processing and hierarchy costs at the firm level. While our specific tests for information processing and hierarchy costs are consistent with differences between quant and fundamental SAs, the unique settings under which they are measured (i.e. initiation of a new stock position or a change in the management team) do not lend themselves to usage in our regression setting. At a broader level, information processing and hierarchy costs should be related to the size of an investment advisor and the number of investment professionals working for that investment advisor. The key insight from tables 7 and 8 is that these costs differ across different types of investment strategy.

To proxy broadly for information processing and hierarchy cost differences across the two types, we simply include dimensions of organization size (i.e. firm assets under management and number of separate accounts), but allow them to differ by investment style – quant or fundamental. To ensure these measures are capturing firm wide dimensions separate from the SA of interest, we calculate them excluding the separate account of interest. As a result, the difference between the coefficients further decreases (0.077). Hence, the inclusion of the liquidity costs, information processing and hierarchy proxies helps to explain the difference in diseconomies of scale between quant and fundamental investment strategies.

3.5 Conclusion

While the recent debate surrounding diseconomies of scale in active asset management has largely centered around econometric issues, of equal importance is identifying and testing the underlying economic mechanism. In this paper, we investigate differences in diseconomies of scale associated with different investment strategies: quantitative versus fundamental. We find that quant strategies exhibit statistically and economically significantly lower diseconomies of scale. To better understand the potential channels through which these two investment styles differ, we first explore the liquidity channel and then the information processing/hierarchy cost channel.

With respect to liquidity costs, we extend the "mutual fund tradeoffs" framework by Pastor, Stambaugh, and Taylor (2020) and find that such equilibrium tradeoffs are very different for quants compared to fundamentals. Further, with respect to information processing and hierarchy costs, we find that quant investment firms show higher speed of information diffusion and that quant strategies are more stable around management changes, both consistent with lower information processing and hierarchy costs in quant SAs. Finally, we relate these differences in both channels to the differences in diseconomies of scale between quant and fundamental SAs and find that accounting for these differences partially explains the differences in diseconomies of scale.

Overall, our results provide an alternative approach to assessing the important issue of diseconomies of scale in the asset management industry – namely, focusing on the underlying economics. Ex ante, quantitative strategies would seem to suffer less from the issue of diseconomies of scale and this is what we find. Additionally, our results shed light on important differences between these two, often competing, investment styles.

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Tables and Figures

Table 1
Summary Statistics

	N	Mean	SD	Percentile 10th	25th	50th	75th	90th	Skewness
Panel A: Summary statistics by SA (Quants)									
Total Assets ($M)	360	386.00	726.00	6.02	36.30	127.00	468.00	1100.00	4.92
Firm Assets ($B)	356	80.02	175.00	0.67	2.62	10.80	53.20	215.00	2.98
Expense Ratio (% p.a.)	363	0.73	0.47	0.29	0.45	0.65	0.87	1.20	2.24
Minimum Investment ($M)	322	12.20	14.70	0.05	0.25	5.00	20.00	25.00	1.30
Number of Holdings (#)	350	155	151	32	72	113	194	301	3.48
Assets in Top 10 Hldgs (%)	343	29	21	12	16	24	31	48	2.20
Net Flow (% p.a.)	348	9.93	29.16	-15.20	-4.35	7.60	21.19	40.24	-0.33
Turnover Ratio (% p.a.)	311	110.33	76.16	26.67	64.39	90.78	131.77	239.53	1.43
Number of Managers (#)	350	2.39	1.14	1.00	1.49	2.18	3.48	4.00	-0.11
Age (years)	363	7.66	4.21	2.96	4.46	7.12	9.92	12.79	1.31
Institutional Focus	88	24.2%							
Retail Focus	18	5.0%							
Institution&Retail Focus	222	61.2%							
Panel B: Summary statistics by SA (Fundamentals)									
Total Assets ($M)	1,402	740.00	1390.00	12.50	56.40	211.00	765.00	1980.00	3.97
Firm Assets ($B)	1,380	60.50	147.00	0.48	1.65	5.99	43.00	158.00	4.60
Expense Ratio (% p.a.)	1,417	0.93	0.59	0.48	0.64	0.81	0.97	1.35	2.40
Minimum Investment ($M)	1,340	7.29	10.70	0.10	0.50	3.00	10.00	25.00	2.47
Number of Holdings (#)	1,408	62	40	30	38	53	76	101	4.30
Assets in Top 10 Hldgs (%)	1,378	34	13	20	25	32	40	50	1.57
Net Flow (% p.a.)	1,386	11.37	22.14	-12.02	-2.38	8.55	22.87	39.25	0.71
Turnover Ratio (% p.a.)	1,293	53.71	41.52	16.81	25.95	41.75	69.31	105.99	2.23
Number of Managers (#)	1,389	2.10	1.01	1.00	1.00	2.00	3.00	3.65	0.34
Age (years)	1,417	9.51	5.59	3.97	5.71	8.21	11.87	16.25	1.68
Institutional Focus	309	21.8%							
Retail Focus	144	10.2%							
Institution&Retail Focus	824	58.2%							

Table 1 cont`d.
Panel C. Market value-weighted common stock holdings

	# SAs		% Holdings				# SAs		% Holdings		
Year	Q	F	Common	Q only	F only	Year	Q	F	Common	Q only	F only
2001	31	120	90.75%	0.70%	8.49%	2011	187	954	98.46%	0.04%	1.62%
2002	47	260	92.02%	0.16%	7.73%	2012	199	975	97.73%	0.07%	2.26%
2003	50	311	93.39%	0.15%	6.26%	2013	190	952	94.38%	0.03%	5.95%
2004	73	382	91.49%	0.21%	8.09%	2014	192	969	97.72%	0.05%	2.28%
2005	100	489	95.37%	0.11%	4.59%	2015	199	952	99.25%	0.05%	0.84%
2006	146	552	94.98%	0.12%	4.78%	2016	190	912	99.08%	0.05%	1.02%
2007	166	648	96.95%	0.11%	2.88%	2017	186	843	97.30%	0.15%	2.57%
2008	221	775	97.83%	0.16%	1.82%	2018	165	776	96.89%	0.17%	2.87%
2009	216	809	97.87%	0.19%	1.80%	Average 2001–2018			95.99%	0.14%	3.85%
2010	201	889	96.40%	0.07%	3.51%						

This table shows summary statistics for a sample of actively managed U.S. domestic equity separate accounts (SAs) from 1990/01 to 2018/12. Panel A shows quantitatively managed SAs, Panel B reports the characteristics of fundamentally managed SAs. The expense ratio is calculated as the difference between gross and net return. Min. investment is minimum initial investment an investor has to make to open an account within a particular SA. The net flow of SA *i* in period *t* is calculated as the change in total assets from period *t-1* to period *t* less value changes due to net returns on assets. Panel C shows market-value weighted statistics on common stock holdings between the universes of quant and fundamental SAs.

Table 2
Annualized Performance and Risk Factor Loadings

	MPB		CAPM		Fama-French		Carhart	
	EW	VW	EW	VW	EW	VW	EW	VW
Panel A: Quants								
Alpha	0.040	-0.254	-0.399	-0.533	-0.714*	-0.675*	-0.954**	-0.884**
	(0.92)	(0.50)	(0.48)	(0.14)	(0.08)	(0.07)	(0.01)	(0.01)
Market	0.987***	0.997***	1.010***	0.986***	0.982***	0.982***	0.997***	0.992***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
SMB					0.208***	0.086***	0.194***	0.077***
					(0.00)	(0.00)	(0.00)	(0.00)
HML					0.101***	0.109***	0.110***	0.117***
					(0.00)	(0.00)	(0.00)	(0.00)
MOM							0.065***	0.041***
							(0.00)	(0.00)
Adj. R^2	0.905	0.944	0.840	0.890	0.912	0.939	0.921	0.945
Panel B: Fundamentals								
Alpha	0.368	-0.153	-0.050	-0.423	-0.254	-0.536*	-0.142	-0.485*
	(0.32)	(0.67)	(0.93)	(0.28)	(0.39)	(0.06)	(0.63)	(0.09)
Market	0.947***	0.969***	1.006***	1.014***	0.963***	0.986***	0.959***	0.979***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
SMB					0.263***	0.154***	0.257***	0.149***
					(0.00)	(0.00)	(0.00)	(0.00)
HML					0.040***	-0.003	0.035***	-0.008*
					(0.00)	(0.46)	(0.00)	(0.08)
MOM							-0.004*	-0.002
							(0.09)	(0.42)
Adj. R^2	0.835	0.868	0.787	0.824	0.866	0.892	0.874	0.900

This table presents annualized alpha/risk-adjusted performance and risk factor sensitivities from a sample of actively managed U.S. domestic equity SAs from 1990/01 to 2018/12. Panel A shows quantitatively managed SAs, Panel B reports fundamentally managed SAs. The alpha/risk-adjusted performance for SA *i* in month *t* is the difference between its actual return and a style benchmark return, which is calculated using a 24-month rolling window regression and multiplying its estimated factor sensitivities from the prior 24 months with the values of the corresponding risk-factors in month *t*. All factor sensitivities are measured using either the manager-preferred benchmark (MPB), the CAPM, the Fama/French (1993) or the Carhart (1997) factor model with 24-month rolling window regressions. ***, **, and * denote significantly different means from two-sided t-tests in means at the 1%, 5%, or 10% level, respectively. p-values are given in parentheses.

Table 3
Hypothesis Tests of Monthly Performance and Risk Factor Loadings

Variable	Quants				Fundamentals				Differences		
	N	Mean	SD	Med	N	Mean	SD	Med	Mean	SD	Median
Carhart alpha	53,605	-0.08	1.36	-0.07	240,079	-0.01	1.71	-0.04	-0.07***	-0.35***	-0.03***
MPB alpha	40,793	0.00	1.27	0.01	206,376	0.03	1.71	0.01	-0.03***	-0.43***	0.00
Market (Carhart)	54,098	1.00	0.12	1.00	241,955	0.96	0.16	0.96	0.05***	-0.03***	0.04***
Market (MPB)	41,359	0.99	0.12	0.99	207,105	0.95	0.17	0.95	0.04***	-0.05***	0.04***
SMB	54,098	0.19	0.38	0.05	241,955	0.26	0.37	0.19	-0.06***	0.01***	-0.14***
HML	54,098	0.11	0.26	0.08	241,955	0.03	0.32	0.04	0.08***	-0.06***	0.05***
MOM	54,098	0.07	0.14	0.04	241,955	0.00	0.17	-0.01	0.07***	-0.02***	0.05***
adj. R2 (Carhart)	54,098	0.93	0.09	0.95	241,955	0.87	0.11	0.90	0.05***	-0.02***	0.04***
adj. R2 (MPB)	41,359	0.91	0.12	0.95	207,087	0.83	0.15	0.88	0.08***	-0.03***	0.06***

This table presents means, standard deviations and medians of monthly alpha/risk-adjusted performance and risk factor sensitivities from a sample of actively managed U.S. domestic equity SAs with either a quantitative or a fundamental investment approach from 1990/01 to 2018/12. The alpha/risk-adjusted performance for SA *i* in month *t* is the difference between its actual return and a style benchmark return, which is calculated using a 24-month rolling window regression and multiplying its estimated factor sensitivities from the prior 24 months with the values of the corresponding risk-factors in month *t*. All factor sensitivities are measured using either the manager-preferred benchmark (MPB) or the Carhart (1997) factor model with 24-month rolling window regressions. ***, **, * indicate significantly different means (medians) ((standard deviations)) from two-sided t-tests in means (Wilcoxon rank-sum tests for differences in medians) ((Levene's robust test for equality of variances)) at the 1%, 5%, and 10% level, respectively.

Table 4

Annualized Performance by Lagged Size Quintile

	All		Quants		Fundamentals	
Total assets$_{t\text{-}1}$	Carhart	MPB	Carhart	MPB	Carhart	MPB
Low	0.19	0.97***	-0.92*	0.50	0.54*	1.08***
	(0.72)	(0.01)	(0.06)	(0.22)	(0.08)	(0.00)
2	-0.17	0.47	-1.11**	-0.04	0.24	0.89***
	(0.58)	(0.21)	(0.01)	(0.93)	(0.47)	(0.00)
3	-0.47	0.09	-0.98**	0.00	-0.30	0.50
	(0.11)	(0.81)	(0.02)	(0.99)	(0.35)	(0.22)
4	-0.67**	-0.06	-0.87**	-0.20	-0.50	0.53
	(0.04)	(0.87)	(0.02)	(0.61)	(0.15)	(0.16)
High	-0.75***	-0.22	-0.99***	-0.22	-0.61**	-0.26
	(0.00)	(0.53)	(0.01)	(0.29)	(0.03)	(0.86)
All	-0.39	0.25	-0.88**	-0.01	-0.13	0.64**
	(0.17)	(0.47)	(0.01)	(0.97)	(0.67)	(0.02)
High-low	-0.93***	-1.21***	-0.06	-0.70*	-1.15***	-1.34***
	(0.00)	(0.00)	(0.88)	(0.09)	(0.00)	(0.00)

This table presents annualized Carhart and MPB alpha/risk-adjusted performance for quarterly rebalanced size-quintile portfolios from a sample of actively managed U.S. domestic equity SAs with either a quantitative or fundamental investment approach from 1990/01 to 2018/12. Carhart alphas for SA *i* in month *t* are the difference between the SA actual net return and a style benchmark return, which is calculated using a 24-month rolling window regression and multiplying its estimated factor sensitivities from the prior 24 months with the values of the corresponding risk-factors in month *t*. ***, **, and * denote significantly different means from two-sided t-tests in means at the 1%, 5%, or 10% level, respectively. P-values are given in parentheses.

Table 5
Panel Regressions of Performance

	M1	M2	M3	M4	M5	M6	M7	M8	M9	M10
Ln TA	-0.021**		-0.019**		-0.023***		-0.149***		-0.092***	
	(0.02)		(0.02)		(0.00)		(0.00)		(0.00)	
Ln TA : D^{Quant}		-0.040		-0.029		-0.045		-0.382***		-0.027**
		(0.25)		(0.34)		(0.13)		(0.00)		(0.03)
Ln TA : $D^{Fundamental}$		-0.115***		-0.107***		-0.115***		-0.603***		-0.081***
		(0.00)		(0.00)		(0.00)		(0.00)		(0.00)
p-Val: Ln TA : D^{Q} – Ln TA : D^{F} = 0		0.03**		0.03**		0.04**		0.01***		0.00***
D^{Quant}	-0.009	0.104	-0.004	0.078	-0.005	0.123			-0.013	-0.035**
	(0.76)	(0.27)	(0.86)	(0.38)	(0.81)	(0.16)			(0.41)	(0.04)
$D^{Fundamental}$	0.076***	0.301***	0.070***	0.279***	0.069***	0.293***			-0.011	-0.029
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)			(0.66)	(0.32)
Net Flow	0.011**	0.011**	0.011**	0.011**	0.012***	0.012***	0.004	0.003	0.007	0.005
	(0.02)	(0.02)	(0.02)	(0.02)	(0.01)	(0.01)	(0.22)	(0.35)	(0.13)	(0.20)
Firm TA	-0.005	-0.005	-0.004	-0.004	-0.001	-0.001	-0.017**	-0.016**	-0.022	-0.008
	(0.28)	(0.27)	(0.36)	(0.35)	(0.87)	(0.79)	(0.03)	(0.04)	(0.35)	(0.15)
Lagged Alpha (1-year)	0.001	0.008	0.001	0.007	0.001	0.009	-0.003***	-0.038***	-0.021	-0.021
	(0.72)	(0.73)	(0.75)	(0.76)	(0.68)	(0.68)	(0.00)	(0.00)	(0.36)	(0.37)
Expense Ratio (% TA p.a.)	-0.020***	-0.020***	-0.020***	-0.020***	-0.017***	-0.017***	0.004	0.005	-0.006	-0.005
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.48)	(0.35)	(0.25)	(0.34)
Minimum Investment	0.013**	0.012*	0.012*	0.012*	0.009	0.008			-0.003	-0.003
	(0.05)	(0.07)	(0.05)	(0.07)	(0.11)	(0.17)			(0.65)	(0.64)
Age	-0.023**	-0.023**	-0.022**	-0.023**	-0.009*	-0.010**	-0.063***	-0.068***	-0.012	-0.017
	(0.02)	(0.01)	(0.02)	(0.01)	(0.06)	(0.03)	(0.00)	(0.00)	(0.60)	(0.44)
D^{Retail}	-0.102***	-0.101***	-0.100***	-0.100***	-0.101***	-0.100***			-0.027*	-0.028**
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)			(0.06)	(0.05)
D^{CIT}	0.026	0.023	0.025	0.023	0.012	0.010			0.004	-0.003
	(0.36)	(0.41)	(0.32)	(0.37)	(0.62)	(0.69)			(0.88)	(0.92)
Style FE			Yes	Yes	Yes	Yes				
Time FE					Yes	Yes				
SA FE							Yes	Yes		
Recursive demeaning (Zhu, 2018)									Yes	Yes
Adjusted R^2	0.00	0.00	0.00	0.00	0.04	0.04	0.01	0.01	0.00	0.00
N	88,690	88,690	88,690	88,690	88,690	88,690	88,690	88,690	86,987	86,987

This table reports panel regressions of SA alpha/risk-adjusted performance on SA size (Log TA) for of actively managed U.S. domestic equity SAs from 1990/01 to 2018/12. Carhart alpha/risk-adjusted performance of SA *i* in month *t* is the Sharpe (1992) out-of-sample performance calculated using 24-month rolling window regressions. All variables are standardized to mean zero and unit standard deviation. Fixed effects are considered using within group demeaning. ***, **, and * denote significance at the 1%, 5%, or 10% level, respectively. Standard errors are 2-dimensionally clustered by SA and time to consider time series and cross-sectional correlation. p-values are reported in parentheses.

