Diseconomies of Scale, Information Processing and Hierarchy Costs: Evidence from Asset Management*

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Abstract

Previous research has suggested that information processing and hierarchy costs play a role in firm-level diseconomies of scale. Using separate accounts (SAs) as a laboratory, we examine if these costs vary across investment approach (quantitative vs. fundamental) and what role they play in producing diseconomies of scale. Consistent with lower hierarchy, the average investment professional (e.g., portfolio manager, research analyst, and trader) at a quantitative advisor manages two to three times more assets than fundamental advisors. Consistent with greater use of hard information and lower information processing costs, quant SAs show higher factor model R^2, more stable factor loadings and higher information diffusion speed. On this basis, we show that the performance of quant SAs is unrelated to size while fundamental SAs exhibit statistically and economically significant diseconomies of scale. Overall, our results suggest that information processing and hierarchy costs are a source of diseconomies of scale in general.

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

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

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1 Introduction

The question of whether 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 academic papers on mutual funds. Sharpe (1966) proposes and tests the competing hypotheses, ultimately concluding that there is no relationship between size and performance.[1] Since that time, fund size has become a standard control variable in performance regressions[2] often with a negative and statistically significant coefficient being interpreted as evidence of diseconomies of scale. Berk and Green (2004), hence, propose an equilibrium model of rational fund and investor behavior taking diseconomies of scale in mutual funds as given without elaborating on any sources and channels. 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 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 among the possible mechanisms for diseconomies of scale: liquidity – the increased trading and price impact costs associated with investing a larger pool of assets and

[1] "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.

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

trading larger positions[3]; information processing – the increased difficulty of timely identifying an increasing 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 get involved in the investment process.

While the liquidity channel has been the subject of many previous studies,[4] the other aspects have not been analyzed in detail thus far. Therefore, our aim in this paper is to explore what role, if any, is played by information processing and hierarchy costs. Using a database of separate accounts (SAs) from 1991 to 2015 as a laboratory, we test these two possible mechanisms for diseconomies of scale across two distinct investment strategies: fundamental and quantitative analysis. 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 impact of information processing costs and the hierarchy costs with increasing firm size to be greater for fundamental analysis.

To add both insight to and anecdotal evidence of this assertion regarding fundamental and quantitative strategies, consider the two investment strategy summaries below. As an example of a fundamentally managed SA, *Ariel Investments, LLC, Small Cap Value SA* describe their investment strategy as follows:

[3] 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).

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

> *"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."*[5]

This description from Ariel suggests both a high degree of soft information analysis and multiple feedback loops between different investment professionals at the firm (i.e. hierarchy costs) before a decision is made to invest in a security. 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."*[6]

The quantitative investment process described by Amalgamated involves an automated analysis with no person-to-person communication, consistent with our assertion that quant strategies rely on the processing of hard information and little or no communication or feedback loops between different investment professionals at the firm.

To provide a framework for our analysis, we turn to the industrial organization literature. Radner and Van Zandt (1992), Radner (1993), Bolton and Dewatripont (1994) and Stein (2002)

[5] Source: Morningstar Direct.
[6] Source: Morningstar Direct.

all model different aspects of the information processing problem in firms without providing empirical evidence. Specifically, Bolton and Dewatripont (1994) analyze "the internal organization of a firm whose only activity…is to process valuable information about its environment"[7], an apt description of the production function of investment management firms. Radner (1993) highlights as a key contribution of his model "…how the costliness of information processing contributes to organization economies or diseconomies of scale."[8] Stein (2002), which motivates the Chen et al. (2004) tests of diseconomies of scale[9], examines how differences in hierarchal structures optimally align with soft and hard information production and the communication of that information throughout the firm. Radner and Van Zandt (1992), Radner (1993), Bolton and Dewatripont (1994) all model separately "…the costs of processing new information and the costs of communicating this information"[10] in examining different aspects of optimal firm organization. These communication or hierarchy costs refer to the cost or delay of communicating information through a firm with greater hierarchy. Information processing costs, on the other hand, are the cost or the delay of different production technologies in analyzing information.

As a first step in our analysis, we propose and test a direct measure of hierarchy costs: the average assets managed per investment professional. Firms with lower assets per investment professional have greater firm hierarchy and associated hierarchy costs as they need more staff to produce a similar output. If our assertion that quantitative analysis relies more on processing and communicating hard information than fundamental strategies, the Radner and Van Zandt (1992),

[7] Bolton and Dewatripont (1994), pg. 813.
[8] Radner (1993), pg. 1110.
[9] In larger organizations, agents who produce soft information (e.g. analysts) may have a more difficult time communicating their information to superiors (e.g. fund managers) in a way that those superiors will act on that information.
[10] Bolton and Dewatripont (1994), pg. 809.

Radner (1993) and Bolton and Dewatripont (1994) models would suggest that quantitative firms will have less hierarchy associated with their investment management/information processing positions. Comparing pure quantitative vs. pure fundamental firms, we find that quantitative investment managers have less hierarchy across all investment functions (portfolio manager, research analyst, and trader). The average firm assets per portfolio manager at a pure quantitative investment advisor is double the assets per manager at a fundamental investment advisor. For research analysts, the average firm assets at a quantitative analysis firm is triple that of a fundamental firm.

As a second step, we examine the processing costs of quantitative vs. fundamental investment strategies. As a first proxy for information processing costs, 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 4.8% and 6.9% 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 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.