Table 6
Separate Account Tradeoffs

	Panel A. Portfolio Liquidity				**Panel B. Portfolio Liquidity Components**				**Panel C. Further SA Tradeoffs**			
	(1)	(2)	(3)	(4)	Divers.	Coverage	Balance	Stock Liq.	Expense Ratio		Turnover Ratio	
Log TA : D^{Quant}	0.011	0.097	-0.136	0.082	0.299*	0.645**	-0.127	-0.355***	-0.187***	-0.181***	-0.139***	-0.133**
	(0.95)	(0.53)	(0.39)	(0.59)	(0.07)	(0.03)	(0.16)	(0.00)	(0.00)	(0.00)	(0.01)	(0.01)
Log TA : $D^{Fundamental}$	0.214***	0.212***	0.085	0.082	0.324***	0.259***	0.336***	-0.041	-0.141***	-0.140***	-0.040	-0.034
	(0.00)	(0.00)	(0.24)	(0.19)	(0.00)	(0.00)	(0.00)	(0.42)	(0.00)	(0.00)	(0.49)	(0.55)
D^{Quant}	0.303	-0.351	0.242	-0.828*	0.072	0.554	0.140	0.710**	-0.190***	-0.124	0.349**	0.298*
	(0.57)	(0.43)	(0.61)	(0.07)	(0.89)	(0.52)	(0.63)	(0.04)	(0.00)	(0.14)	(0.04)	(0.09)
$D^{Fundamental}$	-0.460***	-0.712***	-0.401***	-0.688***	-0.719***	-0.479***	-0.309**	0.106	0.068	-0.003	0.026	0.006
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.03)	(0.32)	(0.13)	(0.96)	(0.83)	(0.96)
Expense Ratio : D^{Q}	-0.035**	-0.030*	-0.012	-0.041**	-0.074***	-0.138***	0.008	0.033**			0.013	0.014*
	(0.04)	(0.06)	(0.40)	(0.01)	(0.00)	(0.00)	(0.53)	(0.03)			(0.13)	(0.10)
Expense Ratio : D^{F}	0.015	0.009	0.016*	0.015	0.003	-0.001	0.006	0.021*			-0.014	-0.014
	(0.14)	(0.32)	(0.10)	(0.11)	(0.67)	(0.86)	(0.62)	(0.06)			(0.13)	(0.13)
Turnover Ratio : D^{Q}	-0.002	-0.002	-0.005	0.001	0.004	0.015	-0.004	0.003	0.013*	0.014*		
	(0.76)	(0.77)	(0.46)	(0.88)	(0.68)	(0.43)	(0.19)	(0.32)	(0.07)	(0.07)		
Turnover Ratio : D^{F}	0.002	0.003	0.003	0.003	-0.005	0.007	-0.010*	-0.004	-0.015*	-0.013		
	(0.66)	(0.44)	(0.48)	(0.45)	(0.31)	(0.10)	(0.08)	(0.18)	(0.08)	(0.10)		
Stock Liquidity : D^{Q}		0.174***			-0.140***	-0.332***	0.075**		-0.022**		-0.002	
		(0.00)			(0.00)	(0.00)	(0.03)		(0.01)		(0.76)	
Stock Liquidity : D^{F}		0.213***			-0.005	-0.087***	-0.035		0.029*		0.021*	
		(0.00)			(0.75)	(0.00)	(0.31)		(0.09)		(0.07)	
Balance : D^{Q}				0.137***		-0.106***						
				(0.00)		(0.00)						
Balance : D^{F}				0.104***		-0.100***						
				(0.00)		(0.00)						
Coverage : D^{Q}				0.301***			-0.046**					
				(0.00)			(0.01)					
Coverage : D^{F}				0.385***			-0.198***					
				(0.00)			(0.00)					
Diversification : D^{Q}			0.255***					0.001		0.001		0.005
			(0.00)					(0.87)		(0.90)		(0.72)
Diversification : D^{F}			0.333***					-0.024***		-0.021***		-0.004
			(0.00)					(0.01)		(0.00)		(0.61)
Quarter-Style FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R2	0.31	0.33	0.43	0.44	0.27	0.34	0.37	0.74	0.06	0.06	0.05	0.05
N	60,489	60,489	60,489	60,489	60,489	60,489	60,489	60,489	60,489	60,489	60,489	60,489

This table reports the results from panel regressions with the PST – portfolio liquidity components as dependent variables (Pastor, Stambaugh, and Taylor, 2020) in the period from 01/2001 to 12/2018. All regressors are measured contemporaneously with the dependent variable. All variables are standardized to mean zero and unit standard deviation. All regressions include sector×quarter fixed effects (FEs) and cluster by SA. ***, **, and * denote significance at the 1%, 5%, or 10% level, respectively.

Table 7

Speed of Information Diffusion within SA Firms

	Panel A. Quant vs. Fundamental Majority Firm			**Panel B. Quant vs. Fundamental Majority Initial Buyers**			**Panel C. Quant vs. Fundamental Majority Following Buyers**		
	Quant	Fund.	Difference	Quant	Fund.	Difference	Quant	Fund.	Difference
Firms ≥ 3 SAs (197 firms)	0.7442	0.5999	0.1443*** (67.60)	0.7347	0.6085	0.1262*** (58.76)	0.7365	0.6086	0.1279*** (59.70)
Firms ≥ 5 SAs (94 firms)	0.7864	0.5851	0.2013*** (79.38)	0.7722	0.6019	0.1702*** (65.81)	0.7747	0.6025	0.1722*** (67.09)
Firms ≥ 7 SAs (42 firms)	0.7037	0.5852	0.1185*** (32.52)	0.6840	0.6169	0.0671*** (18.14)	0.6846	0.6181	0.0665*** (18.11)

This table shows measures of Information Diffusion (ID) following Cici, Jaspersen, and Kempf (2017) within SA firms separately for i) firms majorly (>50%) managing quantitative SAs vs. fundamental SAs, ii) Initial Buys majorly made by quantitative vs. fundamental SAs, and iii) Following Buys majorly made by quantitative vs. fundamental SAs, in the period from 01/2001 to 12/2019. Higher values of ID denote higher speed of Information Diffusion. ID may range from 0 to 1. Statistical significance of the difference (Quant–Fund) is tested by unpaired mean difference t-tests against the H0 that the difference is zero. T-statistics are reported in parentheses. ***, **, * denote statistical significance on the 1%, 5%, 10% level, respectively.

Table 8
Impact of Management Changes

Variable ($t_{-12;-1}$; $t_{1;12}$)	Differences			Diff-in-Diffs
	All	Quants	Fundamentals	(Quants – Fundamentals)
| Carhart market beta diff |	0.196	0.125	0.209	-0.083***
| SMB beta diff |	0.275	0.130	0.301	-0.171***
| HML beta diff |	0.305	0.214	0.322	-0.108***
| MOM beta diff |	0.247	0.125	0.270	-0.144***
| MPB beta diff |	0.115	0.087	0.121	-0.034*
| TrE Carhart diff |	0.471	0.381	0.488	-0.107
| TrE MPB diff |	0.482	0.453	0.488	-0.035
| Adj. R2 Carhart diff |	0.087	0.045	0.095	-0.050***
| Adj. R2 MPB diff |	0.059	0.018	0.068	-0.049***
# Changes	479	97	382	
# Differences in betas (Carhart)	374	73	301	
# Differences in betas (MPB)	301	54	247	

This table shows the results of a difference-in-difference analysis for SAs with a quantitative investment approach and SAs with a fundamental investment approach in the period from 01/1990 to 12/2018. For each point in time, in which a manager leaves the management team (t=0), we measure the absolute differences in different investment strategy measures between the year prior to the change (months t–12 to t–1) and the year after the change (months t+1 to t+12). As measures of investment strategy, we use differences in performance regression model betas including market betas (Carhart and MPB) as well as in risk factor betas for the SMB, HML and MOM factors, tracking errors (TrE) vis-à-vis the Carhart model and the MPB index (e.g., Cremers and Petajisto, 2009) and the R2 statistics from both performance regression models (e.g., Amihud and Goyenko, 2013). ***, **, * indicate significantly different means from two-sided t-tests at the 1%, 5%, and 10% level.

Table 9
Panel regressions of performance with PST Liquidity Components, Family Characteristics and Manager-SA Fixed-Effects

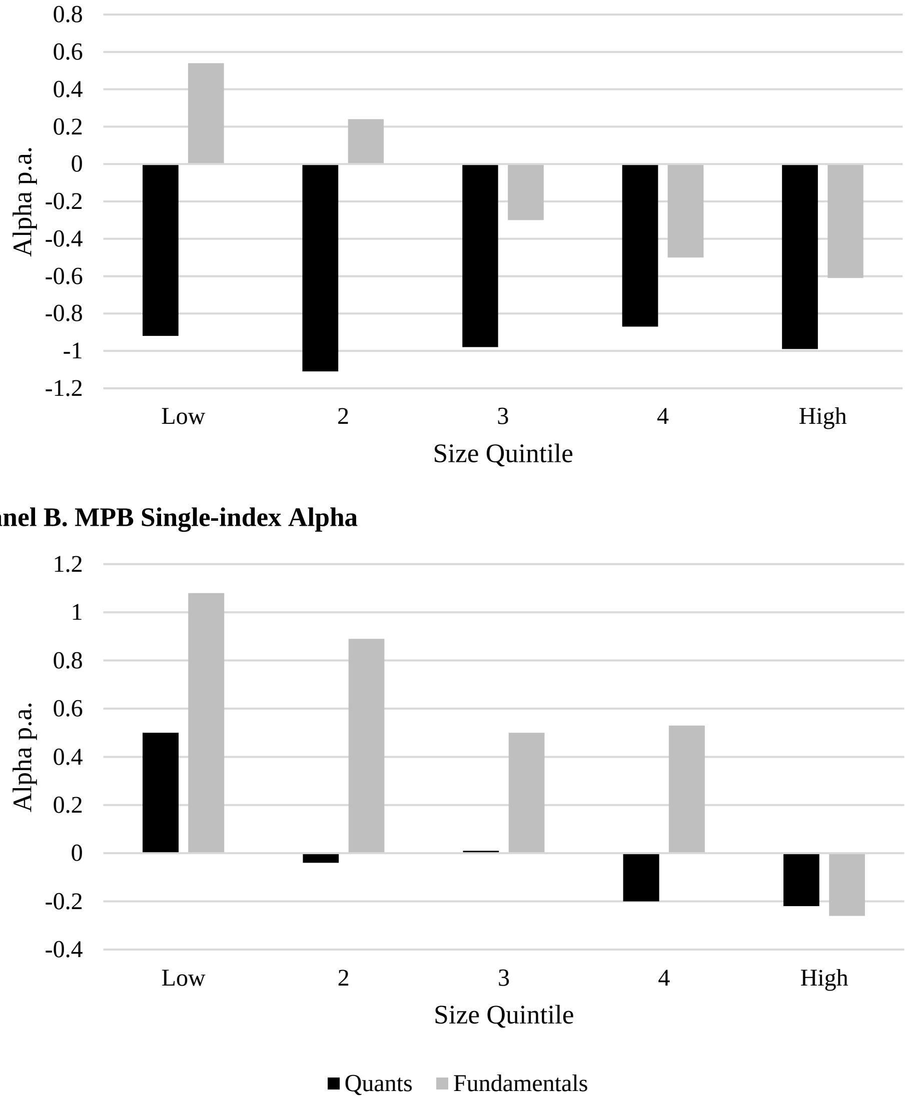
	M1	M2	M3	M4
Ln TA : D^{Quant}	-0.127***	-0.126***	-0.171***	-0.155***
	(0.00)	(0.00)	(0.00)	(0.00)
Ln TA : $D^{Fundamental}$	-0.262***	-0.264***	-0.273***	-0.232***
	(0.00)	(0.00)	(0.00)	(0.00)
p-Val: Ln TA : D^Q – Ln TA : D^F = 0	0.03**	0.03**	0.14	0.25
D^{Quant}	0.280***	0.283***	0.452***	0.384***
	(0.01)	(0.01)	(0.00)	(0.00)
$D^{Fundamental}$	0.541***	0.546***	0.564***	0.465***
	(0.00)	(0.00)	(0.00)	(0.00)
Expense Ratio	-0.033***	-0.033***		
	(0.00)	(0.00)		
PST Turnover Ratio		-0.012**		
		(0.01)		
Stock Liquidity		0.000		
		(1.00)		
Balance		0.007		
		(0.36)		
Coverage		0.027***		
		(0.01)		
Expense Ratio : D^Q			-0.036**	-0.037***
			(0.01)	(0.01)
Expense Ratio : D^F			-0.037***	-0.035***
			(0.00)	(0.00)
Turnover Ratio : D^Q			-0.012***	-0.013***
			(0.00)	(0.00)
Turnover Ratio : D^F			-0.010*	-0.010*
			(0.08)	(0.06)
Stock Liquidity : D^Q			0.024***	0.025***
			(0.00)	(0.00)
Stock Liquidity : D^F			-0.006	-0.003
			(0.56)	(0.74)
Balance : D^Q			-0.011*	-0.008
			(0.09)	(0.22)
Balance : D^F			0.018*	0.021**
			(0.08)	(0.05)
Coverage : D^Q			0.027***	0.027***
			(0.00)	(0.00)
Coverage : D^F			0.022	0.020
			(0.20)	(0.23)
Ln # of Quants in the Family				0.035
				(0.46)
Ln # of Fundamentals in the Family				0.112***
				(0.00)
Family TA in Quant SAs				-0.140***
				(0.00)
Family TA in Fundamental SAs				-0.170***
				(0.00)
Manager-SA FE	Yes	Yes	Yes	Yes
SA and Firm Controls	Yes	Yes	Yes	Yes
Adjusted R^2	0.03	0.03	0.03	0.03
N	100,435	100,435	100,435	100,435

This table reports panel regressions of SA alpha/risk-adjusted performance on SA size (Log TA), Pastor, Stambaugh, and Taylor (2020) Portfolio Liquidity components and family characteristics for of actively managed U.S. domestic equity SAs from 2001/01 to 2018/12. Carhart alpha/risk-adjusted performance of SA *i* in month *t* is the Sharpe (1992) out-of-sample performance calculated using 24-month rolling window regressions. All variables are standardized to mean zero and unit standard deviation. Fixed effects are considered using within group demeaning. ***, **, and * denote significance at the 1%, 5%, or 10% level, respectively. p-values are reported in parentheses.

Figure 1
Alpha/risk-adjusted annualized performance by lagged size quintile

Panel A. Carhart (1997) 4-factor Alpha

Panel B. MPB Single-index Alpha



This figure shows the alphas of quarterly rebalanced size quintile portfolios of quantitative and fundamental US domestic separate accounts in the period from 01/1990 to 12/2018. Alphas are denoted in % p.a. Black bar charts show quant SAs, grey bars show fundamental SAs. Panel A. shows alphas measured against the "academic" Carhart (1997) 4-factor model. Panel B. shows alphas measured against the manager preferred benchmark reported in Morningstar Direct.

Appendix A

List of manager-preferred benchmarks (MPBs)

S&P 500 Dividend point
MSCI EAFE PR USD
Citi Treasury Bill 3 Mon USD
DJ US Select Dividend TR USD
MSCI USA Minimum Volatility GR USD
S&P MidCap 400 TR
CBOE S&P 500 BuyWrite BXM
Russell Mid Cap Value TR USD
Russell Mid Cap Value NR USD
Russell 1000 Growth TR USD
Russell 2500 Growth TR USD
Russell 1000 Growth NR USD
Russell Mid Cap TR USD
MSCI ACWI NR USD
Russell 3000 Growth TR USD
Russell 1000 Growth PR USD
S&P 500 Ig/Commercial & Profe Service PR
Russell 3000E Growth PR USD
Russell 3000 Growth PR USD
S&P 500 Growth TR USD
Russell Mid Cap Growth TR USD
Russell Mid Cap Growth PR USD
S&P Global 1200 TR
MSCI World NR USD
S&P 1000 TR
Russell 2500 TR USD
Russell 2500 NR USD
Russell 2500 PR USD
Russell 2000 Growth TR USD
Russell 2000 Growth PR USD
Russell 2500 Value TR USD
Russell 2500 Value PR USD
Russell 1000 Dynamic TR USD
Russell 1000 TR USD
Russell 3000 TR USD
WisdomTree Dividend TR USD
MSCI USA GR USD
S&P 1500 TR
S&P 500 TR USD
S&P 500 Composite TR USD
S&P 500 TR (1989)
S&P 500 NR USD
S&P 500 PR
Russell 2000 TR USD
Alerian MLP Infrastructure TR USD
Russell 2000 PR USD
Russell Top 200 TR USD
Russell Micro Cap Growth TR USD
Russell Micro Cap Growth PR USD
DJ US Industrials TR USD
DJ US TSM Micro Cap TR USD
S&P 100 TR
S&P SmallCap 600 PR USD
FTSE RAFI US 1000 TR USD
Wilshire US Large Value TR USD
Morningstar US Div Composite TR USD
Russell 1000 Value TR USD
Russell 3000 Value TR USD
Russell 3000 Value PR USD
Russell Micro Cap TR USD
Russell 3000 Equal Weighted TR USD
Russell 2000 Value TR USD
Russell 2000 Value PR USD
S&P 500 Value TR USD
Russell 2000 Growth Energy TR USD
Russell Micro Cap Value TR USD
Russell 2000 Equal Weight NR USD
Russell 2000 Equal Weighted TR USD
Russell Top 200 Value TR USD
Vanguard Russell 1000 Value Index I
MSCI ACWI All Cap GR USD
Wilshire 5000 Total Market Full TR USD
Wilshire Large Company Value Instl
MSCI EAFE GR USD

Appendix B

First stages from Zhu (2018) – M9 and M10 of Table 5

	To M9	To M10	
	Forward demeaned TA	Forward demeaned Quant TA	Forward demeaned Fundamental TA
Ln TA	0.395***		
	(0.00)		
Ln TA : D^{Quant}		2.446***	0.222***
		(0.00)	(0.00)
Ln TA : $D^{Fundamental}$		0.030**	2.006***
		(0.03)	(0.00)
D^{Quant}	0.067***	-7.651***	-0.585***
	(0.00)	(0.00)	(0.00)
$D^{Fundamental}$	-0.133***	-0.050*	-4.356***
	(0.00)	(0.07)	(0.00)
Firm TA	0.001	-0.013***	0.003
	(0.80)	(0.00)	(0.20)
Lagged Alpha 12M	-0.025***	-0.014***	-0.015***
	(0.00)	(0.00)	(0.00)
Flow	0.060***	0.023***	0.047***
	(0.00)	(0.00)	(0.00)
Age	0.297***	0.067***	0.242***
	(0.00)	(0.00)	(0.00)
Expense Ratio	-0.059***	-0.018***	-0.048***
	(0.00)	(0.00)	(0.00)
Minimum Investment	-0.072***	-0.005*	-0.063***
	(0.00)	(0.09)	(0.00)
CIT Dummy	0.327***	0.227***	0.239***
	(0.00)	(0.00)	(0.00)
Retail Dummy	0.220***	0.048***	0.184***
	(0.00)	(0.00)	(0.00)
Adjusted R^2	0.27	0.19	0.29
N	86,987	86,987	86,987

4 Article III: The Effect of Unobserved Constraints on Portfolio Management: Evidence from Separate Account-Mutual Fund Twins

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Abstract. Using a unique sample of separate account-mutual fund twins, we provide evidence for a negative effect of unobserved investment constraints on portfolio management. Since the twin sample controls directly for manager skill, firm efficiency and investment style, differences in portfolio composition are likely to be the result of differential constraints such as regulation and investor preferences. While controlling for observed constraints like size and liquidity, we document a negative effect of unobserved constraints on the risk-adjusted performance of both portfolios. The effect is stronger for separate accounts, which seem to be more strongly constrained than mutual funds.

JEL Classification: G11, G23

Keywords: Mutual fund performance, separate accounts, twins, portfolio holdings, investment constraints

4.1 Introduction

The investment process of a fund manager is a portfolio optimization under various constraints. Such constraints may encompass legal regulation, investor preferences, institutional structures, as well as economic constraints like the managers' skill and time capacity. The mutual fund literature offers a wide variety of papers analyzing how different constraints affect mutual fund performance. Most recently, Pastor, Stambaugh and Taylor (2020) show that managers face trade-offs between several economic constraints such as skill, fund size, and portfolio liquidity, which set limits to a funds' performance. Other studies analyze how investment restrictions (Almazan et al., 2004) or investors' liquidity needs (Rohleder et al., 2018) constrain fund managers and, consequentially, hurt the funds' performance. While many constraints regarding fund, firm and portfolio characteristics are well known and have been studied in depth,[46] there are further constraints that we are aware of, but which are more difficult to observe and quantify directly, like the effect of legal regulation or investors' preferences. Moreover, even more constraints are likely to exist that are still unknown and therefore completely elude observation.

This paper aims at shedding new light on how such unobserved constraints affect portfolio management. However, they are by definition unquantifiable as separate constraints. To solve this problem, we construct an innovative measure to catch the combined effect of all constraints in one quantity. Therefore, we use the portfolio holdings of individual investment managers, who manage a separate account (SA) and a mutual fund (MF) at the same time with the same investment style for the same investment firm. Such SA-MF twins provide us with a unique laboratory to assess the influence of unobserved constraints while directly controlling

[46] For example, Berk and Green (2004), Chen et al. (2004), Pollet and Wilson (2008), Pastor, Stambaugh, and Taylor (2015), and Evans et al. (2020) analyze diseconomies of scale in portfolio management. Yan (2008) analyze the effect of liquidity on portfolio performance. Sirri and Tufano (1998), Edelen (1999), Alexander, Cici and Gibson (2007), Rakowski (2010), Fulkerson and Riley (2016), and Rohleder, Schulte, and Wilkens (2017) investigate the impact of flows and flow risk on fund performance. Cici, and Palacios (2015) and Natter et al. (2016) investigate how the restriction of certain investment practices, like derivative use, impact fund performance. Cici, Dahm and Kempf (2018) look into the trading efficiency of mutual fund families. Evans, Gil-Bazo, and Lipson (2017) analyze diseconomies of scope caused by managers managing multiple mutual funds.

for individual investment ability (i.e. manager skill) and fund family effectiveness (e.g. the trading desk; see Cici, Dahm, Kempf, 2018). Because we can assume that the investment manager would *ceteris paribus* bring the same investment ideas to creating optimal portfolios for both vehicles, differences in the portfolio holdings should be a result of different observed and unobserved investment constraints. This identification follows the idea of Kacperczyk, Sialm, and Zheng (2008) who argue that the difference between the fund return and the buy-and-hold return of the fund's holdings represents unobserved actions of MFs.

Unobserved investment constraints may include, for instance, differences in regulation, investor preferences and the organizational structure of both vehicles. By controlling for a wide range of twin, firm and portfolio characteristics, i.e. observed constraints, we are able to determine the effect of unobserved constraints on portfolio performance. Since larger differences in the constraints should affect managers' efficiency in implementing her optimal investment strategy, we expect a negative impact on her overall portfolio performance. In this context, Evans, Gil-Bazo, and Lipson (2019) show that investment managers managing multiple MFs deliver lower performance, because they allocate less time and attention to each fund. They term this effect "diseconomies of scope". In our view, this negative performance effect should be smaller for side-by-side managed funds with similar constraints because the attention to one portfolio also benefits the other. Likewise, the effect should be larger if these funds have different constraints because they compete for attention.

To identify SA-MF twins, we follow a methodology proposed by Evans and Fahlenbrach (2012). Our sample stems from Morningstar and consists of 907 twin pairs with 22,916 twin-quarter observations in the period from 1997 to 2016 with contemporaneous holdings reports available for both portfolios. Even if the purpose for both vehicles is the same – collecting and investing money for investors – the structure and the institutional conditions are quite different. Besides a lower level of regulation and fewer reporting requirements for

SAs, there is also an important difference between their organizational structures. Within a SA each investor owns an individual account in which she directly holds the respective assets. This structure enables investors to restrict or customize their portfolio, for example by setting style or risk preferences or putting bans on specific stocks. The degree of codetermination or individualization, respectively, depends on the bargaining power of the investor, which depends on the size of the investor's account. MFs do not offer such options because investors own the assets only indirectly via the fund shares. Consequentially, MFs are managed as one homogeneous portfolio. Considering such differences in vehicle structure and constraints, we can expect material deviations in the portfolio composition.

To derive a proxy for differences in usually unobserved constraints between two investment vehicles, we implement a holdings-based portfolio distance measure (PDM) that allows us to determine quarterly portfolio differences for each twin pair. To do so we apply a modification of Cremers and Petajisto's (2009) active share, which originally measures investment activity as deviation from a passive benchmark. In contrast, our PDM compares SA holding weights to those of the corresponding actively managed MF twin. This way, we are able to analyze a time-series of portfolio deviations for each twin pair. A mean of around 22% and a median of around 8% suggest that these twin portfolios are rather similar in general. However, since under equal conditions, a manager should manage both MF and SA in the same optimal way, we consider such portfolio differences noteworthy. Further, the cross-sectional variation in PDM between the twins is strong enough to analyze the impact of unobserved constraints on portfolio performance.

We apply several univariate and multivariate analysis methods. Using a quintile sorting approach based on the PDM, we find first evidence that larger differences in constraints between the twins are associated with a lower risk-adjusted performance in both SAs and MFs. This is in line with the notion that portfolio management suffers when confronted with stricter investment constraints. Furthermore, we document correlations between PDM and several twin characteristics, which is not surprising as PDM captures observed and unobserved constraints. To control for observed constraints, we include a large set of twin, firm and portfolio characteristics in the subsequent regression analyses, including variables for the manager overlap between the twins and the number of managed accounts in the SA, which partly approximate for customization effects and differences in the organizational structure. This way, we are able to quantify the consolidated impact of all unobserved constraints on overall portfolio performance. We find strong and robust evidence that these constraints lead to a decrease in risk-adjusted performance. Even after controlling for differences in the investment risk and style factor exposures between SA-MF twins, our results remain economically unchanged. Furthermore, we find performance decreases in both SAs and MFs, though slightly stronger in SAs. We interpret this result to mean that SAs face stronger constraints on average than their MF twins.

These findings contribute specific new insights to the recent literature on SAs. In related studies, Elton, Gruber and Blake (2014) and Evans et al. (2020) compare the performance of equity MFs and SAs. They show that the SA universe significantly outperforms the MF universe on a risk-adjusted basis. However, in a direct comparison of SAs and MFs offered by the same company, but not necessarily managed by the same manager, Elton, Gruber and Blake (2014) find no significant difference in performance. They conclude that smaller boutique firms are responsible for the better performance of the SA universe compared to the MF universe. Chen et al. (2017) conduct a similar study and reveal that the matching approach on firm level used by Elton, Gruber and Blake (2014) does not correctly control for managerial skill. Therefore, they analyze managers that concurrently manage at least one SA and one MF, which allows them to control for managerial skill as well as firm-level effects. Their results show a significantly better performance for SAs compared to MFs. In our twin analysis, we can confirm these findings for net returns but not for gross returns. Thus, considering that the negative impact of investor preferences in SAs tends to be stronger than in MFs, an initially higher SA performance, which might be due to a lower level of regulation and fewer reporting requirements, seems to compensate for this difference.

Overall, the contribution of this work is threefold. First, it is the most comprehensive SA-MF twin analysis to date, which will lead to more reliable insights into SA-MF twin arrangements. Second, by comparing holdings between two actively managed institutional investment vehicles using PDM, we propose a method to measure differences in portfolio compositions. Third, by establishing this measure as a proxy for all differences in unobserved constraints between the twins, we are the first to show empirical evidence for the consolidated negative impact of such usually non-measurable constraints on portfolio performance. Hence, investors should be careful when investing in investment vehicles that show a substantial portfolio difference compared to a side-by-side managed twin, since the performance tends to be lower for both the MF and the SA. In the process, we confirm and extend previous studies on SAs in general, a so-far understudied class of investment vehicle considering their importance for institutional investors.

4.2 Data and Methodology

4.2.1 Data

The aim of this work is to analyze differences in portfolio management between investment vehicles exhibiting similar starting conditions, i.e. vehicles with the same manager, same investment company, same style, but with different regulatory, organizational or economic constraints. We find such a comparison laboratory in the contrast between US domestic equity MFs, which mainly target retail investors and are therefore highly regulated to provide customer protection, and US domestic equity SAs, which mainly target institutional investors and are unregulated but still face constraints due to the bargaining power of their investors and their organizational structure. This allows us to discover usually unobserved institutional and organizational constraints influencing the portfolio management of an asset manager and to examine their effect on portfolio performance. Since one could expect that under equal conditions she would implement her best investment ideas in both vehicles, observed deviations between the two portfolios are most likely a result of different investment constraints.

To identify such SA-MF twins, we apply the methodology of Evans and Fahlenbrach (2012) to our sample, which comes from Morningstar Direct. Before the twin-matching, the data comprises 3,152 MFs and 3,781 SAs for the period from 1990 to 2016. It is thus one of the most comprehensive samples in recent SA literature. Morningstar provides detailed information on the names and terms of individual managers for both vehicles, the investment company as well as on the investment style, via the Morningstar equity style box. Matching US domestic equity SAs and MFs based on these criteria, results in 1,463 MF-SA twin pairs with 14,297 unique twin years. This represents around four times as many twin pairs as those used by Evans and Fahlenbrach (2012) and almost eight times as many twin years as in Chen et al. (2017).[47] As more than 40% of all funds in our sample are a part of a twin arrangement, it seems to be common practice for investment firms to offer SA-MF twins to different kind of investors. To be included in later analyses, these twins must pass through the following filters: i) We remove passively managed twins identified by fund name following Elton, Gruber and Blake (2014). ii) We require a minimum of 36 monthly observations for net and gross returns per twin. iii) There must be at least five contemporary holding reports for both vehicles showing at least one equity holding. Our final sample consists of 907 twin pairs with available holdings data for the period 1997 to 2016.[48] Obtaining all SA and MF holdings from Morningstar conveniently

[47] We define a twin as a separate account and a mutual fund, both stemming from the same investment firm, with the same investment objective, and at least one common manager. In unreported alternative tests, we require both management teams to be identical, i.e., 100% common managers. This stricter matching requirement reduces our sample significantly; however, the main results regarding PDM stay economically unchanged. To control for a different management composition in both vehicles, we include the variable *percentage of common managers* in all panel regressions.
[48] To our best knowledge, Chen et al. (2017) is the only other paper using SA holdings.

allows us to use an internal Morningstar identifier to match the holdings across both portfolios, which ensures a high-quality match.[49]

Table 1 describes and compares common twin characteristics on a quarterly basis for MFs (Panel A) and SAs (Panel B). SAs are larger on average than their MF twins. The minimum investment of roughly $13.1M is clearly higher for SAs than for MFs ($0.3M), which restricts SAs factually to institutional investors and very wealthy individuals. The higher the contribution of these clients to the SA, the stronger their bargaining power becomes. MFs are therefore more expensive than SAs. While investors in MFs pay on average 1.25% per year, SA investors only pay approximately 1.11%. Besides the negotiation of fees, they might also influence the portfolio composition, e.g., by putting bans on specific types of stocks. As expected from the twin nature of the data, there is only a minor difference in the number of holdings. The turnover ratio seems to be slightly higher in MFs, but this might be primarily due to the higher fluctuation in cash flows caused by the higher number of retail investors in MFs. Moreover, the turnover ratio data is often missing for SAs, which might bias the statistic. With respect to age, it is surprising that with 14.3 years the SAs are on average older than the MFs with 10.6 years. This may be related to fund incubation, as Evans (2010) reports that successful SA strategies are often subsequently offered to the public via MFs.

[Insert Table 1 here]

4.2.2 Performance Measurement

We evaluate SA-MF twins using both absolute and risk-adjusted returns from the CAPM, the Fama and French (1993) 3-Factor, and the Carhart (1997) 4-Factor model.[50] To obtain a time-series of alphas, we follow Sharpe (1992) and run rolling regressions (Eq. 1) to calculate the

[49] We have a coverage of 99.3% for all equity holdings over time. If the Morningstar identifier was not available, we first used CUSIP9 and then the security name as an alternative. The security name was always available.
[50] We thank Kenneth French for providing the corresponding risk-factors on: http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html.

out-of-sample performance (Eq. 2) for each SA and each MF in each month $t + 1$ using style-betas estimated over the 24-month window ending in t.

$$ER_{i,t} = \alpha_{i,(t)} + \beta^{m}_{i,(t)} ER_{m,t} + \beta^{SMB}_{i,(t)} SMB_t + \beta^{HML}_{i,(t)} HML_t + \beta^{MOM}_{i,(t)} MOM_t + \varepsilon_{i,t} \quad (1)$$

$$\alpha_{i,t+1} = ER_{i,t+1} - \left(\beta^{m}_{i,(t)} ER_{m,t+1} + \beta^{SMB}_{i,(t)} SMB_{t+1} + \beta^{HML}_{i,(t)} HML_{t+1} + \beta^{MOM}_{i,(t)} MOM_{t+1}\right) \quad (2)$$

$ER_{i,t}$ is the monthly excess return of vehicle i in month t over the risk-free rate, $ER_{m,t}$ is the excess return of the market, and $\varepsilon_{i,t}$ is the error term. Without further factors, $\alpha_{i,(t)}$ corresponds to the in-sample Jensen (1968) or CAPM alpha of vehicle i during the window ending in t. By adding SMB_t and HML_t, we obtain the Fama and French alpha and by further adding MOM_t we obtain the Carhart alpha. $\beta^{m}_{i,(t)}$, $\beta^{SMB}_{i,(t)}$, $\beta^{HML}_{i,(t)}$, and $\beta^{MOM}_{i,(t)}$ are the style betas of vehicle i during the window ending in t. For the quarterly panel regression, we sum the monthly alphas during the respective quarter and multiply the result by four to obtain an annualized measure. Twin alphas are calculated as the total assets-weighted average of the out-of-sample alphas estimated separately for SAs and MFs.[51]

Table 2 reports the summary statistics on MF (Panel A) and SA (Panel B) performance. With a difference of 1 bp per year, the annualized gross return is almost identical in both panels; however, after the consideration of fees, SAs exhibit a performance 12 bps higher due to their lower expense ratio. With respect to risk-adjusted returns, the difference between SAs and MFs becomes slightly larger. For example, the difference in their average gross (net) Carhart alpha is 7 (15) bps per year. These statistics are in line with existing literature. Elton, Gruber and Blake (2014) and Evans et al. (2020) report that SAs outperform MFs on average, however, without focusing on twins and thus neglecting differences in manager skill. Similar to Chen et al. (2017), this paper addresses this issue by implementing a twin analysis.

[51] The use of equal weighting does not change later reported results economically.

[Insert Table 2 here]

4.2.3 Portfolio Distance Measure

To measure potential differences in portfolio management, caused by all kinds of investment constraints, we apply a holdings-based portfolio distance measure (PDM), which is a modification of the active share (Cremers and Petajisto, 2009). Instead of comparing the SA portfolio to a passive reference index to measure investment activity, we use the corresponding MF twin portfolio as the reference, as shown in equation (3). This way, we receive a time-series of portfolio differences for each twin pair:

$$PDM_{TW,t} = \frac{1}{2}\sum_{j=1}^{N}\left|w_{SA,j,t} - w_{MF,j,t}\right| \tag{3}$$

For each quarter t and twin pair TW, $PDM_{TW,t}$ is the sum of the absolute differences between matched equity holding weights between the two portfolios, divided by two to avoid double counting. $w_{SA,j,t}$ refers to the SA portfolio weight of stock j in quarter t and $w_{MF,j,t}$ to the MF holdings weight in the same stock. Stocks exclusively held in one vehicle exhibit a weight of zero in the corresponding twin. Given this definition, the PDM is identical for both twins. This procedure is favorable to a comparison employing return based measures like, e.g. the tracking error, since the comparison between the portfolios is based on actual portfolio composition rather than solely on correlations, which may understate the differences (see Cremers and Petajisto, 2009).

[Insert Table 3 here]

Panel A of Table 3 reports descriptive statistics for PDM, presented pooled, by quarter and by twin. The pooled mean of 21.99% and the corresponding median of about 7.88% suggest that twin portfolios are in general rather similar. Following the interpretation in Cremers and Petajisto (2009), an average SA (MF) is 100% long in its reference MF (SA) and beyond that it is invested with 21.99% in a long-short portfolio, that is long in over-weighted assets and short in under-weighted assets. Since a manager, all else being equal, can generally be expected to manage both MFs and SAs in the same way, we consider such differences noteworthy. This is in line with our expectation that investment managers encounter different restrictions in the management of these two vehicles, which affect the portfolio composition of one or both. Figures calculated by quarter and by twin support this notion. The by twin standard deviation of 26.47% represents the cross-sectional variation of PDM between twins. In contrast, Panel B shows an average within twin time-series standard deviation of 6.01%. Thus, it seems that PDM is rather stable within twins compared to a strong cross-sectional variation between twins.

4.3 The Effects of Differences in Constraints on Performance

4.3.1 Univariate Quintile Sorting

Investment companies typically offer the same investment strategy via MFs to retail investors and via SAs to institutions. Even when the same manager manages both vehicles, we observe different portfolio compositions as seen in Section 2 introducing the PDM. Assuming an unconstrained portfolio manager would establish the same optimal strategy in both vehicles; these differences are likely due to investment constraints forcing her to deviate from this optimal strategy in at least one of those vehicles. In this section, we want to examine whether this inefficiency in portfolio management causes a significant decrease in performance.