As another direct proxy for hierarch and information processing costs, we look at the speed of information diffusion within SA firms following the method of Cici, Jaspersen and

Kempf (2017).[11] If quant SA firms use hard information to a higher degree and their investment decision process involves fewer to no feedback loops (hierarchy), information can be expected to spread faster through quant firms than through fundamental ones. Using detailed portfolio holdings information of quant and fundamental SAs, the test confirms this expectation in that information diffusion speed is higher at quant firms, consistent with lower information processing costs. Moreover, with an increase in SA firm size, information diffusion speed decreases for fundamental firms but remains constant for quant firms, which is also consistent with our assertion that firm-level diseconomies of scale are driven by hierarchy and information processing costs.

After documenting distinctive differences between quant and fundamental SAs with respect to hierarchy and information processing costs, we directly examine the change in performance associated with changes in SA size. In a univariate quintile sort in the spirit of Chen et al. (2004), we find no statistically significant difference in the performance of quantitative SAs between the first and fifth quintile of size. For the fundamental SAs, however, not only is the performance difference strongly statistically significant but performance declines monotonically as the SA size increases. Using panel regressions, we find no statistically significant relationship between SA size and performance for quant SAs, but a strong statistically and economically significant relationship between SA size and performance for fundamental SAs. These results are robust to a wide range of regression specifications including the recursive demeaning approach suggested by Paster, Stambaugh and Taylor (2015) to control for the

[11] 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.

endogeneity between size and performance. For a fundamentally managed SA, a one standard deviation increase in Log size thus translates to a decrease in performance of 0.57% per quarter.

Finally, to further differentiate between the different channels of diseconomies of scale, we plug several proxies of fund liquidity, hierarchy and information processing costs directly into the panel regressions. As expected, explicitly controlling for liquidity does not change the results confirming that hierarchy and information processing costs independently contribute to diseconomies of scale. Further including the proxies for hierarchy and information costs reveals cost advantages for quant SAs. Once controlling for these advantages, also quant SAs show slight evidence for diseconomies of scale while the results for fundamentals are unchanged. Overall, this represents strong evidence for our hypothesis that hierarchy information costs are an important and independent channel of diseconomies of scale in asset management.

There are two recent papers that analyze the performance of quantitative vs. fundamental investment strategies. Harvey, Rattray, Sinclair, and Van Hemert (2017) examine the performance of discretionary vs. systematic (quant) 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 these papers, our contribution is three fold. First, we use the difference in information processing technology of quant and fundamental strategies to examine whether or not information processing and hierarchy costs play a role in diseconomies of scale. Second, we document underperformance of quantitative strategies relative to fundamental strategies with respect to classic factor models in a sample of institutional separate accounts. Third, we explore the economics of investment advisors that employ quantitative vs. fundamental investment strategies. We find that quantitative advisors manage significantly more assets per investment professional and are growing at a similar rate than fundamental advisors.

The paper proceeds as follows. Section 2 introduces our dataset, explains how we measure performance and presents summary statistics. Section 3 establishes differences in hierarchy and information processing costs between quant and fundamental SAs. Section 4 tests if those differences lead to differences in the impact of size on performance between quant and fundamental SAs. Section 5 explicitly controls for the different channels of diseconomies of scale. Section 6 concludes.

2 Data and Performance measurement

2.1 Data and sample construction

We obtain survivorship bias-free data on actively managed US domestic equity separate accounts (SAs) in the period 1991 to 2015 from Morningstar Direct.[12] 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

[12] 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. They conclude that the data is unbiased.

value" or "large neutral"). 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 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.[13] We exclude "specialty" SAs by their names and by stock market betas below 0.2 from the performance regression. Further, we obtain time invariant information grouping SAs into those with a clear quantitative and a clear fundamental investment approach.[14] The final sample contains 1,780 SAs of which 363 are quants and 1,417 are fundamentals. For those, we obtain quarterly SA characteristics as well as further information on management firm level including firm size and the numbers of employees with different functions within the firm. Moreover, we obtain quarterly SA level portfolio holdings for a subset (70.4%) of the 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 ($340m vs. $644m). Their annual expense ratio, calculated as the difference between reported gross and net returns, is lower than for fundamentals (0.72% vs. 0.92%). These comparatively low costs for quants may be attributed to the higher average minimum investment of $12.20m compared to $7.29m for fundamentals. The average annual turnover of 110.15% for quants is double as high as the turnover of fundamentals (55.56%). Quants have 156 different holdings on average with 29% of

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

TA in the top 10 holdings. Fundamentals are clearly less diversified with only 62 different holdings on average and 34% of TA in the top 10. Quants are younger with 6.66 years compared to 8.35 years on average for fundamentals. A slightly higher fraction of quants that have an institutional focus (24.2% to 21.8%) and only half as many quants have a retail focus (5.0% vs. 10.2%). Overall, this shows that quant and fundamental SAs are very different in their average characteristics.

SAs of both investment strategies have experienced substantial annual implied percentage net flow with 13.60% for quants and 15.74% for fundamentals. We calculate quarterly implied percentage net flow (hereafter "flow") from quarterly TA and quarterly 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 25 years.