To test this premise, we start with a quarterly quintile sorting based on the PDM. In Table 4, Quintile 1 contains the 20% of twin observations with the lowest PDM and thus the smallest differences in constraints. Likewise, Quintile 5 contains the largest 20% of differences in constraints. Pooled means and medians are calculated across all twins and quarters. Besides CAPM, Fama French and Carhart alphas, we also show several vehicle characteristics like total assets, expense ratio, minimum investment, number of holdings, turnover ratio, and age. Panel A shows MFs while Panel B shows SAs. For PDM, which is naturally identical in both panels, Quintile 1 shows an average close to zero. This suggests that a significant number of twins hold the exact same portfolio. Conversely, we also observe twins with a very high portfolio difference in Quintile 5 showing an average PDM of 68%. This means that more than two-thirds of the twin portfolios are different, suggesting large differences in the investment constraints between the vehicles.

[Insert Table 4 here]

The comparison of returns and alphas across the quintiles and especially the significant 5–1 differences indicate that greater portfolio differences and thus larger differences in constraints lead to lower performance for both SAs and MFs. For example, the average annualized 5–1 difference in the Carhart MF alpha equals 40 bp and is significant at the 5% level. With regard to returns, the difference is smaller but still significant. Panel B shows similar results for SAs with even larger differences. Overall, these first results tend to confirm our expectation that stronger investment constraints negatively affect both twin vehicles, MFs and SAs. Moreover, it seems that SAs are affected more strongly.

With regard to the other fund characteristics, it is striking that Quintile 5 with the highest average PDM seems to be rather different in general.[52] For example, accordingly allocated twin-quarter observations for total assets are significantly lower on average compared to the remaining four quintiles. This is also diverges from previous findings on diseconomies of scale, an observed investment restriction, which suggests larger portfolios underperform smaller ones (e.g., Chen et al., 2004, for MFs and Evans et al., 2019, for SAs). With respect to age, Quintile 5 observations are from younger portfolios than the observations of the remaining quintiles. Conversely, expense ratios, the numbers of holdings and turnover ratios increase almost monotonically over all PDM quintiles in both panels.

[52] Section 3.5 presents a robustness analysis excluding Quintile 5 to control for potentially false twin matches.

4.3.2 Panel Regressions of Joint Twin Alphas

In the previous section, we document univariate evidence that PDM correlates negatively with performance. However, we also note correlations of PDM with a number of other fund characteristics. This is not surprising, since PDM is based on the difference in holdings between the SA and MF and therefore captures all differences in observed and unobserved constraints between the twins. By considering as many controls for observed constraints as possible in the following regressions, we hope to isolate the effect of unobserved constraints on portfolio efficiency and performance. For this reason, we explain joint twin out-of-sample alphas with PDM and a broad range of portfolio characteristics to obtain the consolidated effect of all unobserved constraints following Eq. (4):

$$\alpha_{TW,t+1} = b_0 + b_1 PDM_{TW,t} + \sum_{j=2}^{7} b_j \, Level_{TW,t}^{j} + \sum_{j=8}^{13} b_j \, Diff_{TW,t}^{j} + \sum_{k=14}^{19} b_j \, Controls_{TW,t}^{j} + \varepsilon_{TW,t} \tag{4}$$

$\alpha_{TW,t+1}$ is the joint twin out-of-sample gross alpha in quarter $t+1$ using either the respective CAPM, Fama and French or Carhart model. $PDM_{TW,t}$ is the PDM as introduced in equation (3). $Level_{TW,t}^{j}$ and $Diff_{TW,t}^{j}$ correspond to several twin characteristics j, such as log total assets, expense ratio, flow, age, cash holdings and turnover ratio. More specifically, $Level_{TW,t}^{j}$ is the average of the respective SA and MF characteristics in quarter t and is included to capture cross-sectional differences between twin pairs, while $Diff_{TW,t}^{j}$ is the difference between the SA and MF characteristic in quarter t and is included to capture differences within a twin pair. $Controls_{TW,t}^{k}$ refers to the levels of further control variables for which the level-difference separation is not applicable. Those include the holdings' average bid-ask spread to capture liquidity and the log number of holdings to capture diversification. The SA-MF difference of both measures is by construction highly correlated with PDM.[53] The log number of accounts within the SA captures differences in the organizational structure and client customization effects, while the fraction of institutional share classes in the MF may control for outside monitoring effects. Both variables are exclusive to the respective vehicle. The log firm total assets and the percentage of common managers are identical for both twins. We cluster standard errors by twin to account for the low time-series variation of PDM within the twins compared to the strong cross-sectional variation between the twins shown in Table 3. Considering all those control variables, we expect coefficient b_1 to measure the consolidated effect of unobserved constraints on portfolio performance.

[Insert Table 5 here]

Table 5 reports the corresponding regression results. Column 1 shows a pooled regression with a significantly negative coefficient of PDM on the twin Carhart alpha, which confirms our expectation of a negative effect of unobserved constraints on portfolio management efficiency and performance. Columns 2 to 4 show economically similar results for regressions, including style- and/or time fixed effects. The simultaneous application of style- and time fixed effects reduces the significance of the effect to the 5% level. In Columns 6 and 7, we obtain results similar to those in Column 4 using the Fama and French and CAPM alphas as the dependent variable, respectively. Only an analysis considering twin-fixed effects in Column 5 produce a statistically insignificant coefficient of PDM on performance. This is no surprise, however, because one may assume that unobserved constraints, such as legal regulations, are rather stable over time within a twin pair. As already indicated in Table 3, the within twin standard deviation of PDM is relatively small compared to the cross-sectional variation. Overall, we interpret these

[53] A larger difference in those variables automatically induces a stronger difference in portfolio holdings. However, their inclusion in unreported alternative regressions does not change our results economically.

results as strong evidence of a harmful effect of unobserved constraints on portfolio performance.[54]

4.3.3 Panel Regressions of Separate Twin Alphas

So far, we show that differences in unobserved constraints between the twins harm their joint performance, the average twin alpha. In the next step, we want to determine whether this negative impact equally affects both investment vehicles or if it differs in strength between SAs and MFs. On the one hand, customization wishes regarding the portfolio construction or specific liquidity needs of institutional investors could drive PDM. Such constraints directly affect portfolio management in SAs but not in MFs. On the other hand, MFs are constrained by strict regulation and oversight by the SEC in order to assure customer protection, while SAs are not. Hence, it is *per se* unclear whether the negative effect of PDM on portfolio performance is greater for SAs than for MFs. A first indication may be derived from the quintile sorting in Table 4 where the univariate effect is slightly stronger for SAs. To shed further light on this question, we repeat the investigation from Section 3.2, but instead of using the joint twin performance as the dependent variable, we directly explain SA and MF alphas by using each twin observation twice. Following Eq. (5), we conduct a piecewise linear regression by including two separate PDM variables to measure their separated influence on the SA and MF alpha:

$$\alpha_{i,t+1} = b_0 + b_1^{SA} PDM_{i,t}^{SA} + b_1^{MF} PDM_{i,t}^{MF} + \sum_{j=2}^{7} b_j \, Level_{TW,t}^{j} + \sum_{j=8}^{13} b_j \, Diff_{TW,t}^{j} + b_{14} D_{i,t} + \sum_{j=15}^{20} b_j \, Controls_{TW,t}^{j} + \varepsilon_{i,t} \tag{5}$$

[54] Table 5 contains only a selection of our regression models. In non-reported results, we conduct further performance regressions using net and gross alphas of the CAPM, the Fama French 3-Factor and the Carhart 4-Factor model. In all specifications, we obtain economically similar results. They are available upon request.

$\alpha_{i,t+1}$ is the out-of-sample gross alpha of SA or MF i in quarter $t+1$.[55] $PDM_{i,t}^{SA}$ refers to the PDM of the twin pair if the alpha is from the SA and 0 otherwise. The opposite applies to $PDM_{i,t}^{MF}$. We maintain all control variables at twin level and for the SA-MF difference by duplicating the observations. We add a SA dummy to capture a potential average performance difference between SAs and MFs. We cluster standard errors by vehicle.

[Insert Table 6 here]

Table 6 shows the corresponding results. In Column 1 to 5, we explain Carhart alphas, in Column 6 Fama and French alphas, and in Column 7 CAPM alphas, respectively. For all models, the effect of PDM on performance is stronger for SAs than for MFs. For example, considering Column 1 and the average PDM of 22% in Table 3, the annualized risk-adjusted performance decreases by 32bp for SAs and only by 21bp for MFs. Considering time fixed effects, the negative impact of the PDM on the risk-adjusted performance turns insignificant for MFs, but remains highly significant for SAs. Thus, SAs seem to be more constrained in their management process than their MF twins. Which constraints drive this difference cannot be told due to the catch-all construction of PDM. However, one may speculate that differential preferences and customization wishes by SA investors represent stronger constraints than the uniform regulation in MFs.

4.3.4 Controlling for Different Style and Risk Factor Exposures

Up to now, we have shown that different unobserved constraints harm the joint portfolio performance of a twin manager and that investor preferences in SAs seem to have a stronger impact than regulation constraints in MFs. An important sort of investor preference in SAs are specific risk factor targets. Thus, higher PDM values might be the result of retail and institutional investors having different risk factor objectives, since clients in MFs usually cannot

[55] We receive economically similar results when we use net instead of gross alphas.

specify individual targets. On the one hand, taking risk-adjusted performance as the dependent variable should already account for such differences. On the other hand, setting caps and floors for several risk factor parameters presumably restricts portfolio management in more complex ways than simply levering an otherwise optimal portfolio up or down to the desired factor beta. To address these concerns, we repeat our investigation from Section 3.2 by including style betas in the regression following Eq. (6):[56]

$$\alpha_{TW,t+1} = \mathrm{b}_0 + b_1 PDM_{TW,t} + \sum_{j=2}^{7} b_j\, Level_{TW,t}^{j} + \sum_{j=8}^{13} b_j\, Diff_{TW,t}^{j} + \sum_{j=14}^{17} b_j\, StyleLevel_{TW,t}^{j} + \sum_{j=18}^{21} b_j\, StyleDiff_{TW,t}^{j} + \sum_{j=22}^{27} b_k\, Controls_{TW,t}^{j} + \varepsilon_{TW,t} \quad (6)$$

$StyleLevel_{TW,t}^{j}$ are the joint value-weighted twin betas with respect to the Market, SMB, HML and MOM. Analogously, we include for each twin $StyleDiff_{TW,t}^{j}$ as the beta difference between the SA and MF. This way, we are able to control directly for differences in risk factor characteristics between SA-MF twins.

[Insert Table 7 here]

Table 7 contains the regression results using the Carhart alpha as the dependent variable.[57] For reasons of comparability, Columns 1 and 2 repeat Columns 2 and 4 from Table 5. Columns 3 and 4 include the market beta, Columns 5 and 6 the Fama French betas, and Columns 7 and 8 all betas from the Carhart 4-Factor model. In all model specifications, we find highly significant and negative coefficients at the 1% level for the joint twin market beta. Thus, twins with higher average market betas achieve a systematically lower risk-adjusted performance. One reason for

[56] In unreported results, we repeat model (5) from Section 3.3 with similar interpretations.
[57] The use of CAPM or Fama and French alphas leads to economically similar results. The same applies to net returns.

this finding might be the low-beta anomaly as reported in Frazzini and Pedersen (2014), who show that portfolios of high-beta assets have lower alphas than portfolios of low-beta assets. We observe similar, but less pronounced, results for the SMB beta. The coefficient is significant at the 5% level in a regression that includes style fixed effects; however, when we consider time fixed effects this significance disappears. Looking at the differences, we find no evidence for an impact of style betas on the risk-adjusted performance.

With regard to the PDM, we observe only slightly lower negative coefficients with the same level of significance when we compare Columns 3 to 8 with Columns 1 and 2. Hence, even without considering risk targets set by investors as part of the unobserved constraints, there is a statistically highly significant consolidated effect of the remaining unobserved constraints on risk-adjusted portfolio performance.

4.3.5 Exclusion of High PDM Twins

The quintile sorting in Section 3.1 shows that Quintile 5 of the highest PDM observations is very different from the remaining quintiles. While we consider our matching of SA-MF twins based on manager names, investment company and investment style to be very reliable, we do not want to ignore the possibility of "false" twins in our sample.[58] Since such false twins would end up primarily in Quintile 5, Table 8 repeats the analysis from Section 3.2 by excluding this quintile from the regression.[59]

[Insert Table 8 here]

In Columns 1 to 4, we exclude all twin observations allocated to Quintile 5 based on a quarterly rebalancing according to Table 4. In Columns 5 to 8, we exclude entire twin pairs sorted into Quintile 5 using their average PDM to avoid a time-varying exclusion of twins from the regressions. Overall, we obtain very similar results to the previous tables; in all models the

[58] A high reliability is indicated by calculated return correlations of over 99%.
[59] Again, our results are very similar for all kinds of risk-adjusted performance measures.

PDM shows a statistically significant negative coefficient. Thus, removing potentially false twins does not change the economical interpretation of our results. We provide robust evidence that differences in unobserved constraints harm portfolio performance.

4.4 Conclusion

In an ideal world, the job of an investment manager would be easy as she would construct – given her level of skill and knowledge – an optimal portfolio without any constraints. Changes to the portfolio would only be necessary when she acquires relevant new information. However, such an ideal world does not exist. Instead, investment managers face several constraints to the way they construct and manage their portfolios. Such constraints may stem from legal regulation, from investor preferences or may be organizational and economic in nature.

In this paper, we propose an innovative way to quantify the impact of unobserved constraints on portfolio management and performance. We exploit the existence of SA-MF twins, two portfolios managed by the same manager for the same company with the same style, but affected by different investor preferences, regulations and organizational structure. Hence, these twins represent an ideal laboratory, as differences between the portfolios are most likely due to differences in the constraints on each portfolio but remain unaffected by the manager's skill or the investment firm's organizational efficiency.

Based on our datasets of 3,781 US equity SAs and 3,152 US equity MFs, we find, that almost 40% of the SAs and even more than 40% of the MFs, are managed as part of a SA-MF twin arrangement. By measuring the difference between the portfolios using a holdings-based portfolio distance measure, we are able to analyze a time-series of portfolio deviations for each twin pair, which we use to infer the impact of observed and unobserved constraints on risk-adjusted portfolio performance. By controlling for as many observed and quantifiable constraints as possible, we isolate the consolidated impact of all usually unobserved and unquanfiable constraints and find strong and robust evidence that differences in these constraints lead to a decrease in risk-adjusted performance. Even after controlling for potential differences in risk factor exposures between both twin vehicles, our results remain economically unchanged. Furthermore, we find the performance decrease to be stronger within SAs. We interpret this result as support for our presumption that unobserved constraints like customization demands set by SA investors restrict managers more strongly than regulations controlling MFs.

These novel findings have several implications: First, investors should be careful when investing in investment vehicles that show a substantial portfolio difference compared to a side-by-side managed twin, since the performance tends to be lower for both the MF and the SA. Second, despite research has already revealed numerous constraints, we are able to show that there are still some unexplored constraints affecting portfolio performance. Consequently, it is important for future research to keep finding ways of quantifying known, but so far unobserved, unquantifiable constraints and to continue searching for so-far unknown constraints affecting portfolio management. Third, while there exists an abundance of literature on MFs, research on investment restrictions in SAs, one of the most important investment vehicles for institutional investors, is rather underdeveloped given our finding that such restrictions have stronger negative effects in SAs than in MFs.

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Tables

Table 1
Twin Characteristics

	Obs	Mean	SD	Percentile				
				10	25	50	75	90
Panel A: Mutual Funds								
Total Assets (in mio.)	22,601	1,420	3,600	19	69	264	1,070	3,800
Min. Investment (in mio.)	22,916	0.27	0.82	0.00	0.00	0.00	0.03	1.00
Number of Holdings	22,916	75.08	58.57	32.00	45.00	64.00	92.00	122.00
Expense Ratio (in %)	22,916	1.25	0.42	0.78	0.97	1.19	1.43	1.93
Turnover Ratio (in %)	22,453	60.99	46.27	17.00	28.00	49.00	81.00	119.00
Age	22,916	10.55	9.16	1.91	4.25	8.68	14.41	20.51
Panel B: Separate Accounts								
Total Assets (in mio.)	22,056	2,090	3,530	36	136	546	2,220	6,650
Number of Accounts	21,734	200.06	558.63	2.00	6.00	22.00	76.00	416.00
Min. Investment (in mio.)	22,183	13.29	16.48	0.10	1.00	10.00	25.00	50.00
Number of Holdings	22,915	75.78	52.42	33.67	46.00	66.00	93.00	121.67
Expense Ratio (in %)	22,916	1.11	0.90	0.36	0.60	0.84	1.08	3.00
Turnover Ratio (in %)	15,111	57.39	42.17	16.40	27.34	47.82	75.72	109.00
Age	22,916	14.34	8.32	4.33	8.01	13.24	19.50	25.75

This table shows descriptive statistics for fund characteristics of separate account-mutual fund twins on a quarterly basis. The sample consists of 907 twin pairs over the period 1997 to 2016. A twin is defined as a separate account and a mutual fund, both from the same investment firm, with the same investment objective, and having at least one common manager. Expense ratio and turnover ratio is annualized. Statistics are listed for mutual funds and separate accounts separately.

Table 2
Twin Performance

	Obs	Mean	SD	Percentile 10	25	50	75	90
Panel A: Mutual Funds								
Gross Returns								
Excess Return	22,916	11.06	16.82	-32.35	-3.51	13.53	31.08	49.40
Carhart Alpha	21,257	0.39	5.67	-12.64	-5.54	0.47	6.34	13.19
Fama French Alpha	21,257	0.42	5.56	-12.29	-5.51	0.44	6.23	13.16
CAPM Alpha	21,257	0.25	6.63	-15.13	-6.93	0.22	7.28	15.84
Net Returns								
Excess Return	22,916	9.91	16.78	-33.36	-4.54	12.41	29.93	48.21
Carhart Alpha	21,257	-0.72	5.66	-13.76	-6.66	-0.55	5.24	11.91
Fama French Alpha	21,257	-0.69	5.56	-13.45	-6.60	-0.58	5.12	11.94
CAPM Alpha	21,257	-0.86	6.65	-16.18	-7.97	-0.81	6.14	14.71
Panel B: Separate Accounts								
Gross Returns								
Excess Return	22,916	11.07	16.67	-32.16	-3.59	13.68	31.03	49.14
Carhart Alpha	22,143	0.46	5.60	-12.38	-5.64	0.50	6.51	13.16
Fama French Alpha	22,143	0.48	5.49	-12.21	-5.47	0.53	6.39	12.95
CAPM Alpha	22,143	0.29	6.57	-14.81	-6.88	0.23	7.45	15.70
Net Returns								
Excess Return	22,916	10.03	16.64	-33.10	-4.63	12.61	29.89	48.16
Carhart Alpha	22,143	-0.57	5.62	-13.51	-6.72	-0.52	5.49	12.14
Fama French Alpha	22,143	-0.54	5.51	-13.32	-6.55	-0.50	5.42	11.99
CAPM Alpha	22,143	-0.73	6.58	-15.96	-7.94	-0.77	6.41	14.73

This table shows descriptive statistics for excess returns and risk-adjusted performance measures of separate account-mutual fund twins on a quarterly basis. The sample consists of 907 twin pairs over the period 1997 to 2016. A twin is defined as a separate account and a mutual fund, both from the same investment firm, with the same investment objective, and having at least one common manager. Excess returns are returns subtracted by the U.S. one-month treasury bill rate. The annualized excess return is the multiplicative sum of its monthly returns. Risk-adjusted returns are out-of-sample alphas calculated via factor loadings obtained from 24-month rolling window regressions from t-1 to t-24 using the CAPM, Fama French 3 factor and Carhart 4 factor model. The alpha of a quarter is the sum of its three monthly out-of-sample alphas multiplied by four to obtain annualized figures. Net returns are gross returns minus the expense ratio. Statistics are listed for mutual funds and separate accounts separately.