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

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):

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

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

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

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

where $ER_{i,t}$ is the return of SA i in month t in excess of the 1-month T-Bill rate, $\alpha_i^{\text{Carhart}}$ 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 French's webpage.[15] As MPBs, we use 74 different self-stated benchmarks indices for which we obtain monthly returns from Morningstar Direct.[16] 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 to be used in 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 return (Eq. 6a) is defined as the sum of the SA's sensitivities to the respective risk factors $k = 1, \ldots, K$ during the 24-month "in sample" rolling window from t–25 to t–1 ($\beta_{i,t\text{-}1}^{k}$) times the risk factor (excess) returns in month t ($f_{k,t}$).[17] It thus represents a passive benchmark with an a priori similar style as the SA. Consequentially, the SAs out-of-sample performance in month t is the difference between the SAs excess return ($ER_{i,t}$) and the style return (Eq. 6b). To account for outliers and estimation errors in the rolling regressions, we winsorize the out-of-sample performance to the 1% and 99% percentiles.

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[15] http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html. We thank Kenneth French for providing the data.

[16] See Appendix A for a list of the 74 MPBs.

[17] Alternative in sample window lengths of 12 and 36 months yield economically similar results.

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

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

Table 2 reports annualized average out-of-sample alphas as well as in-sample risk-factor coefficients 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 SAs, respectively.[18] Looking first at the single index CAPM and MPB results, we see that both the quant and fundamental SAs have EW alphas above zero and slightly negative VW alphas, but neither are statistically different from zero. 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 role for fundamentals but not for quants.

[Insert Table 2 here]

Regarding risk factor sensitivities, 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 beta, consistent with momentum being a quant strategy rather than a fundamental one. Lastly, with respect to the

[18] 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.

model fit, quants show consistently higher R^2 statistics than fundamentals with differences between 4.8% and 6.9% depending on the model.

In the following, we concentrate on the MPB and Carhart models as the most relevant models from practical and academic standpoints, respectively.[19] For a more in depth analysis of the differences between quant and fundamental SAs, Table 3 presents summary statistics on the monthly out-of-sample alphas, in-sample risk factor sensitivities and R^2 statistics together with respective hypothesis tests for equality. The first three columns report statistics for quants, the next three for fundamentals and the last 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, especially in the median.

[Insert Table 3 here]

3 Differences in Hierarchy and Information Processing of Quant and Fundamental SAs

3.1 Hierarchy costs

To test our hypothesis that hierarchy costs play a role in asset management diseconomies of scale, we first have to establish that the two groups of SAs we use in our analysis are different with respect to hierarchy. Therefore, Table 4 reports cross-sectional summary statistics as of

[19] Similar analyses using the CAPM and the Fama/French model yield qualitatively similar results.

December 2015 on firm assets by employee for SA firms purely managing quant SAs (left columns) and fundamental SAs (middle columns). The numbers show for all stages of the production process—be it CFAs, client service agents, marketing specialists, portfolio managers, research analysts or traders—that quantitative firms have higher assets per employee compared to fundamentals. Specifically, the assets per portfolio manager at are twice as high ($2.82b vs. $1.44b), assets per CFA are almost three times as high ($2.89b vs. $1.05b) and assets per research analyst are more than three times as high at quant firms compared to fundamental firms ($3.76b vs. $1.13b). This is a clear indication of lower hierarchy at quant firms than at fundamental firms.

[Insert Table 4 here.]

3.2 Hard vs. Soft Information

To examine whether or not information processing costs play a role in diseconomies of scale, we first examine the difference in information processing costs between quant and fundamental SAs. To do this, we analyze the nature of the information content processed by both types of SAs. Our evidence suggests that fundamental SAs process more soft information and that the information processing technology used by these SAs relies more on personal involvement by the portfolio manager who derives investment decisions from personal views and opinions. While initial evidence in support of this assertion can be drawn from Table 1 where quant SAs, despite handling more assets per employee, have twice the turnover (110.15% vs. 55.56%) and handle almost 2.5 times the number of different holdings compared to fundamentals (156 vs. 62) on average. Two more formal tests of this assertion are described below.

As a first test of whether or not fundamentals process more soft information while quants process more hard information can be derived from Table 2. The risk factor loadings of quant SAs show distinctively lower standard deviations than those of fundamental SAs and the regression R^2 statistics from the Carhart and MPB performance models are higher for quant than for fundamental SAs. Both results are in line with quants maintaining more stable exposures to systematic risk factors, and hence relying more strongly on systematic or hard information.

As a second test of the differences in information processing costs, we examine the impact of changes in the management team on the investment strategy of that SA. If the managers of fundamental SAs process more soft information, the investment strategy is likely to change with a new investment team with new views, rules, opinions and approach 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 specifically at changes in the factor exposures of the two different strategies across a manager change event using a difference-in-differences analysis. We identify those SA-date observations where there is a replacement of the entire management team.[20] For each of these manager 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 such differences for all SAs and separately for quant and fundamental, as well as the diff-in-differences between the two groups. As measures of consistency in the

[20] 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.

investment strategy, we first look at differences in performance regression betas and document that changes in market betas (Carhart and MPB) as well as in other risk factor betas for SMB and MOM are higher for fundamentals than for quants as indicated by statistically significant and negative difference in differences. The HML beta diff-in-diff for fundamental SAs also has a larger point estimate, although the difference between fundamental and quant SAs is not statistically significant. Thus, we can show, that the overall investment strategy of quants is less effected by a manager change, which indicates a more stable production function relying predominantly on hard information.

[Insert Table 5 here.]

We also look at differences in fit and active risk as measures of potential changes in investment strategy across the manager change. 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).[21] Again, the differences are higher for fundamentals than for quants as indicated by negative diff-in-diffs, but only statistically significant in the case of R^2. Overall, the results in Table 5 confirm our assertion that quant SAs rely more on hard information, indicative of lower information processing costs.

3.3 Information Processing Speed

As a last test of differences in hierarchy and information processing costs between quant and fundamental SAs, we look at the speed with which new information spreads through the SA

[21] The tracking error with respect to the Carhart (1997) model is the performance regression's root mean squared error (RMSE). The MPB tracking error is the standard deviation of the simple return difference between the SA and the MPB.

investment advisor. We follow the method of Cici, Jaspersen and Kempf (2017) who analyze the information diffusion speed (*ID*) within mutual fund families and find that mutual funds from families with higher *ID* outperform funds from families with lower *ID*. To measure the *ID* of SA firms, we obtain the portfolio holdings in the period 10/1992 to 08/2017 for a subset (70.4%) of the SAs in our analysis from Morningstar and calculate *ID* following Eq. (7)[22].

$$ID_{f,s,q} = \frac{I_{f,s,q} - 1}{I_{f,s.q} + J_{f,s,q} - 1} \qquad (7)$$

I is the number of SAs in firm *f* buying stock *s* in reporting period *q* (initial buy) and *J* is the number of SAs in the firm that follow during the information interval. This interval is defined as the period during which the valuation[23] regarding the stock within the firm does not change, i.e. before an initial buyer removes the stock from the portfolio (Cici, Jaspersen, Kempf, 2017, pg 151). Hence, higher values of *ID* indicate higher information diffusion as more SAs buy the stock in the same reporting period as the initial buyer. Lower values indicate lower speed as more SAs follow in later reporting periods.

The results are reported in Table 6 where Panel A shows *ID* in all firms with 3 or more SAs, Panel B with 5 or more SAs and Panel C with 7 or more SAs.[24] In order to isolate information sharing between SAs with a similar investment approach (e.g. quant sharing with other quant SAs) we focus on those investment advisors where all SAs are fundamental ("Pure Fundamental") or entirely quantitative ("Pure Quant"). In Panel A, the mean *ID* of pure fundamental firms is 0.6088 compared to 0.6491 for pure quant firms, suggesting that

[22] Eq. (1) from Cici, Jaspersen, Kempf (2017), pg. 151.
[23] E.g., Alexander, Cici and Gibson (2007).
[24] Cici, Jaspersen, Kempf (2017) report firms with 5 or more funds as the default and use 3 and 10 funds as unreported robustness checks. An important difference between fund families and SA firms is that SA firms report all accounts that are managed following a common objective as one SA. Thus, the number of SAs in a firm is naturally lower than the number of mutual funds in a family.

information diffuses more quickly through quant investment advisors. The difference is statistically significant and the probability that a random draw from the population of initial buys of fundamental firms is higher than a random draw from the initial buys of quant firms is below clearly below 50%. This is consistent with the assertion that new information spreads faster through quant firms than through fundamental firms, consistent with lower information processing costs.

[Insert Table 6 here.]

Comparing Panel A with Panels B and C, which require more SAs in the firm, the differences in *ID* between pure fundamentals and pure quants becomes larger with a higher number of firm SAs and thus with larger firm size. Moreover, this increase of the difference is driven almost entirely by the *ID* decreasing for fundamentals while virtually remaining constant for quants. The probability of a higher random draw from fundamentals decreases to only 0.4376 in Panel C. These results suggest that new information spreads more quickly through quant firms than through fundamental firms, consistent with lower information processing and hierarchy costs, and that these costs depend on firm size at fundamentals while being size independent at quant firms.

4 Differences in the Impact of Size on Performance

4.1 Portfolio Sorting by SA Size

After establishing in the previous sections that quant SAs have lower hierarchy and information processing costs than fundamental SAs, we now directly test the impact of SA size on performance for the two groups. In a first step, we therefore follow Chen et al. (2004) and calculate the average performance of quarterly rebalanced size-quintile portfolios. Table 7 reports the results for all SAs (left columns) and separately for quant (middle columns) and fundamental SAs (right columns). For all SAs, the performance of the "Low" size quintile is positive and statistically significant at 0.59% p.a. for the Carhart model and 1.00% p.a. for the MPB models, respectively. The performance of the "High" size quintile is slightly negative but statistically insignificant. The "High-low" difference is negative and statistically significant, consistent with the existence of diseconomies of scale. 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" differences for quants are close to zero and statistically insignificant, especially for the Carhart model, where all size quintiles show very similar performance at around –0.75% p.a. 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 (0.78% p.a) to the significant "high" quintile (-0.68% p.a.). This is a first indication in favor of our hypothesis that diseconomies of scale in active management are an outcome of hierarchy and information processing costs.

[Insert Table 7 here.]