Table 3
Portfolio Distance Measure

	Obs	Mean	SD	Percentile				
				10	25	50	75	90
Panel A: Descriptive Statistics								
Pooled	22,916	21.99	26.67	0.04	1.10	7.88	37.96	65.26
By Quarter	80	19.57	9.09	0.00	20.77	21.79	24.16	26.74
By Twin	907	24.89	26.47	0.99	2.79	12.97	42.01	67.51
Panel B: Within Twin Standard Deviation								
PDM	907	6.01	5.99	1.00	2.05	4.01	7.80	14.24

This table shows descriptive statistics of the portfolio distance measure (PDM) for each twin pair on a quarterly basis. The sample consists of 907 twin pairs over the period 1997 to 2016. A twin is defined as a separate account and a mutual fund, both from the same investment firm, with the same investment objective, and having at least one common manager. For each quarter t and twin TW, $PDM_{TW,t}$ is the sum of the absolute differences between matched holding weights of the separate account and mutual fund equity portfolio divided by two: $PDM_{TW,t} = \frac{1}{2}\sum_{j=1}^{N}\left|w_{SA,j,t} - w_{MF,j,t}\right|$. Non-included holdings in a portfolio exhibit a weight of zero. In Panel A, statistics are calculated pooled and for quarter as well as twin averages of the PDM. Panel B shows statistics of the within twin standard deviation of the PDM measure. All values are in %.

Table 4

Quintile Sorting based on PDM

	PDM		Excess Gross Return		4F Alpha Gross		3F Alpha Gross		CAPM Alpha Gross		Total Assets (mio USD)		Expense Ratio		Min. Investment		# Holdings		Turnover Ratio		Age	
Panel A: Mutual Funds																						
	mean	med	mean	med	mean	med	mean	med	mean	med	mean	med	mean	med	mean	med	mean	med	mean	med	mean	med
Low PDM	0.17	0.04	11.27	13.79	0.59	0.63	0.70	0.66	0.36	0.26	1,380	356	1.25	1.19	0.28	0.00	67.96	63	59.80	52.00	10.80	9.00
2	1.96	1.74	11.01	13.71	0.71	0.70	0.57	0.57	0.05	0.00	1,520	338	1.24	1.18	0.31	0.00	69.14	62	57.64	47.00	10.89	9.00
3	9.11	7.96	11.00	13.30	0.36	0.59	0.39	0.48	0.44	0.32	1,670	347	1.28	1.21	0.28	0.00	72.96	61	59.83	42.10	10.63	8.67
4	31.74	31.70	11.03	13.39	0.07	0.33	0.16	0.31	0.32	0.41	1,810	242	1.24	1.17	0.26	0.00	73.81	63	62.55	53.00	10.62	8.51
High PDM	67.54	65.28	11.00	13.46	0.20	0.18	0.27	0.15	0.09	0.08	671	117	1.29	1.22	0.17	0.00	93.39	76	65.24	53.00	9.68	8.03
5-1 PDM	67.37	65.24	-0.27	-0.33	-0.40	-0.44	-0.42	-0.51	-0.28	-0.18	-709	-239	0.04	0.03	-0.12	0.00	25.43	13	5.43	1.00	-1.12	-0.97
	(0.00)	(0.00)	(0.07)	(0.22)	(0.05)	(0.11)	(0.37)	(0.64)	(0.09)	(0.13)	(0.00)	(0.00)	(0.00)	(0.03)	(0.00)	(0.31)	(0.00)	(0.00)	(0.00)	(0.06)	(0.29)	(0.00)
Panel B: Separate Accounts																						
	mean	med	mean	med	mean	med	mean	med	mean	med	mean	med	mean	med	mean	med	mean	med	mean	med	mean	med
Low PDM	0.17	0.04	11.28	13.85	0.63	0.70	0.72	0.71	0.42	0.34	2,340	811	1.03	0.84	13.46	5.00	70.97	66	55.32	49.03	13.64	12.92
2	1.96	1.74	11.06	13.76	0.75	0.71	0.64	0.61	0.14	0.08	2,650	828	1.05	0.84	14.66	10.00	80.65	68	51.13	41.41	14.47	13.30
3	9.11	7.96	10.95	13.26	0.56	0.75	0.56	0.71	0.47	0.39	1,940	539	1.13	0.82	11.20	5.00	73.30	60	55.07	40.41	16.46	15.25
4	31.74	31.70	10.98	13.35	0.15	0.33	0.16	0.39	0.32	0.17	2,310	655	1.16	0.76	15.64	10.00	76.91	63	60.91	51.52	14.68	13.42
High PDM	67.54	65.28	11.09	14.04	0.17	0.06	0.29	0.21	0.11	0.20	1,200	207	1.17	0.84	11.41	5.00	77.12	72	65.41	57.40	12.45	11.34
5-1 PDM	67.37	65.24	-0.19	0.19	-0.46	-0.63	-0.43	-0.50	-0.31	-0.13	-1,140	-604	0.15	0.00	-2.05	0.00	6.15	6	10.09	8.37	-1.19	-1.58
	(0.00)	(0.00)	(0.07)	(0.22)	(0.01)	(0.02)	(0.01)	(0.02)	(0.02)	(0.06)	(0.00)	(0.00)	(0.00)	(0.66)	(0.00)	(0.46)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)

This table shows descriptive statistics of a quarterly quintile sorting based on the portfolio distance measure (PDM). Quintile 1 contains the lowest 20% of PDM values for each quarter and Quintile 5 the highest 20%. Means and medians are calculated pooled across all quarters. 5-1 is the difference between the top and bottom quintile. The sample consists of 907 twin pairs over the period 1997 to 2016. A twin is defined as a separate account and a mutual fund, both from the same investment firm, with the same investment objective, and having at least one common manager. For each quarter t and twin TW, $PDM_{TW,t}$ is the sum of the absolute differences between matched holding weights of the separate account and mutual fund equity portfolio divided by two: $PDM_{TW,t} = \frac{1}{2}\sum_{j=1}^{N}\left|w_{SA,j,t} - w_{MF,j,t}\right|$. Non-included holdings in a portfolio exhibit a weight of zero. Depending on the quarterly sorting of the PDM (%), statistics are also shown for fund characteristics and performance measures including total assets (mio), expense ratio (% p.a.), minimum investment of the vehicle (mio), number of holdings in the portfolio, turnover ratio (% p.a.), and age in years. Excess returns are fund gross returns subtracted by the U.S. one-month treasury bill rate. The annualized excess return is the multiplicative sum of its monthly returns. Risk-adjusted returns are out-of-sample gross alphas calculated via factor loadings obtained from 24-month rolling window regressions from t-1 to t-24 using the CAPM, Fama French 3 factor and Carhart 4 factor model. The annualized alpha is the sum of its three monthly alphas multiplied by four to obtain annualized figures (%). Statistics are listed for mutual funds and separate accounts separately. P-values from two-sided t-tests in means are in parentheses.

Table 5
Performance Regression with Joint Twin Alphas

	(1) 4F Alpha	(2) 4F Alpha	(3) 4F Alpha	(4) 4F Alpha	(5) 4F Alpha	(6) 3F Alpha	(7) CAPM Alpha
PDM	-1.2550***	-1.2154***	-0.9328***	-0.7653**	-0.6987	-0.8010**	-0.8680**
Ln(Total Assets)	-0.1259**	-0.1744***	-0.1010*	-0.1381**	-1.1597***	-0.1290**	-0.1124*
Diff. SA-MF	0.0538	0.0635*	0.0139	0.0144	0.2853**	0.0101	-0.0347
Expense Ratio	0.6255	0.3348	0.0216	-0.4006	4.0993***	-0.4596	-0.9730**
Diff. SA-MF	-0.5357**	-0.4150*	-0.0920	0.0817	-2.1961***	0.1030	0.3124
Flow	0.0253***	0.0259***	0.0116	0.0114	0.0032	0.0132*	0.0020
Diff. SA-MF	-0.0083**	-0.0084**	-0.0028	-0.0025	-0.0033	-0.0044	-0.0019
Age	-0.0269*	-0.0243*	-0.0082	-0.0051	-0.0809	-0.0066	-0.0188
Diff. SA-MF	-0.0090	-0.0097	-0.0003	0.0008	-0.0280	-0.0007	-0.0043
Cash	-0.0022	-0.0050	0.0088	0.0019	-0.1175**	-0.0042	0.0406
Diff. SA-MF	-0.0064	-0.0104	-0.0088	-0.0120	-0.0059	0.0030	-0.0054
Turnover	0.6250	0.3853	0.1882	-0.0571	2.3352***	0.2979	0.5923
Diff. SA-MF	-0.2336	-0.1026	-0.2581	-0.1343	-0.1702	0.1711	0.3725
Bid Ask Spread	0.0407**	0.0444**	0.0001	-0.0059	0.0973***	-0.0107	0.0160
Ln(# of Holdings)	0.7885***	0.7752***	0.7260***	0.5319***	-0.8154	0.6495***	0.4362**
Ln(#Accs)	0.0085	0.0414	-0.0828*	-0.0383	-0.1264	-0.0397	0.0297
Ln(TA Firm)	0.0308	0.0330	0.0344	0.0517	-0.1032	0.0485	0.0614
% Inst. Shareclass	0.3520	0.2848	0.4027*	0.2035	0.1353	0.2151	0.3561
% Common Managers	-0.3251	-0.1275	0.1010	0.1420	-0.9299	0.1703	0.7292*
Style Fixed Effects	No	Yes	No	Yes	No	Yes	Yes
Time Fixed Effects	No	No	Yes	Yes	No	Yes	Yes
Twin Fixed Effects	No	No	No	No	Yes	No	No
N	13,923	13,923	13,923	13,923	13,923	13,923	13,923
Adj.R2	0.00776	0.00876	0.0928	0.0939	0.0179	0.0898	0.136

This table shows performance regressions using average gross out-of-sample twin alphas of quarter t+1 as dependent variable. The sample consists of 907 twin pairs over the period 1997 to 2016. A twin is defined as a separate account and a mutual fund, both from the same investment firm, with the same investment objective, and having at least one common manager. The twin alpha is the value-weighted average of the calculated separate account and mutual fund alpha using the total assets of the vehicles. A vehicle's out-of-sample alpha is calculated via factor loadings obtained from 24-month rolling window regressions from t-1 to t-24 using the CAPM, Fama French 3 factor and Carhart 4 factor model. The quarterly alpha is the sum of its three monthly alphas multiplied by four to obtain annualized figures. Besides the portfolio distance measure (PDM), the regression includes several controls for fund and firm characteristics at quarter t. For each quarter t and twin TW, $PDM_{TW,t}$ is the sum of the absolute differences between matched holding weights of the separate account and mutual fund equity portfolio divided by two: $PDM_{TW,t} = \frac{1}{2}\sum_{j=1}^{N}\left|w_{SA,j,t} - w_{MF,j,t}\right|$. Non-included holdings in a portfolio exhibit a weight of zero. Control variables for the logarithm of total assets, expense ratio (% p.a.), flow (%), age (years), cash proportion in the portfolio (%), and turnover (% p.a.) are at twin level, which is the average of the separate account and the mutual fund characteristic at quarter t. The regression also includes variables for the difference between the separate account and the mutual fund characteristic. ***, **, * denote significance of the estimated parameters at the 1%, 5%, and 10% level, respectively. Standard errors are clustered at twin level.

Table 6
Performance Regression separating between SA and MF Alphas

	(1) 4F Alpha	(2) 4F Alpha	(3) 4F Alpha	(4) 4F Alpha	(5) 4F Alpha	(6) 3F Alpha	(7) CAPM Alpha
PDM SA | SA Alpha or 0	-1.4550***	-1.3876***	-1.1632***	-0.9590***	-1.1140	-0.9595***	-0.9546**
PDM MF | MF Alpha or 0	-0.9558**	-0.9152**	-0.5937	-0.4336	-0.5947	-0.5145	-0.6952*
Ln(Total Assets)	-0.1329***	-0.1683***	-0.1247***	-0.1477***	-1.2119***	-0.1384***	-0.1073**
Diff. SA-MF	0.0655**	0.0759***	0.0226	0.0223	0.2594***	0.0136	-0.0290
Expense Ratio	0.5455*	0.3083	-0.0932	-0.4308	3.9357***	-0.5088*	-1.0881***
Diff. SA-MF	-0.5239***	-0.4143***	-0.1103	0.0409	-2.2705***	0.0748	0.3423**
Flow	0.0238***	0.0243***	0.0104**	0.0101**	0.0014	0.0118**	0.0010
Diff. SA-MF	-0.0075***	-0.0075***	-0.0021	-0.0017	-0.0021	-0.0036	-0.0016
Age	-0.0270***	-0.0239**	-0.0108	-0.0063	-0.0770**	-0.0083	-0.0176*
Diff. SA-MF	-0.0092	-0.0093*	-0.0025	-0.0008	-0.0271	-0.0031	-0.0056
Cash	0.0084	0.0064	0.0179	0.0122	-0.1119***	0.0085	0.0546**
Diff. SA-MF	-0.0089	-0.0123	-0.0107	-0.0135	-0.0024	-0.0005	-0.0118
Turnover	0.5450*	0.3334	0.1301	-0.0784	2.3165***	0.3233	0.6068*
Diff. SA-MF	-0.2367	-0.1112	-0.2679	-0.1524	-0.1900	0.1620	0.3988
Bid Ask Spread	0.0466***	0.0496***	0.0089	0.0022	0.0954***	-0.0020	0.0219**
Ln(# of Holdings)	0.7463***	0.7188***	0.7099***	0.5026***	-1.0151	0.6094***	0.3914***
Ln(#Accs)	0.0023	0.0253	-0.0691	-0.0362	-0.0461	-0.0386	0.0147
Ln(TA Firm)	0.0414	0.0428	0.0464	0.0613*	-0.0277	0.0574	0.0651*
% Inst. Shareclass	0.1706	0.1110	0.1917	0.0273	-0.1778	0.1004	0.3370
% Common Managers	-0.4340	-0.2636	-0.0028	0.0301	-0.8829	0.1007	0.6131*
Dummy SA	0.1523	0.0437	0.4106*	0.2176	0.1542	0.2468	0.1624
Style Fixed Effects	No	Yes	No	Yes	No	Yes	Yes
Time Fixed Effects	No	No	Yes	Yes	No	Yes	Yes
Twin Fixed Effects	No	No	No	No	Yes	No	No
N	27,846	27,846	27,846	27,846	27,846	27,846	27,846
Adj.R2	0.00852	0.00960	0.0899	0.0912	0.0388	0.0880	0.133

This table shows performance regressions using gross out-of-sample twin alphas for separate accounts and mutual funds of quarter t+1 as dependent variable. The sample consists of 907 twin pairs over the period 1997 to 2016. A twin is defined as a separate account and a mutual fund, both from the same investment firm, with the same investment objective, and having at least one common manager. The regression includes both alphas of a twin in the same model, the alpha of the separate account and the mutual fund. A vehicle's out-of-sample alpha is calculated via factor loadings obtained from 24-month rolling window regressions from t-1 to t-24 using the CAPM, Fama French 3 factor and Carhart 4 factor model. The quarterly alpha is the sum of its three monthly alphas multiplied by four to obtain annualized figures. Besides the portfolio distance measure (PDM), the regression includes several controls for fund and firm characteristics at quarter t. For each quarter t and twin TW, $PDM_{TW,t}$ is the sum of the absolute differences between matched holding weights of the separate account and mutual fund equity portfolio divided by two: $PDM_{TW,t} = \frac{1}{2}\sum_{j=1}^{N}\left|w_{SA,j,t} - w_{MF,j,t}\right|$. Non-included holdings in a portfolio exhibit a weight of zero. For measuring separate effects on the out-of-sample alpha, the regression includes two PDM variables. One variable for the separate account, which is zero if the alpha is from the mutual fund and vice versa. Control variables for the logarithm of total assets, expense ratio (% p.a.), flow (%), age (years), cash proportion in the portfolio (%), and turnover (% p.a.) are at twin level, which is the average of the separate account and the mutual fund characteristic at quarter t. The regression also includes variables for the difference between the separate account and the mutual fund characteristic. To be able to regress those variables on the alpha of the separate account and the mutual fund, each value is duplicated. The regression also includes a dummy variable equaling 1 if the depended variable refers to a separate account alpha and is zero otherwise. ***, **, * denote significance of the estimated parameters at the 1%, 5%, and 10% level, respectively. Standard errors are clustered at vehicle level