4.2 Panel Regressions

While the quintile sort regression in Table 7 are compelling, Table 8 reports a wide range of panel regression approaches, where we explain quarterly future net Carhart performance with SA size (Log TA), fundamental and quant fixed effects[25] and various other SA and firm specific

[25] To include both dummies without imposing multicollinearity, we run the regressions without a global constant.

control variables (Eq. 8a). 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. 8b). The different panel regressions include pooled regressions (M1, M2), style-fixed effects regressions (M3, M4), style- and time-fixed effects regressions (M5, M6),[26] and recursive demeaning two-stage least squares regressions (M7, M8) following Pastor, Stambaugh and Taylor (2015). All variables are standardized to a unit standard deviation to ease comparisons between the coefficients. Standard errors are two-dimensionally clustered by SA and date to consider time-series and cross-sectional correlations following Petersen (2009).

$$\begin{aligned} a^{ooS,\ Carhart}_{t+1,\ t+3} = {} & \varphi_1\ Log\ TA_t \\ & + \varphi_2\ D^{Fundamental} + \varphi_3\ D^{Quant} + \varphi_4\ Net\ flow_t + \varphi_5\ a^{ooS,\ Carhart}_{t\text{-}11,\ t} \\ & + \varphi_6\ Expense\ ratio_t + \varphi_7\ Log\ Minimum\ Investment\ + \\ & + \varphi_8\ Age_t + \varphi_9\ D^{Retail} + \varphi_{10}\ D^{CIT} + \eta_{t+1,t+3} \end{aligned} \tag{8a}$$

$$\begin{aligned} a^{ooS,\ Carhart}_{t+1,\ t+3} = {} & \varphi_{1a}\ Log\ TA_t \times D^{Fundamental} + \varphi_{1b}\ Log\ TA_t \times D^{Quant} \\ & + \varphi_2\ D^{fundamental} + \varphi_3\ D^{quant} + \varphi_4\ Net\ flow_t + \varphi_5\ a^{ooS,\ Carhart}_{t\text{-}11,\ t} \\ & + \varphi_6\ Expense\ ratio_t + \varphi_7\ Log\ Minimum\ Investment\ + \\ & + \varphi_8\ Age_t + \varphi_9\ D^{Retail} + \varphi_{10}\ D^{CIT} + \eta_{t+1,t+3} \end{aligned} \tag{8b}$$

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 7. As for the control variables, the fundamentally managed SA indicator variable has a positive effect on performance, consistent with the higher average performance in Table 2. A higher expense ratio decreases future

[26] We consider style- and time-fixed effects via within group demeaning.

performance, in line with the previous literature.[27] A higher minimum investment amount increases future SA performance while a retail investor focus decreases SA performance, both consistent with better monitoring by more sophisticated and institutional investors (Evans and Fahlenbrach, 2012). Industry size (Pastor, Stambaugh and Taylor, 2015) is unrelated to SA performance.[28]

[Insert Table 8 here.]

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 7, the coefficient for fundamentals is negative and statistically and economically significant. A one standard deviation increase in Log TA is associated with a 0.185 standard deviation decrease of future performance, or equivalently, a decrease of future Carhart alpha of 0.57% per quarter. In contrast, the coefficient for quant SAs is statistically insignificant and the point estimate is close to zero.[29] The effects are significantly different from each other as indicated by the respective p-values. Moreover, the coefficient of Log TA for fundamentals is also higher in magnitude than the coefficients on all control variables except the fundamental dummy, which emphasizes its economic relevance. Repeating the regressions considering differently specified fixed effects (M3 – M6) or Pastor, Stambaugh and Taylor's (2015) approach to control for the endogeneity between size and performance (M7, M8) does not change the results materially.[30] Overall, this

[27] Similar panel regressions using future gross returns as dependent variable yields economically similar coefficients.
[28] Industry size is calculated as the sum of AUM across all US domestic equity funds and SAs available in Morningstar direct, divided by the total market value of all stocks held by such funds and SAs.
[29] A one standard deviation increase in Log TA is associated with a 0.055 standard deviation decrease of future performance or equivalently, a decrease of future quarterly Carhart alpha of 0.13%.
[30] Variables, which are constant within the SA (quant, fundamental, minimum investment amount, retail focus and CIT) are included in the regressions in their un-demeaned form. All other variables are recursively demeaned following the instructions on pg. 28-29 in Pastor, Stambaugh and Taylor (2015). The first stage results of the 2SLS regression approach are available upon request.

evidence is consistent with our hypothesis that diseconomies of scale in active management exist and are driven, in part, by the higher hierarchy and information processing costs associated with a fundamental investment process.

5 The effects of liquidity, hierarchy and information processing costs on performance

To show the important role of information processing and hierarchy costs with regard to diseconomies of scale in active asset management, we next analyze the direct effect of our hierarchy and information processing proxies on the performance of both investment strategies. Furthermore, we explicitly control for any differences in the holdings liquidity, the second channel of diseconomies of scale. Therefore, we follow Pollet and Wilson (2008) and include the log number of holdings and log ownership, defined as the number of shares held divided by the number of shares outstanding at that particular time, and changes in both variables from t-1 to t to our piecewise panel regressions.

According to Pollet and Wilson (2008) asset managers have two possible ways how they can respond to growth in total assets: They scale their existing holding positions or they diversify by adding new stocks. However, both options are not ideal and imply different kinds of costs. Larger holding positions imply higher liquidity costs or more specifically, higher market impact costs and higher flow risks. To avoid these costs of ownership, asset managers need to increase their number of holdings. However, developing new investment ideas, our definition of information processing costs, is equally costly. Either the management needs to hire new investment professionals to develop new equally good investment ideas, which would increase their hierarchy and associated hierarchy costs, or the management is forced to invest in second-best investment ideas, which would worsen their risk-return profile. Either way, the performance will probably suffer from growth in total assets.

However, this dilemma applies mainly to fundamental investors with a bottom-up investment strategy, in which every new investment decision is based on a certain level of research and the corresponding processing of soft information, similar to the description of a typical fundamental investment process shown in the beginning of the paper. In contrast, a quantitative investment strategy might be able to avoid this dilemma by following a top-down investment approach that is mainly based on hard information. As a result, quantitative asset managers have lower information processing costs. Thus, they should be able to manage more holdings and also more assets per investment professional, which might protect them from being exposed to increasing liquidity, information processing and hierarchy costs associated with growth in total assets.

5.1 Liquidity costs

To guarantee that we always use the maximum information available,[31] we first analyze each proxy separately before we combine them. Table 9 shows the results including both liquidity proxies in our panel regressions. We find a positive and statistically significant coefficient of log number of holdings for quantitative strategies and a negative but statistically insignificant coefficient for fundamental strategies. This is consistent with the consideration that quantitative strategies rely more on hard information, which enables them to manage more different assets without suffering from an increase in their information processing and their hierarchy costs. Thus, their top-down investment approach that is mainly based on hard information enables quantitative strategies to mitigate liquidity costs.

[Insert Table 9 here.]

[31] As we need detailed information regarding firm characteristics and portfolio holdings for our proxies, our subsamples vary in the numbers of observations.

The same argument explains the negative coefficient for quantitative and the positive and slightly significant coefficient of log ownership for fundamental strategies. By diversifying, quantitative strategies are able to mitigate liquidity costs, however when they scale their existing positions, it hurts their performance due to higher ownership costs. Therefore, the preferable response to asset growth for quantitative strategies should be the addition of new holdings. Fundamental investment strategies show a positive relation between log ownership and their subsequent performance. This is somewhat surprising, as it contradicts the results from Pollet and Wilson (2008) for mutual funds, who find that diversification is the smaller evil compared to scaling. However, this result might be explained by the different investor structure in SAs and mutual funds. SAs have typically a higher minimum investment 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. These kind of investors usually have a longer investment horizon which might reduce their flow risk, as flows are predictable through constant communication between manager and investor. This might enable SAs to hold larger holding positions than mutual funds.

The coefficient for changes of log number of holdings and log ownership for quantitative strategies show that scaling existing positions is better than building new positions in the short term, however in the long term, it is preferable to add new positions to avoid liquidity costs. For fundamental strategies short term changes in the log number of holdings and log ownership do not seem to have significant impact on performance.

5.2 Hierarchy and information costs

Next we analyze the effects of hierarchy costs on performance and on diseconomies of scale of both investment strategies. In a prior chapter, we showed that the top-down investment process in quantitative strategies enables them to manage two to three times as many assets per investment professional compared to fundamental strategies. To adequately consider these differences in hierarchy, we include two hierarchy proxies in our piecewise panel regressions: Managed firm assets per investment professional and the ratio of investment professionals to the total number of employees.

[Insert Table 10 here.]

The results are completely in line with our expectations, as Table 10 shows a statistically significant positive relationship between assets per investment professionals and performance for quantitative strategies and a negative and insignificant relationship for fundamental strategies. When we consider differences regarding their hierarchy in our panel regressions, we can observe that the relationship between size and performance becomes stronger and statistically significant for quantitative strategies. Thus, if we explicitly consider the source of the hierarchy cost advantage of quantitative vis-à-vis fundamental investment strategies, the remaining negative effect of total assets becomes stronger. This gets even more pronounced when we include both hierarchy proxies.

5.3 Liquidity, hierarchy and information processing costs combined

To be able to understand how all of these different proxies interact with each other, Table 11 includes all proxies combined in various model specifications.

[Insert Table 11 here.]

Overall, we can see that the effects for the hierarchy and the information processing costs remain constant and strongly significant over all model specifications. The earlier described effects for the liquidity proxies become weaker and in most specifications they are not statistically significant anymore. However, the most interesting finding is that for quantitative strategies the negative relationship between size and performance become stronger and statistically significant over all specifications, indicating that by considering liquidity, hierarchy and information processing cost proxies, we catch the general advantages of quantitative top-down strategies over fundamental bottom-up strategies. Consequently, it is necessary to consider liquidity proxies as well as hierarchy and information processing costs proxies to be able to measure the relationship between size and performance correctly.

6 Conclusion

While the recent debate surrounding diseconomies of scale in active asset management has largely centered around econometric issues, of equal importance is identify and testing the underlying economic mechanism. In this paper, we suggest information processing and hierarchy costs as a possible mechanism for diseconomies of scale and we test that mechanism by analyzing institutional separate accounts that use quantitative and fundamental investment processes. We find evidence that quantitatively managed separate accounts have less hierarchy overall and lower hierarchy costs as the total assets managed per investment professional at quantitative advisors is much higher than at fundamental advisors. We also find evidence consistent with greater use of hard information, higher information processing speed and overall lower information processing costs at quantitative SAs than at fundamental SAs. Finally, controlling for liquidity costs, we find direct evidence of diseconomies of scale for fundamental SAs, but no evidence for quantitative SAs. In a univariate sort, we find no statistically significant difference in the performance of quantitative SAs between the first and fifth quintile of size. For the fundamental SAs, however, not only is the performance difference strongly statistically significant but performance declines monotonically as the SA size increases. Repeating the analysis using a wide range of fixed-effects and recursive demeaning panel regression setting, we find no statistically significant relationship between size and quantitative SA performance, but a strong statistically and economically significant relationship between size and performance for fundamental SAs. Overall, our results suggest that information processing and hierarchy costs are a source of diseconomies of scale in asset management specifically and on firm level in general.