Table 7
Performance Regression with Style Betas

	(1) 4F Alpha	(2) 4F Alpha	(3) 4F Alpha	(4) 4F Alpha	(5) 4F Alpha	(6) 4F Alpha	(7) 4F Alpha	(8) 4F Alpha
PDM	-1.2154***	-0.7653**	-1.1406***	-0.7302**	-1.1369***	-0.7066**	-1.1421***	-0.7105**
Ln(Total Assets)	-0.1744***	-0.1381**	-0.1788***	-0.1495***	-0.1925***	-0.1577***	-0.1918***	-0.1575***
Diff. SA-MF	0.0635*	0.0144	0.0603	0.0134	0.0627*	0.0174	0.0625*	0.0172
Expense Ratio	0.3348	-0.4006	0.4626	-0.2409	0.5567	-0.2186	0.5622	-0.2174
Diff. SA-MF	-0.4150*	0.0817	-0.5190**	-0.0467	-0.5597**	-0.0536	-0.5651***	-0.0559
Flow	0.0259***	0.0114	0.0236***	0.0080	0.0240***	0.0084	0.0241***	0.0084
Diff. SA-MF	-0.0084**	-0.0025	-0.0078**	-0.0013	-0.0080**	-0.0014	-0.0080**	-0.0014
Age	-0.0243*	-0.0051	-0.0235*	-0.0036	-0.0201	-0.0030	-0.0201	-0.0029
Diff. SA-MF	-0.0097	0.0008	-0.0094	0.0003	-0.0088	0.0008	-0.0088	0.0009
Cash	-0.0050	0.0019	-0.0593*	-0.0630*	-0.0638*	-0.0650*	-0.0637*	-0.0647*
Diff. SA-MF	-0.0104	-0.0120	-0.0183	-0.0155	-0.0179	-0.0151	-0.0180	-0.0152
Turnover	0.3853	-0.0571	0.6520	0.3215	0.5998	0.2846	0.6059	0.2858
Diff. SA-MF	-0.1026	-0.1343	-0.1367	-0.1771	-0.0734	-0.1382	-0.0896	-0.1492
Bid Ask Spread	0.0444**	-0.0059	0.0434**	-0.0064	0.0426*	-0.0070	0.0423*	-0.0072
Ln(# of Holdings)	0.7752***	0.5319***	0.8245***	0.5869***	0.8445***	0.6146***	0.8410***	0.6088***
Ln(#Accs)	0.0414	-0.0383	0.0424	-0.0330	0.0352	-0.0347	0.0347	-0.0348
Ln(TA Firm)	0.0330	0.0517	0.0344	0.0501	0.0229	0.0446	0.0233	0.0450
% Inst. Shareclass	0.2848	0.2035	0.2228	0.1717	0.2322	0.1771	0.2388	0.1823
% Common Managers	-0.1275	0.1420	-0.0803	0.2242	-0.1165	0.2039	-0.1055	0.2139
Market Beta 4F			-6.0110***	-6.6226***	-6.2934***	-6.7682***	-6.3017***	-6.7699***
Diff. SA-MF			-0.1374	1.9334	-0.0092	1.9459	-0.0335	1.9342
SMB Beta 4F					-1.3231**	-0.4228	-1.3318**	-0.4156
Diff. SA-MF					-0.5892	-0.4000	-0.4635	-0.3251
HML Beta 4F					-0.6610	-0.4562	-0.6616	-0.4698
Diff. SA-MF					0.1078	0.8888	-0.0044	0.8175
MOM Beta 4F							-0.0387	0.0957
Diff. SA-MF							1.2337	0.7772
Style Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time Fixed Effects	No	Yes	No	Yes	No	Yes	No	Yes
N	13,923	13,923	13,923	13,923	13,923	13,923	13,923	13,923
Adj.R2	0.00876	0.0939	0.0121	0.0979	0.0138	0.0991	0.0136	0.0990

This table shows performance regressions using average gross out-of-sample twin alphas of quarter t+1 as dependent variable. The sample consists of 907 twin pairs over the period 1997 to 2016. A twin is defined as a separate account and a mutual fund, both from the same investment firm, with the same investment objective, and having at least one common manager. The twin alpha is the value-weighted average of the calculated separate account and mutual fund alpha using the total assets of the vehicles. A vehicle's out-of-sample alpha is calculated via factor loadings obtained from 24-month rolling window regressions from t-1 to t-24 using the Carhart 4 factor model. The quarterly alpha is the sum of its three monthly alphas multiplied by four to obtain annualized figures. For each quarter t and twin TW, $PDM_{TW,t}$ is the sum of the absolute differences between matched holding weights of the separate account and mutual fund equity portfolio divided by two: $PDM_{TW,t} = \frac{1}{2}\sum_{j=1}^{N}\left|w_{SA,j,t} - w_{MF,j,t}\right|$. Non-included holdings in a portfolio exhibit a weight of zero. To account for investment strategies, the strategy beta of a quarter is the average of its three monthly factor loadings. On twin level, the quarterly beta is the value-weighted average of the separate account and mutual fund beta using the total assets. ***, **, * denote significance of the estimated parameters at the 1%, 5%, and 10% level, respectively. Standard errors are clustered at twin level.

Table 8
Performance Regression excluding Quintile 5

	(1) 4F Alpha	(2) 4F Alpha	(3) 4F Alpha	(4) 4F Alpha	(5) 4F Alpha	(6) 4F Alpha	(7) 4F Alpha	(8) 4F Alpha
Quintile Allocation	Quarterly	Quarterly	Quarterly	Quarterly	Twin	Twin	Twin	Twin
PDM	-1.8463**	-1.9080**	-2.1566***	-1.8430**	-1.4799**	-1.5164**	-1.7249***	-1.4716**
Ln(Total Assets)	-0.1036	-0.1533**	-0.1202*	-0.1515**	-0.1220*	-0.1609**	-0.1324**	-0.1547**
Diff. SA-MF	0.0576	0.0662	0.0124	0.0093	0.0647	0.0733	0.0303	0.0273
Expense Ratio	0.3324	0.1765	-0.2587	-0.5743	0.3478	0.2308	-0.2148	-0.5031
Diff. SA-MF	-0.3802	-0.3229	0.0209	0.1494	-0.3869	-0.3424	0.0070	0.1237
Flow	0.0289***	0.0299***	0.0117	0.0121	0.0270***	0.0278***	0.0109	0.0111
Diff. SA-MF	-0.0118***	-0.0121***	-0.0046	-0.0046	-0.0095**	-0.0097**	-0.0029	-0.0029
Age	-0.0198	-0.0153	-0.0023	0.0035	-0.0182	-0.0150	-0.0027	0.0017
Diff. SA-MF	-0.0098	-0.0099	-0.0033	-0.0012	-0.0085	-0.0084	-0.0026	-0.0002
Cash	-0.0255	-0.0290	-0.0065	-0.0145	-0.0132	-0.0154	0.0072	-0.0002
Diff. SA-MF	-0.0163	-0.0163	-0.0210	-0.0178	-0.0345	-0.0343	-0.0437	-0.0402
Turnover	0.4338	0.2680	-0.0202	-0.2504	0.3616	0.2118	-0.1306	-0.3441
Diff. SA-MF	-0.1881	-0.0982	-0.3568	-0.2561	-0.1798	-0.1112	-0.2893	-0.2113
Bid Ask Spread	0.0995***	0.1067***	0.0339*	0.0213	0.0973***	0.1055***	0.0310	0.0194
Ln(# of Holdings)	0.6477***	0.6408***	0.6615***	0.4511**	0.6722***	0.6947***	0.6975***	0.5157**
Ln(#Accs)	0.0314	0.0593	-0.0565	-0.0232	0.0297	0.0501	-0.0556	-0.0266
Ln(TA Firm)	0.0431	0.0492	0.0366	0.0533	0.0566	0.0564	0.0446	0.0563
% Inst. Shareclass	0.1348	0.1630	0.2597	0.1496	0.2212	0.2591	0.2973	0.1972
% Common Managers	0.1860	0.3356	0.4172	0.4389	0.0751	0.2284	0.3312	0.3667
Style Fixed Effects	No	Yes	No	Yes	No	Yes	No	Yes
Time Fixed Effects	No	No	Yes	Yes	No	No	Yes	Yes
N	11,113	11,113	11,113	11,113	11,410	11,410	11,410	11,410
Adj.R2	0.0117	0.0123	0.0961	0.0970	0.0113	0.0117	0.0958	0.0963

This table shows performance regressions using average gross out-of-sample twin alphas of quarter t+1 as dependent variable. The sample consists of 907 twin pairs over the period 1997 to 2016. A twin is defined as a separate account and a mutual fund, both from the same investment firm, with the same investment objective, and having at least one common manager. The twin alpha is the value-weighted average of the calculated separate account and mutual fund alpha using the total assets of the vehicles. A vehicle's out-of-sample alpha is calculated via factor loadings obtained from 24-month rolling window regressions from t-1 to t-24 using the Carhart 4 factor model. The quarterly alpha is the sum of its three monthly alphas multiplied by four to obtain annualized figures. Besides the portfolio distance measure (PDM), the regression includes several controls for fund and firm characteristics at quarter t. For each quarter t and twin TW, $PDM_{TW,t}$ is the sum of the absolute differences between matched holding weights of the separate account and mutual fund equity portfolio divided by two: $PDM_{TW,t} = \frac{1}{2}\sum_{j=1}^{N}\left|w_{SA,j,t} - w_{MF,j,t}\right|$. Non-included holdings in a portfolio exhibit a weight of zero. At each quarter t, observations with PDM values in Quintile 5 are excluded from the regression in Column (1) to (4). In Column (5) to (8) we exclude all twins showing an average PDM above the 80% percentile instead. ***, **, * denote significance of the estimated parameters at the 1%, 5%, and 10% level, respectively. Standard errors are clustered on twin level.

5 Article IV: The Value of Separate Accounts for Different Types of Investors

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Abstract. Using a comprehensive sample of separate accounts (SAs), this paper provides new evidence for the existence of skill in the asset management industry. While the average SA is able to achieve a risk-adjusted outperformance compared to common passive benchmarks before costs, predominantly SAs with an institutional product focus can generate sufficient risk-adjusted returns to cover their costs. The results from a bootstrapping approach suggest that the risk-adjusted returns of the best performing SA managers cannot solely be explained by pure luck.

JEL Classification: G11, G23
Keywords: Institutional investing, performance, separate accounts

5.1 Introduction

One of the central questions in academic financial literature is whether fund managers can achieve a superior risk-adjusted performance (“alpha”) compared to common passive benchmarks. Based on equilibrium accounting (Fama and French, 2010), the market is a zero-sum game, which means that every risk-adjusted outperformance of one market participant must be matched by at least one other’s underperformance, both positions with equivalent size in terms of market value. Fund managers, who are able to succeed this zero-sum-game in the long run are commonly referred to as skilled. These fund managers are able to generate risk-adjusted returns that exceed their own trading costs and commissions and thus, depending on their costs, they have the potential to add value for their investors beyond the value of a purely passive investment strategy. However, many recent studies show that over the last few decades the asset management industry and especially mutual fund managers were on average not able to produce sufficient risk-adjusted returns to cover their costs. Nevertheless, several studies show that separate accounts (SAs), which are commonly referred to as an exclusive investment vehicle for institutional investors, have outperformed the mutual fund universe significantly.

Based on a dataset that consists of 3,781 separate accounts in the period from 1990 to 2017, this study provides new uni- and multivariate evidence that SAs are able to succeed in this zero-sum game in the long run. Compared to prior studies on SAs, which predominantly use quarterly returns, I use monthly return data, which reduces interim trading bias (e.g. Ferson and Khang, 2002) and allows for a more precise performance measurement. Following a bootstrapping methodology from Fama and French (2010), which is a modification of Kosowski et al. (2006), my results suggest that even in a world in which every SA manager has the ability to generate expected returns to cover their trading costs and commissions, SAs are able to achieve risk-adjusted gross returns that cannot be explained by pure luck. Furthermore, to the best of my knowledge, I am the first who considers SAs as a real investment alternative to mutual funds for retail investors. Although, according to recent SA literature, the very high minimum investment requirements make most retail investors unable to participate in this value-creating investment universe, I find that only 26% of the SAs in my sample are exclusively for institutional investors. Around 62% of the SAs in my dataset are open for both kind of investors, institutional and retail investors, and around 12% of all SAs in my sample are even exclusively for retail investors. Thus, given the significantly positive risk-adjusted gross performance, private investors who meet the minimum investment requirement of $100k in the median and $150k in the 75% percentile for pure retail SAs, could potentially benefit from skilled SA managers.

These findings contribute specific new insights to the recent literature on SAs. Busse, Goyal and Wahal (2010) focus specifically on the performance and persistence in the performance of SAs. They analyze a large sample of 3,842 SAs based on quarterly net and gross returns over the period from 1991 to 2008 and find that an equally weighted SA portfolio was able to achieve a significantly positive risk-adjusted Carhart performance of 80 bp p.a. before costs and a risk-adjusted performance of 20 bp p.a. after costs. These results indicate that SAs might be able to succeed in this zero-sum-game in the long run. Furthermore, several studies show that SAs have outperformed the mutual fund universe significantly. Elton Gruber and Blake (2014) compare the monthly performance of a large sample of SA and a sample of mutual funds that have a minimum investment requirement of at least one million USD over the period 2000 to 2009. They find an annualized difference in risk-adjusted Carhart performance of 60 bp. Similarly, Evans et al. (2020a) find a statistically significant difference in risk-adjusted Carhart performance of almost 1% p.a. based on a nearest neighbor matching between a sample of US equity SAs and US equity mutual funds in the period from 1990 to 2015. In the second part of their analysis, Elton Gruber and Blake (2014) directly compare SAs and MFs offered by the same company, but not necessarily managed by the same manager and find no significant difference in performance. They conclude that smaller boutique firms are responsible for the better performance of the SA universe compared to the MF universe. Chen et al. (2017) conduct a similar study and reveal that the matching approach on firm level used by Elton, Gruber and Blake (2014) does not control for managerial skill. Therefore, they analyze managers that concurrently manage at least one SA and one MF, which allows them to control for managerial skill as well as firm-level effects. Their results show a significantly better performance for SAs compared to MFs. In a similar study, Rohleder et al. (2020) find a statistically significant difference in risk-adjusted Carhart performance based on net, but not on gross returns.

By dividing my sample into three subsamples based on a time-invariant indicator variable, the SA's product focus[60], I am able to evaluate and differentiate the benefit of SAs as an investment alternative to mutual funds for different types of investors. In the first step, I analyze core SA characteristics and differences in these characteristics descriptively. It is interesting to note that purely institutional SAs and SAs in which both kind of investors, institutional and retail investors, can invest are relatively similar to each other but differ significantly from the retail SA group. Retail SAs have almost 40% lower asset under management (AUM) compared to the average SA, they have a four times higher number of individual investors and an average expense ratio that is almost two and a half times higher compared to the average SA. In terms of risk-adjusted performance it is striking that the SA universe as whole is able to achieve a long-term Carhart performance of 81 bp before and -11 bp after costs. These numbers are in line with recent SA literature and they are a strong indication for the existence of skill in the SA universe. With respect to the three subsamples, it is remarkable that all three groups show a similar risk-adjusted gross performance, the significantly higher expense ratios of the retail SAs however, result in a significant

[60] The data for this study stems from Morningstar Direct. Amongst many other things, they provide the variable "Product Focus", which indicates whether the respective SA has a purely institutional ("Institutional"), purely retail ("Retail") or no specific product focus ("Both").

underperformance of 1.44% p.a. after costs while the other groups achieve a small but positive risk-adjusted Carhart performance.

In the next step, I combine the SA characteristics and the SA performance in a multivariate setting and analyze the risk-adjusted SA performance considering SA characteristics by running several panel regressions. The regression results are consistent to the previous results and show a significant underperformance for retail SAs and a small, but significant outperformance for institutional SAs after costs. Based on gross returns the underperformance of retail SAs disappears, which suggests that the underperformance is mainly driven the difference in expense ratios rather than by a systematical difference in the level of skill.

In order to analyze the existence of skill in the SA universe more thoroughly, I follow Fama and French (2010) and test for the existence of a true nonzero SA alpha by applying a bootstrap simulation approach on monthly SA returns. This way, I generate 1,000 zero true alpha cross-sections and use them as a benchmark for the actual SA alpha cross-section. The results from this analysis suggest that the SA managers in each of the three subsamples have on average sufficient skill to extract money from the capital market on a risk-adjusted basis. However, based on risk-adjusted net returns, the average SA manager is not able to beat a simulated benchmark, in which by definition every manager is able to produce risk-adjusted returns that cover all their costs. In other words, based on net returns, I find no statistically significant evidence that the average SA manager is able to produce risk-adjusted Carhart returns that cannot also be explained by pure luck (sampling variation).

Relative to recent SA literature the contribution of my work is threefold. First, it is one of the most comprehensive SA analysis to date using monthly rather than quarterly return data, which reduces interim trading bias and allows for a more precise performance measurement.

Second, this paper provides new evidence that SAs are able to achieve risk-adjusted gross returns that cannot be explained by pure luck (sampling variation). Third, by dividing the SA universe into three subsamples depending on the SA's product focus, this paper is the first to evaluate and differentiate the benefit of SAs as an investment alternative to mutual funds for different types of investors. In the process, I confirm and extend the results from previous studies on SAs in general, a so-far understudied class of investment vehicle considering the value of their managed assets.

The paper proceeds as follows. Section 2 introduces the dataset and presents summary statistics including SA characteristics and performance. Section 3 examines risk-adjusted performance based on panel regressions. Section 4 tests for the existence of skill in the SA universe based on a bootstrapping approach. Section 5 concludes.

5.2 Data, summary statistics and performance

5.2.1 Separate account characteristics

SAs have a unique organizational structure, where each SA investor owns an individual account in which she directly holds the respective assets. This structure enables investors to restrict or customize their portfolio by setting style or risk preferences. This results in a higher management complexity compared to mutual funds (e.g. Evans et al., 2020b), which is why the fee structure and the degree of customization depends on the bargaining power of the investor, which depend on the size of the investor's account. All individual accounts that follow a common overall strategy (e.g. "small-value" or "large-neutral") are managed in conjunction with the other investor's accounts. Thus, the reported SA returns are composite returns, i.e. the weighted average of the realized returns of the individual accounts within an SA.

The data stems from Morningstar Direct and consists of 3,781 SAs for the period from 1990 to 2017. It comprises monthly net and gross returns, quarterly SA characteristics and several time invariant snapshot variables, which makes it to one of the most comprehensive samples in recent SA literature. To be included in the sample I require a minimum of 36 monthly observations for net and gross returns. Compared to prior studies, which predominantly use quarterly returns, monthly return data reduces interim trading bias and allows for more precise performance measurement. Furthermore, I follow Elton, Gruber and Blake (2014) and exclude all passively managed and specialty SAs.[61] Table 1 presents descriptive statistics of common SA characteristics. Panel A provides the characteristics of the whole SA sample, Panel B contains only SAs that are open for investment for institutional and retail investors, Panel C displays SAs that are exclusively for institutional investors and Panel D shows descriptive characteristics of pure retail SAs.