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

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Table 1
Summary statistics

			Standard	Percentile					
Variable	N	Mean	Deviation	10th	25th	50th	75th	90th	Skewness
Panel A: Summary statistics by SA (Quants)									
Total Assets (Mio. USD)	360	340.00	571.00	3.95	24.90	118.00	404.00	971.00	3.63
Firm Assets (Bio. USD)	351	69.70	160.00	0.46	2.51	8.43	34.30	180.00	3.14
Expense Ratio (% p.a.)	363	0.72	0.48	0.27	0.44	0.65	0.86	1.16	2.14
Min. Investment (Mio.	322	12.20	14.70	0.05	0.25	5.00	20.00	25.00	1.30
Number of Holdings (#)	349	156	158	29	71	112	197	310	3.49
Assets in Top10 Holdings	319	29	21	12	16	24	32	48	2.18
Net Flow (% p.a.)	333	13.60	32.98	-14.26	-3.89	8.42	26.58	48.93	0.34
Turnover (% p.a.)	297	110.15	77.79	27.50	60.00	92.30	135.20	235.00	1.44
Number of Managers (#)	335	2.45	1.07	1.00	1.54	2.20	3.49	4.00	0.13
Age (years)	363	6.66	3.93	2.41	3.84	5.91	8.62	11.60	1.64
Institutional focus	88	24.2%							
Retail focus	18	5.0%							
Both	222	61.2%							
Panel B: Summary statistics by SA (Fundamentals)									
Total Assets (Mio. USD)	1,399	644.00	1,170.00	9.83	48.00	187.00	677.00	1,800.00	3.62
Firm Assets (Bio. USD)	1,357	55.00	135.00	0.24	1.09	4.96	39.90	152.00	4.68
Expense Ratio (% p.a.)	1,417	0.92	0.60	0.46	0.63	0.81	0.98	1.29	2.35
Min. Investment (Mio.	1,340	7.29	10.70	0.10	0.50	3.00	10.00	25.00	2.47
Number of Holdings (#)	1,406	62	41	29	38	52	76	102	4.35
Assets in Top10 Holdings	1,306	34	13	20	25	32	40	49	1.58
Net Flow (% p.a.)	1,368	15.74	26.17	-11.59	-0.84	11.91	27.99	47.16	1.22
Turnover (% p.a.)	1,278	55.56	43.46	17.18	26.73	42.95	71.50	111.77	2.36
Number of Managers (#)	1,362	2.11	1.01	1.00	1.00	2.00	3.00	3.76	0.48
Age (years)	1,417	8.35	5.43	3.04	4.70	6.96	10.46	14.95	1.78
Institutional focus	309	21.8%							
Retail focus	144	10.2%							
Both	824	58.2%							

This table shows summary statistics for a sample of actively managed U.S. domestic equity separate accounts (SAs) from 1990/01 to 2015/12. Panel A shows SAs with a clear quantitative investment approach, Panel B reports the characteristics of SAs with a clear fundamental investment approach. 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.

Table 2
Annualized performance and risk factor coefficients of separate accounts

	MPB		CAPM		Fama-French		Carhart	
	EW	VW	EW	VW	EW	VW	EW	VW
Panel A: Quants								
Performance	0.118	-0.182	0.117	-0.263	-0.552	-0.566	-0.771*	-0.758*
(% p.a.)	(0.79)	(0.65)	(0.85)	(0.58)	(0.24)	(0.16)	(0.08)	(0.05)
Market risk	0.989***	0.996***	1.017***	0.989***	0.991***	0.989***	1.004***	0.997***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
SMB					0.209***	0.082***	0.191***	0.071***
					(0.00)	(0.00)	(0.00)	(0.00)
HML					0.113***	0.115***	0.115***	0.119***
					(0.00)	(0.00)	(0.00)	(0.00)
MOM							0.068***	0.044***
							(0.00)	(0.00)
Adj. R^2	0.913	0.950	0.847	0.890	0.915	0.944	0.924	0.950
Panel B: Fundamentals								
Performance	0.492	-0.093	0.356	-0.264	-0.048	-0.444	0.064	-0.412
(% p.a.)	(0.23)	(0.81)	(0.56)	(0.58)	(0.89)	(0.16)	(0.85)	(0.20)
Market risk	0.952***	0.975***	1.009***	1.020***	0.967***	0.989***	0.962***	0.983***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
SMB					0.268***	0.164***	0.262***	0.159***
					(0.00)	(0.00)	(0.00)	(0.00)
HML					0.044***	0.001	0.039***	-0.003
					(0.00)	(0.90)	(0.00)	(0.55)
MOM							0.001	0.003
							(0.80)	(0.19)
Adj. R^2	0.844	0.881	0.792	0.831	0.866	0.894	0.874	0.902

This table presents annualized performance and risk factor sensitivities from a sample of actively managed U.S. domestic equity SAs from 1990/01 to 2015/12. Panel A shows SAs with a clear quantitative investment approach, Panel B reports SAs with a clear fundamental investment approach. 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 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 coefficients