[Insert Table 1 here]

Average total assets (TA) are about 820 million US dollar. The number of accounts, which is the number of different investors within an SA, is 120 on average. The expense ratio, calculated as the difference between reported gross and net returns, is on average 0.91% which is lower than comparable numbers for US domestic equity mutual funds (e.g, 1.20% p.a., Rohleder et al., 2018). The comparatively low costs can partly be attributed to the high average minimum investment of 8.65 million US dollar and to the relatively low annual turnover of 64.05%, which is distinctively lower than that of US domestic equity mutual funds where annual turnover is on average around 85% (e.g., Pastor et al., 2017). In the period from 1990 to 2017, SAs have experienced substantial annual implied percentage net flow of 6.61%. I calculate quarterly implied percentage net flow (hereafter flow) from quarterly TA and quarterly returns following

[61] My definition of "specialty SAs" also include all SAs with an average systematic market beta below 0.2 based on 24-month rolling window regressions.

Sirri and Tufano (1998). The positive average flow attests to the growing importance of SAs over these 28 years.

Around 62% of the observed SAs in my sample (2,332 SAs) are included in Panel B, which means, they are open for investment for both kind of investors. Therefore, I take this group as a benchmark to compare them with the characteristics of the pure institutional SAs in Panel C and the pure retail SAs in Panel D. Especially retail SAs in Panel D show remarkable differences in their core characteristics. They are much smaller; almost 40% on average compared to Panel B, and have a distinctively higher number of accounts of 415 compared to 97. Furthermore, their average expense ratio is almost two and a half times higher, which might be partly explained by the lower minimum investment requirement of $0.79 million on average and $0.1 million in median. Compared to those numbers, the institutional SAs in Panel C are larger with almost $1 billion total assets and have a smaller number of different investors. Together with a minimum investment requirement of $12.5 million on average, this results in a strong bargaining power, high customization capabilities and a lower level of fees of 0.67% p.a. on average for those investors.

5.2.2 Performance Measurement

The broader aim of this work is to analyze whether the SA universe as a whole is able to achieve a long-term outperformance before costs relative to common benchmarks. To investigate this question, I examine the SA performance using both absolute and risk-adjusted returns from the CAPM, the Fama and French (1993) 3-Factor, and the Carhart (1997) 4-Factor model.[62] To obtain a time-series of alphas, I follow Sharpe (1992) and run rolling regressions (Eq. 1) to calculate the out-of-sample performance (Eq. 2) for each SA in each month $t + 1$ using style-betas estimated over the 24-month window ending in t.

[62] I thank Kenneth French for providing the corresponding risk-factors on: http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html.

$$ER_{i,t}= \alpha_{i,(t)} + \beta^{m}_{i,t} ER_{m,t} + \beta^{SMB}_{i,t} SMB_t + \beta^{HML}_{i,t} HML_t + \beta^{MOM}_{i,t} MOM_t + \varepsilon_{i,t} \tag{1}$$

$$\alpha_{i,t+1}= ER_{i,t+1} - \left(\beta^{m}_{i,t} ER_{m,t+1} + \beta^{SMB}_{i,t} SMB_{t+1} + \beta^{HML}_{i,\mathrm{t}} HML_{t+1} + \beta^{MOM}_{i,t} MOM_{t+1}\right) \tag{2}$$

$ER_{i,t}$ is the monthly excess return of vehicle i in month t over the risk-free rate, $ER_{m,t}$ is the excess return of the market, and $\varepsilon_{i,t}$ is the error term. Without further factors, $\alpha_{i,t}$ corresponds to the in-sample Jensen (1968) or CAPM alpha of vehicle i during the window ending in t. By adding SMB_t and HML_t, I obtain the Fama and French alpha and by further adding MOM_t I obtain the Carhart alpha. $\beta^{m}_{i,t}$, $\beta^{SMB}_{i,t}$, $\beta^{HML}_{i,t}$, and $\beta^{MOM}_{i,t}$ are the style betas of vehicle i during the window ending in t. Table 2 reports the summary statistics on SA performance. Similar to Table 1, Panel A contains all SAs, Panels B-D show the performance of the three subsamples "Both" in Panel B, "Institutional" in Panel C and "Retail" in Panel D.

[Insert Table 2 here]

In Panel A, it is remarkable that the SA universe is able to achieve a long-term Carhart performance of 81 bp before and -11 bp after costs. These statistics are in line with the results of Busse, Goyal and Wahal (2010), Elton, Gruber and Blake (2014) and Evans et al. (2020b). As previously mentioned, equilibrium accounting states that a long-term outperformance before costs of one investment group must result in an underperformance of at least one other market participant with equivalent size. Thus, the results above indicate that over the period 1990 to 2017 SA managers were on average able to extract money from the capital markets on a risk-adjusted basis, which is a strong indication for the existence of skill in the SA universe. This means that some managers have the potential to deliver an additional value beyond a purely passive investment strategy to their investors. The key question at this point is whether this counts for all three of the subsamples.

It is interesting to notice, that even before costs institutional SAs in Panel C achieve a distinctively higher excess return than the other subsamples, which however, does not seem to lead to significant higher risk-adjusted gross returns. Furthermore, it is remarkable that based on gross returns, retail SAs in Panel D achieve similar excess and risk-adjusted returns before costs, after costs however, they show a significant underperformance of 1.44% p.a. This number is similar or even a little worse to the Carhart performance of mutual fund l (e.g. Carhart, 1997; Cremers and Petajisto, 2009; Rohleder, Scholz and Wilkens, 2011; Edelen, Evans and Kadlec, 2013). Thus, although all three subsamples show significantly positive risk-adjusted gross returns, which I interpret as indication of skill and therefore as potential to deliver value to investors, especially retail SAs in Panel D have such high expense ratios of almost 2% on average, that this potential to create value to investors is more than overcompensated, which finally results in a significant underperformance.

5.3 Panel Regressions

In the previous chapter, I document that SA characteristics as well as performance differ between the three subsamples “Both”, “Institutional” and “Retail”. In this chapter, I combine both aspects and analyze the risk-adjusted performance considering the differences in SA characteristics between the subsamples by running the following quarterly panel regressions (Eq. 3):

$$\alpha_{i,q+1}^{ooS} = \varphi_0 + \varphi_1 Institutional_i + \varphi_2\, Retail_i + \sum_{m=3}^{M} \varphi_m\, Control_{i,q}^{m} + \eta_{i,q} \qquad (3)$$

$\alpha_{i,q+1}^{ooS}$ is the annualized out-of-sample alpha in quarter $t+1$ using either the respective CAPM or Carhart model based on net or gross returns. $Institutional_i$ and $Retail_i$ are two dummy variables indicating whether the SA is an institutional or a retail SA respectively. $Controls_{i,t}^{m}$ refers to SA characteristics seen above in the descriptive statistics and commonly used as control variables in previous SA studies such as log total assets to consider the effect of diseconomies of scale (e.g. Chen et al., 2004), the log number of accounts within the SA to capture the unique organizational structure of SAs (e.g. Evans et al., 2020b) and potential client customization effects, the minimum investment requirement, total firm assets, expense ratio, flow and age. Further, I use different combinations of style-fixed and time-fixed effects by demeaning by style or quarter (within transformation). Standard errors are clustered by SA. Table 3 provides the results for the Carhart and CAPM performance based on gross and net returns respectively.

[Insert Table 3 here]

In the model specifications M1 to M4, I find a significantly negative coefficient for the retail dummy over all model specifications, indicating that retail SAs significantly underperform based on net returns. This is consistent with my previous results in Table 2. Equally in line with previous results is the significantly positive coefficient for the institutional dummy, which shows that institutional SAs are able to outperform the rest of the sample even when I consider differences in SA characteristics between the subsamples. Based on gross returns, the coefficient of the retail dummy becomes insignificant and even changes from negative to slightly positive in M5 to M8. These results show, that retail SAs do not significantly underperform the rest of the SA universe before costs, which would be an indication for systematically lower level of skill. The underperformance after costs seems to be mainly due to the very high expense ratios of retail SAs. The significantly positive coefficient for institutional SAs becomes slightly smaller, however stays highly significant at the 5% level for all model specifications. This indicates that while considering differences in SA characteristics, institutional SAs are able to outperform the SA universe significantly.

As shown in Tables 1 and 2 in the previous chapter, the average SA manager is able to extract money from the capital market on a risk-adjusted basis in the long run, which is a strong indication for skill in the SA universe. Although it is remarkable that institutional SAs have been able to produce a superior performance while considering differences in SA characteristics, I find a highly positive risk-adjusted performance before costs for all three subsamples. However, examining net returns, my results show that especially retail SAs do not produce sufficient risk-adjusted returns to cover their costs. Thus, from a performance perspective, pure retail SAs do not seem to be a more attractive investment vehicle than the average mutual fund. On the contrary, from the perspective of an institutional or high-net-worth individual investor, SAs seem to be a very attractive investment vehicle, as the slightly positive risk-adjusted return after costs is more than competitive compared to mutual funds and passive ETFs.

5.4 Luck versus Skill

In the previous sections, I document uni- and multivariate evidence that the SA universe as a whole as well as all three subsamples separately are able to achieve a long-term outperformance compared to passive benchmarks. To examine whether this long-term outperformance stems from luck or from skill, I test whether there exists a nonzero true alpha in the cross-section of the SA universe that cannot solely be explained by pure luck. Therefore, I follow a methodology from Fama and French (2010), which is a modification of Kosowski et al. (2006), and apply a bootstrapping approach to generate 1,000 zero alpha cross-sections and use them as a benchmark for the actual SA alpha cross-section. This procedure allows me to consider non-normally distributed alpha cross-sections because normality might be a poor approximation for SA returns. According to Kosowski et al. (2006), non-normally distributed alpha cross-sections can stem from two sources, 1) from non-normal individual fund return distributions and 2) from a heterogeneous fund sample. Typical reasons for non-normal return distributions include the heavily concentrated stock portfolios of SAs as well as non-normally distributed market returns, varying levels of autocorrelations in SA returns and dynamic investment strategies with varying levels of risk-taking. For these reasons, normality might be a poor approximation for SA returns and thus, it is important to consider the possibility of nonnormally distributed returns. Even if individual SA returns are normally distributed, there is still the chance that the cross-section of SA returns is not. Cross-sectional differences in the SA's live span, its level of risk-taking as well as fat tails and skewed distributions in individual SA residuals influence the cross-sectional shape of the SAs' alpha distributions.

To test for existence of a true nonzero SA alpha, I apply a bootstrap simulation approach on monthly SA returns through the following steps: First, I estimate the true alpha over the whole sample period from 1990 to 2017 for several performance models. Second, to obtain a zero alpha time-series for each SA, I subtract the estimated SA alpha from its monthly return series. Third, in each of the 1,000 simulation runs, I draw a random time-series (with replacement) of 336 months and estimate each SA's alpha based on the zero-alpha time-series from the previous step. This way, I get 1,000 different alpha cross-sections, which I can use as a benchmark for the actual alpha time-series. I repeat this procedure for several performance models, including the CAPM, Fama/French and Carhart model based on gross and net returns respectively.[63] Furthermore, instead of using the actual alpha estimates, which are the common measure for abnormal performance, I concentrate on the t-statistic of the alpha estimates to avoid a potential lack of precision in the construction of confidence intervals (Kosowski et al., 2006). For example, SAs with a short life span and a high risk-taking strategy tend to have extremely high (or low) estimated alphas. By using the t-statistic (t(a)) instead of the alpha estimate, I normalize extreme alpha values by dividing them through their standard error and thus considering their high variance-estimated alpha distributions. Tables 4 shows the results for gross returns in Panel A and for net returns in Panel B. According to Fama and French (2010), the interpretation of the simulated cross-sectional values depend upon whether they are

[63] For reasons of simplicity, I focus my analysis on the Carhart model. The results for the other performance models are available upon request.

based on gross or net returns. Setting gross alphas to zero implies a world in which every manager is able to generate risk-adjusted returns that cover all their trading costs and commissions. Setting net alpha to zero implies a world in which every manager has sufficient skill to produce risk-adjusted returns that cover all their costs. Columns 1-3 present the results for the whole SA universe and Columns 4-12 show the results of the three subsamples “Both”, “Institutional” and “Retail”. The columns “Act” contain the t(a) estimates at selected percentiles based the actual SA returns. The columns “Sim” present the average estimated t(a) values from the 1,000 simulation runs. The columns “%>Act” show the percentage of simulation runs that produce t(a) values that are greater than the actual values. This measure can be interpreted similar to a p-value.

[Insert Table 4 here]

In Panel A of Table 4, I find for most of the percentiles higher actual than simulated values. For the whole SA universe in Columns 1-3, all percentiles above the 30% percentile show higher actual than simulated values in more than 90% of the cases. This means that in a world in which every SA manager has sufficient skill to generate expected returns to cover their trading costs and commissions, SAs are able to achieve risk-adjusted returns that cannot be explained by pure luck, which is covered by the sampling variation of the simulation. In line with previous results in the chapters 2 and 3, all three subsamples “Both”, “Institutional” and “Retail” show similar performance results based on gross returns. For institutional SAs, all percentiles above the 20% percentile show higher actual than simulated t(a) values in more than 90% of the cases. For retail SAs the 30% percentile is still indistinguishable from their simulated counterparts. Overall, this result is again a strong indication that SA managers have on average sufficient skill to extract money from the capital market on a risk-adjusted basis. However, looking at net returns in Panel B, in none of the percentiles the actual t(a) values are higher than the simulated values in more than 90% of the cases. In other words, I cannot find any statistically significant evidence that SA managers have on average sufficient skill to deliver risk-adjusted returns that significantly exceed a benchmark, in which every manager is able by definition to produce risk-adjusted returns to cover all of their costs. Examining the subsamples separately, I find for the institutional subsample (subsample for both kinds of investors) that every percentile above the 20% percentile (70% percentile) show higher actual than simulated average values. This means, there are many SA managers who are able to produce risk-adjusted returns that cover their costs, however, when I consider the aspect of sampling variation, my results suggest their long-term performance after costs is not statistically indistinguishable from pure luck. For the subsample for retail SAs, the results show that none of the percentiles of the actual t(a) values are higher than their average simulated values. This is consistent to the results from the previous chapters and demonstrates again that retail SA managers are not able to produce sufficient risk-adjusted returns to cover their high expense ratios.

5.5 Conclusion

Since early on, performance measurement and the analysis of performance persistence are central topics in the academic financial literature. Most recent studies focus on the mutual fund industry and while they regularly find a persistent underperformance relative to common benchmarks, this paper provides new evidence that the average SA manager is able to extract money from the capital market on a risk-adjusted basis in the long run. By dividing my sample depending on the SA's product focus, I am able evaluate and differentiate the benefit of SAs as an investment alternative to mutual funds for different types of investors. Although it is remarkable that institutional SAs have been able to produce a superior performance while considering differences in SA characteristics, I find a highly positive risk-adjusted Carhart performance before costs for all three subsamples. This means that all kind of investors could potentially benefit from this value-creating class of investment vehicles. However, examining net returns, my results show that especially retail SA do not produce a sufficient risk-adjusted return to cover their expense ratio. Thus, from a pure performance perspective, retail SAs do not seem to be more attractive than the average mutual fund. On the contrary, from the perspective of an institutional or high-net-worth individual investor, SAs seem to be a very attractive investment vehicle. Besides a slightly positive risk-adjusted return after costs, which is more than competitive compared to mutual funds and passive ETFs, there is another advantage of SAs compared to other investment vehicles: Their unique organizational structure where each investor owns an individual account in which she directly holds the respective assets instead of holding a fund share. This enables investors to customize their portfolio composition by setting style or risk preferences independently from other investors and furthermore, it gives investors the opportunity to implement specific tax-loss harvesting strategies. The combination of these qualitative advantages and an above-average risk-adjusted performance compared to other investment vehicles make SA's an important, so-far understudied class of investment vehicles considering their market share in the asset management industry.

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Tables

Table 1
SA Characteristics

	Obs	Mean	SD	Percentile				
				10	25	50	75	90
Panel A: All Separate Accounts								
Total assets (in mio. USD)	732,691	820	2070	3	21	130	614	1980
# Accounts	656,611	120	395	1	3	13	51	223
Firm assets (in bio. USD)	679,000	108	288	0	1	7	62	301
Expense ratio (p.a.)	821,018	0.91	0.90	0.00	0.36	0.72	1.00	2.52
Netflow (p.a.)	699,515	6.61	45.85	-12.04	-4.15	-0.19	4.10	19.20
# Holdings	451,515	88	105	29	40	59	93	153
Turnover ratio (p.a.)	281,555	64.05	54.34	15.89	27.00	49.00	83.00	129.00
Min. investment (in mio. USD)	758,636	8.65	13.30	0.10	0.25	3.00	10.00	25.00
Panel B: Separate Accounts for institutional and retail investors								
Total assets (in mio. USD)	490577	894	2140	4	27	162	727	2160
# Accounts	445210	97	318	1	4	13	48	189
Firm assets (in bio. USD)	442254	86	226	0	1	6	49	247
Expense ratio (p.a.)	533423	0.82	0.77	0.00	0.36	0.72	0.96	1.56
Netflow (p.a.)	469413	6.59	45.49	-12.11	-4.11	-0.16	4.34	19.50
# Holdings	296826	77	77	28	40	57	89	136
Turnover ratio (p.a.)	189957	66.63	56.13	16.30	28.30	50.66	86.90	135.99
Min. investment (in mio. USD)	514578	8.57	12.60	0.10	0.50	5.00	10.00	25.00

Table 1 cont'd.
SA Characteristics

	Obs	Mean	SD	Percentile				
				10	25	50	75	90
Panel C: Separate Accounts for institutional investors only								
Total assets (in mio. USD)	171851	988	2370	3	30	161	693	2590
# Accounts	148204	65	275	1	2	8	28	94
Firm assets (in bio. USD)	160641	175	387	1	3	13	140	559
Expense ratio (p.a.)	198080	0.67	0.60	0.00	0.26	0.65	0.85	1.08
Netflow (p.a.)	165707	6.08	44.94	-11.08	-3.89	-0.23	3.06	16.35
# Holdings	106334	127	164	31	47	73	122	291
Turnover ratio (p.a.)	59860	63.52	53.08	16.00	27.18	49.70	82.00	128.00
Min. investment (in mio. USD)	166157	12.50	16.50	0.05	1.00	5.00	20.00	50.00
Panel D: Separate Accounts for retail investors only								
Total assets (in mio. USD)	70263	551	1900	1	7	53	286	1080
# Accounts	63197	415	798	2	9	55	324	1574
Firm assets (in bio. USD)	76105	176	367	1	4	23	164	490
Expense ratio (p.a.)	89515	1.95	1.35	0.00	0.50	1.88	3.00	3.05
Netflow (p.a.)	64395	8.17	50.52	-14.23	-5.17	-0.28	5.56	25.06
# Holdings	48355	63	58	28	38	52	73	101
Turnover ratio (p.a.)	31738	49.58	42.16	13.80	22.83	37.30	65.00	98.00
Min. investment (in mio. USD)	77901	0.79	3.33	0.05	0.10	0.10	0.15	1.00

This table shows descriptive statistics for fund characteristics of separate accounts (SAs) on a monthly basis. The sample consists of 3,781 SAs over the period 1990 to 2017. Panel A shows descriptive statistics for the whole sample; Panel B contains SAs for institutional and retail investors; Panels C includes institutional SAs and Panel D contains retail SAs.

Table 2
SA Performance

	Obs	Mean	SD	Percentile				
				10	25	50	75	90
Panel A: All Separate Accounts								
Net Returns								
Excess retun (p.a.)	821,018	8.17	15.86	-63.24	-21.84	12.12	41.88	72.93
Carhart alpha (p.a.)	698,042	-0.11	6.31	-22.86	-10.69	-0.44	9.97	22.92
Fama/French alpha (p.a.)	698,042	-0.11	6.22	-22.83	-10.69	-0.38	10.00	22.80
CAPM alpha (p.a.)	698,042	0.30	7.29	-26.77	-11.99	-0.26	11.92	28.07
Gross Returns								
Excess retun (p.a.)	821,018	9.09	15.86	-62.28	-20.88	13.08	42.74	73.80
Carhart alpha (p.a.)	698,042	0.81	6.28	-21.84	-9.76	0.39	10.86	23.82
Fama/French alpha (p.a.)	698,042	0.81	6.20	-21.81	-9.76	0.44	10.89	23.72
CAPM alpha (p.a.)	698,042	1.22	7.27	-25.78	-11.04	0.57	12.82	28.99
Panel B: Separate Accounts for institutional and retail investors								
Net Returns								
Excess retun (p.a.)	533,423	8.12	16.06	-64.32	-22.44	12.12	42.24	73.78
Carhart alpha (p.a.)	456,345	0.03	6.60	-23.85	-11.05	-0.36	10.58	24.25
Fama/French alpha (p.a.)	456,345	0.04	6.51	-23.83	-11.04	-0.29	10.65	24.13
CAPM alpha (p.a.)	456,345	0.51	7.60	-27.71	-12.31	-0.12	12.68	29.61
Gross Returns								
Excess retun (p.a.)	533,423	8.95	16.06	-63.48	-21.60	12.90	43.08	74.64
Carhart alpha (p.a.)	456,345	0.86	6.57	-22.93	-10.22	0.40	11.38	25.05
Fama/French alpha (p.a.)	456,345	0.87	6.48	-22.89	-10.22	0.46	11.43	24.96
CAPM alpha (p.a.)	456,345	1.34	7.58	-26.81	-11.48	0.63	13.47	30.44

Table 2 cont'd.
SA Performance

	Obs	Mean	SD	Percentile				
				10	25	50	75	90
Panel C: Separate Accounts for institutional investors only								
Net Returns								
Excess retun (p.a.)	198,080	8.81	15.79	-62.64	-21.00	12.84	42.69	73.20
Carhart alpha (p.a.)	165,834	0.13	5.70	-20.56	-9.47	-0.16	9.28	21.08
Fama/French alpha (p.a.)	165,834	0.09	5.63	-20.54	-9.51	-0.13	9.27	20.84
CAPM alpha (p.a.)	165,834	0.35	6.84	-25.43	-11.15	-0.07	11.24	26.58
Gross Returns								
Excess retun (p.a.)	198,080	9.49	15.78	-61.92	-20.37	13.54	43.32	73.95
Carhart alpha (p.a.)	165,834	0.80	5.69	-19.80	-8.80	0.41	9.94	21.83
Fama/French alpha (p.a.)	165,834	0.76	5.62	-19.83	-8.84	0.43	9.91	21.56
CAPM alpha (p.a.)	165,834	1.03	6.84	-24.71	-10.46	0.49	11.90	27.29
Panel D: Separate Accounts for retail investors only								
Net Returns								
Excess retun (p.a.)	89,515	7.08	14.76	-57.60	-20.40	10.80	38.16	66.60
Carhart alpha (p.a.)	75,863	-1.44	5.74	-22.17	-11.34	-1.56	8.13	19.43
Fama/French alpha (p.a.)	75,864	-1.41	5.64	-22.06	-11.27	-1.54	8.20	19.34
CAPM alpha (p.a.)	75,863	-1.07	6.25	-24.21	-11.97	-1.45	9.30	22.39
Gross Returns								
Excess retun (p.a.)	89,515	9.05	14.76	-55.68	-18.48	12.72	40.08	68.68
Carhart alpha (p.a.)	75,863	0.56	5.70	-19.93	-9.31	0.31	10.09	21.39
Fama/French alpha (p.a.)	75,864	0.58	5.61	-19.86	-9.21	0.33	10.12	21.30
CAPM alpha (p.a.)	75,863	0.92	6.22	-22.06	-9.96	0.45	11.23	24.46

This table shows descriptive statistics for annualized excess returns and risk-adjusted performance measures of separate accounts (SAs). The sample consists of 3,781 SAs over the period 1990 to 2017. Panel A shows descriptive statistics for the whole sample; Panel B contains SAs for institutional and retail investors; Panels C includes institutional SAs and Panel D contains retail SAs. Excess returns are returns subtracted by the U.S. one-month treasury bill rate. The annualized excess return is the multiplicative sum of its monthly returns. Risk-adjusted returns are out-of-sample alphas calculated via factor loadings obtained from 24-month rolling window regressions from t-1 to t-24 using the CAPM, Fama French 3 factor and Carhart 4 factor model.

Table 3
Performance Regressions

	Net returns				Gross returns			
	Carhart alpha		CAPM alpha		Carhart alpha		CAPM alpha	
	M1	M2	M3	M4	M5	M6	M7	M8
Retail Dummy	-0.733***	-0.663***	-0.607***	-0.525***	-0.008	0.075	0.116	0.212
	(0.00)	(0.00)	(0.00)	(0.00)	(0.96)	(0.58)	(0.44)	(0.16)
Inst Dummy	0.251***	0.286***	0.219**	0.268***	0.235**	0.269***	0.201**	0.248**
	(0.01)	(0.00)	(0.03)	(0.01)	(0.01)	(0.00)	(0.04)	(0.01)
Ln Total Assets	-0.067***	-0.076***	-0.094***	-0.108***	-0.055***	-0.065***	-0.080***	-0.095***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Ln #Accs	-0.129***	-0.101***	-0.111***	-0.089***	-0.155***	-0.121***	-0.141***	-0.113***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Firm TA (bio)	-0.000*	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000
	(0.08)	(0.12)	(0.35)	(0.34)	(0.11)	(0.18)	(0.46)	(0.50)
Expense Ratio	-0.251***	-0.283***	-0.217***	-0.266***	0.174***	0.137***	0.210***	0.158***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Age	-0.003	-0.002	-0.006	-0.006	-0.001	-0.000	-0.005	-0.005
	(0.62)	(0.72)	(0.32)	(0.28)	(0.86)	(0.96)	(0.43)	(0.37)
Min.Invest (mio)	0.010***	0.011***	0.014***	0.015***	0.010***	0.011***	0.014***	0.015***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Net Flow	0.002***	0.002***	0.002*	0.002*	0.002***	0.002***	0.002*	0.002*
	(0.01)	(0.01)	(0.09)	(0.09)	(0.01)	(0.01)	(0.09)	(0.08)
Constant	0.287	0.423	0.929***	1.006***	0.626	0.742	1.2648***	1.394***
	(0.70)	(0.57)	(0.00)	(0.00)	(0.40)	(0.31)	(0.00)	(0.00)
Style FE	No	Yes	No	Yes	No	Yes	No	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R2	0.09	0.09	0.16	0.16	0.09	0.09	0.16	0.16
N	111,669	111,669	111,669	111,669	111,669	111,669	111,669	111,669

This table shows performance regressions using net and gross out-of-sample Carhart alphas of quarter t+1 as dependent variable. The sample consists of 3,781 SAs over the period 1990 to 2017. An out-of-sample Carhart alpha is calculated via factor loadings obtained from 24-month rolling window regressions from t-1 to t-24 Carhart 4 factor model. ***, **, * denote significance of the estimated parameters at the 1%, 5%, and 10% level, respectively. Standard errors are clustered by SA.

Table 4
Percentiles of Carhart t(a) for actual and simulated SA returns

	All			Both			Institutional			Retail		
Column	1	2	3	4	5	6	7	8	9	10	11	12
Pct	Act	Sim	%>Act	Act	Sim	%>Act	Act	Sim	%>Act	Act	Sim	%>Act
Panel A: Gross returns												
1	-2.41	-2.57	0.43	-2.44	-2.49	0.49	-2.52	-2.73	0.45	-2.30	-2.73	0.23
2	-2.01	-2.18	0.42	-1.97	-2.14	0.45	-2.11	-2.26	0.46	-2.02	-2.23	0.36
3	-1.75	-1.96	0.36	-1.73	-1.94	0.38	-1.78	-2.01	0.38	-1.74	-1.99	0.29
4	-1.58	-1.81	0.34	-1.52	-1.79	0.36	-1.67	-1.86	0.41	-1.64	-1.86	0.33
5	-1.43	-1.69	0.31	-1.38	-1.67	0.32	-1.55	-1.72	0.41	-1.41	-1.72	0.23
10	-0.98	-1.29	0.23	-0.94	-1.28	0.24	-1.00	-1.31	0.26	-1.02	-1.32	0.23
20	-0.42	-0.83	0.12	-0.42	-0.83	0.13	-0.37	-0.84	0.09	-0.49	-0.85	0.15
30	-0.06	-0.51	0.08	-0.06	-0.51	0.09	0.00	-0.51	0.06	-0.14	-0.52	0.13
40	0.26	-0.23	0.06	0.24	-0.23	0.07	0.32	-0.23	0.04	0.24	-0.25	0.06
50	0.54	0.02	0.05	0.52	0.02	0.06	0.59	0.03	0.04	0.58	0.01	0.04
60	0.81	0.28	0.05	0.80	0.27	0.05	0.82	0.28	0.05	0.82	0.27	0.04
70	1.12	0.55	0.04	1.11	0.54	0.04	1.15	0.56	0.04	1.11	0.54	0.04
80	1.49	0.87	0.03	1.49	0.86	0.03	1.50	0.88	0.03	1.49	0.87	0.03
90	2.00	1.32	0.02	1.99	1.31	0.02	2.05	1.33	0.02	1.99	1.33	0.03
95	2.51	1.71	0.01	2.45	1.69	0.01	2.58	1.73	0.01	2.52	1.73	0.02
96	2.61	1.82	0.01	2.58	1.80	0.01	2.73	1.85	0.01	2.59	1.86	0.03
97	2.75	1.97	0.02	2.73	1.95	0.01	2.83	1.99	0.02	2.65	2.00	0.05
98	2.97	2.18	0.02	3.02	2.15	0.02	3.00	2.22	0.02	2.82	2.24	0.08
99	3.38	2.56	0.02	3.50	2.49	0.02	3.25	2.66	0.09	3.18	3.09	0.24
Panel B: Net returns												
1	-3.52	-2.57	0.97	-3.16	-2.49	0.92	-3.18	-2.70	0.79	-4.50	-2.71	0.99
2	-3.04	-2.18	0.97	-2.74	-2.14	0.90	-2.63	-2.25	0.77	-4.02	-2.22	1.00
3	-2.70	-1.96	0.95	-2.40	-1.94	0.86	-2.25	-2.01	0.70	-3.87	-1.98	1.00
4	-2.51	-1.81	0.94	-2.15	-1.79	0.81	-2.07	-1.85	0.69	-3.40	-1.85	1.00
5	-2.28	-1.69	0.92	-2.00	-1.67	0.79	-1.94	-1.72	0.69	-3.31	-1.72	1.00
10	-1.74	-1.30	0.86	-1.54	-1.28	0.75	-1.38	-1.31	0.60	-2.70	-1.31	1.00
20	-1.11	-0.83	0.77	-0.96	-0.83	0.65	-0.80	-0.83	0.49	-2.13	-0.85	1.00
30	-0.69	-0.51	0.68	-0.60	-0.51	0.60	-0.42	-0.50	0.43	-1.67	-0.52	1.00
40	-0.37	-0.23	0.65	-0.31	-0.24	0.57	-0.13	-0.23	0.41	-1.33	-0.25	1.00
50	-0.08	0.02	0.61	-0.03	0.02	0.54	0.15	0.03	0.36	-0.93	0.01	1.00
60	0.23	0.27	0.53	0.27	0.27	0.49	0.37	0.28	0.38	-0.59	0.27	1.00
70	0.53	0.54	0.48	0.58	0.54	0.42	0.62	0.56	0.38	-0.17	0.54	1.00
80	0.87	0.86	0.45	0.90	0.86	0.42	0.99	0.88	0.33	0.32	0.86	0.97
90	1.40	1.31	0.37	1.41	1.31	0.36	1.51	1.33	0.28	0.87	1.32	0.95
95	1.85	1.70	0.31	1.86	1.68	0.28	2.00	1.72	0.19	1.32	1.72	0.90
96	1.98	1.82	0.29	1.99	1.79	0.26	2.17	1.84	0.16	1.49	1.86	0.87
97	2.17	1.96	0.25	2.17	1.94	0.23	2.31	1.98	0.16	1.67	1.99	0.83
98	2.34	2.16	0.29	2.35	2.14	0.24	2.40	2.20	0.27	1.79	2.24	0.89
99	2.79	2.54	0.22	2.81	2.47	0.15	2.71	2.63	0.39	2.16	3.27	0.89

This table shows the results from a bootstrapping approach based on a sample that consists of 3,781 SAs over the period 1990 to 2017. The columns "Act" contain the t(a) estimates at selected percentiles of the cross-sectional alpha distribution based on actual returns. The columns "Sim" present the average estimated t(a) values from 1,000 simulated true zero-alpha cross-sections. The columns "%>Act" show the percentage of simulation runs that produce t(a) values that are greater than the actual values. This measure can be interpreted similar to a p-value.

6 Conclusion

This dissertation aims to improve the general understanding of SAs and thus benefit research, regulation and various market participants.

The first major topic addressed in Articles I and II is the diminishing effect of scale on risk-adjusted performance. Article I takes the unique organizational structure of SAs into account and shows that in SAs two dimensions of size − size in terms of total assets and in terms of number of accounts − diminish risk-adjusted performance respectively. Although the second effect prevails, both effects exist simultaneously side by side, so that the risk-adjusted performance of large SAs with many accounts suffer the most. This finding is novel, highly relevant and contributes to a better general understanding of SAs as it highlights the impact of their unique organizational structure on performance. Since we report an annualized difference in risk-adjusted performance before costs of 2.12% between the smallest SAs with the lowest number of accounts and the largest SAs with the highest number of accounts, this finding provides direct economic value for investors. Future studies on SAs need to consider these diminishing effects of scale in both dimensions.

Article II addresses and contributes mainly to two important streams of academic literature. First, it contributes to the academic debate around the general mechanisms leading to diseconomies of scale. While most previous studies either focus on econometric issues or investigate the liquidity costs channel, only few studies have so far been able to test the information processing/hierarchy cost channel empirically. By contrasting SAs that pursue either a quantitative or a fundamental investment approach, we circumvent the issue of not knowing the firm’s level of soft information production and communication. This way, we are able to test our hypotheses on the mechanisms that are responsible for diseconomies of scale directly. In the process, we use and extend the equilibrium framework proposed by Pastor, Stambaugh and Taylor (2020) by showing that equilibrium “tradeoffs” differ substantially for quantitative and fundamental investment strategies.

Second, Article II also contributes to the literature on the performance of quantitative vs. fundamental investment strategies. While previous studies like Harvey et al. (2017) or Abis (2017) relied mainly on algorithmic text analysis to divide their sample into quantitative and fundamental investment strategies, we take advantage of the fact that SAs publicly disclose their investment style. This enables us to test and extend pervious assumptions and predictions based on a comprehensive sample with a reliable classification into quantitative and fundamental SAs.

Article III of this dissertation proposes an innovative way to quantify the impact of unobserved constraints on portfolio management and performance. To analyze the simultaneous management of MFs and SAs, which is a common practice in the asset management industry due to economies of scale, it is important to enhance the general understanding of managerial incentives, economies of scale, and the business model of advisory firms in general.

Future studies might use our portfolio difference measure (PDM) as an indicator of unobserved constraints and thereupon try to isolate specific constraints and examine their impact on manager behavior and performance. This way, future research might further contribute to the discussions of potential policy implications and regulators will be able to formulate specific policy guidelines. In addition, our study provides direct advice to investors. Since performance tends to be lower for both the MF and the SA, investors should be careful when investment vehicles show a substantial portfolio difference.

Article IV focuses on the risk-adjusted performance and the value that SAs can provide to its investors. The results show that on average SAs significantly outperform the market before costs and that the achieved outperformance is not solely explainable by pure luck. Moreover, their risk-adjusted net performance is close to zero, which is considerably better than most other actively managed investment alternatives like MFs. These results represent a promising foundation for future analyses. Following the approaches of Treynor and Mazuy (1966), Henriksson and Merton (1981), Ferson and Schadt (1996), Busse et al. (1999) or Elton et al. (2012), it might be interesting to investigate whether the measured outperformance is attributable to superior market timing or superior stock selection. A holdings-based analysis following Grinblatt and Titman (1993), Daniel et al. (1997) or Rohleder et al. (2017) could lead to even more accurate results.

Another key aspect of Article IV is the extent to which retail investors can participate in the outperformance of the SA universe. While less than 30 years ago, customized portfolio management services were exclusively limited to institutional investors and ultra-rich individuals, today, digital solutions enable investment advisors to offer customized portfolio management services to various kinds of investors starting at a minimum investment amount of $50,000. However, Article IV emphasizes that although institutional and retail SAs achieve a similar risk-adjusted performance before costs, an average expense ratio of almost 2% leads to a significant underperformance of retail SAs based on net returns. Considering, that the recent studies of Barber, Huang and Odean (2016), Berk and van Binsbergen, (2016), Ben-David et. al. (2019) and Choi and Robertson (2020) on MFs identify expense ratios, returns and especially performance rankings to be the main drivers of new investor flows, from a retail perspective, SAs do currently not seem to be the favorite investment choice. However, if investment advisors manage to become even more efficient in their digital solutions so that they are able to offer customized portfolio management services at competitive costs, then the SA market has an enormous potential for future growth in the retail segment. In this case, it becomes even more important for regulators, researchers and other market participants to broaden their understanding of SAs, to which the insights of this dissertation make an essential contribution.

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