Variable	Quants				Fundamentals				Diff. in		
	N	mean	sd	med	N	mean	sd	med	mean	sd	median
Carhart performance	44,786	-0.06	1.40	-0.05	200,690	0.01	1.77	-0.02	-0.07***	-0.37***	-0.04***
MPB performance	34,510	0.01	1.30	0.01	172,113	0.04	1.74	0.01	-0.03***	-0.44***	0.00
Market risk (Carhart)	45,261	1.00	0.12	1.01	202,459	0.96	0.16	0.97	0.04***	-0.04***	0.04***
Market risk (MPB)	34,855	0.99	0.11	1.00	173,583	0.95	0.17	0.96	0.04***	-0.05***	0.04***
SMB	45,261	0.19	0.38	0.04	202,459	0.26	0.38	0.20	-0.07***	0.01***	-0.15***
HML	45,261	0.12	0.27	0.09	202,459	0.04	0.33	0.04	0.08***	-0.06***	0.05***
MOM	45,261	0.07	0.14	0.04	202,459	0.00	0.17	-0.01	0.07***	-0.02***	0.05***
adj. R2 (Carhart)	45,261	0.92	0.08	0.95	202,459	0.87	0.11	0.90	0.05***	-0.02***	0.04***
adj. R2 (MPB)	34,855	0.91	0.11	0.95	173,565	0.84	0.14	0.89	0.07***	-0.03***	0.06***

This table presents means, standard deviations and medians of monthly performance and risk factor sensitivities from a sample of actively managed U.S. domestic equity SAs with either a clear quantitative or a clear fundamental investment approach 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 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
Firm characteristics per employee

Variable	Pure Quants			Pure Fundamentals			Diff. in	
	N	mean	median	N	mean	median	mean	median
Firm Assets per CFA	89	2.89	0.77	492	1.05	0.53	1.84***	0.24***
Firm Assets per Client Service	72	3.21	1.34	440	1.83	0.77	1.38*	0.57***
Firm Assets per Marketing specialist	87	4.39	1.67	391	1.66	0.95	2.73***	0.72**
Firm Assets per other staff	79	1.04	0.52	474	1.22	0.32	-0.18	0.20**
Firm Assets per PF-Manager	89	2.82	1.73	537	1.44	0.62	1.38***	1.11***
Firm Assets per Research Analyst	80	3.76	1.78	426	1.13	0.63	2.63***	1.15***
Firm Assets per Trader	79	10.4	3.55	457	3.39	1.52	7.01***	2.03**

This table shows a statistic of firm assets (in billion USD) per employee of firms, managing U.S. domestic equity SAs with either a clear quantitative or a clear fundamental investment approach, from 1990/01 to 2015/12. ***, **, * indicate significantly different means (medians) from two-sided t-tests in means (Wilcoxon rank-sum tests for differences in medians) at the 1%, 5%, and 10% level, respectively.

Table 5
Impact of management changes

Variable ($t_{-12;-1}$; $t_{1;12}$)	Diff. All	Diff. Quants	Diff. Fundamentals	Diff-in-Diffs (Quants – Fundamentals)
| Carhart market beta diff |	0.182	0.142	0.191	-0.049**
| SMB beta diff |	0.293	0.132	0.326	-0.194***
| HML beta diff |	0.309	0.258	0.319	-0.062
| MOM beta diff |	0.245	0.137	0.267	-0.130***
| MPB beta diff |	0.116	0.078	0.124	-0.046***
| TrE Carhart diff |	0.483	0.395	0.501	-0.106
| TrE MPB diff |	0.490	0.400	0.508	-0.109
| Adj. R2 Carhart diff |	0.066	0.029	0.074	-0.046***
| Adj. R2 MPB diff |	0.069	0.020	0.079	-0.059***
# changes	377	73	304	
# differences in betas (Carhart)	298	51	247	
# differences in betas (MPB)	247	42	205	

This table shows the results of a difference-in-difference analysis for SAs with a clear quantitative investment approach and SAs with a clear fundamental investment approach. For each point in time, in which a manager leaves the management team (t=0), we measure the absolute differences in a wide range of production outcomes 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 production outcomes, we use differences in performance regression betas and document that changes in market betas (Carhart and MPB) as well as in risk factor betas for SMB, MOM, 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 6
Speed of information diffusion within SA firms

	# Firms	# Initial buys	Information Diffusion (*ID*) Mean	SD	Fund.-Quant	Pr(Fund. >! Quant)
Panel A. All firms with ≥ 3 SAs (147 firms)						
Pure Fundamental	63	27,188	0.6088	0.4616	-0.0404***	0.4813
Pure Quant	12	16,845	0.6491	0.4404		
Panel B. All firms with ≥ 5 SAs (58 firms)						
Pure Fundamental	21	12,882	0.5877	0.4518	-0.0678***	0.4628
Pure Quant	5	14,194	0.6554	0.4328		
Panel C. All firms with ≥ 7 SAs (29 firms)						
Pure Fundamental	5	5,602	0.5649	0.4411	-0.1049***	0.4376
Pure Quant	4	13,085	0.6698	0.4263		

This table shows measures of Information Diffusion (*ID*) following Cici, Jaspersen and Kempf (2017) within SA firms separately for firms managing fundamental and quant SAs in the period from 10/1992 to 08/2017. Higher values of *ID* denote higher information diffusion speed. *# Initial buys* denotes the number of initial buys of a stock observed in the pooled sample of all firms. *Fund.-Quant* is the difference in the means between fundamental and quant firms. *Pr(Fund. >! Quant)* denotes the probability of a random draw from the population of fundamental *ID*s is higher than a random draw from the population of quant *ID*s. ***, **, * denotes statistical significance on the 1%, 5%, 10% level, respectively.

Table 7

Performance of quintiles based on lagged size

	All		Quants		Fundamentals	
Total assets$_{t-1}$	Carhart	MPB	Carhart	MPB	Carhart	MPB
Low	0.59*	1.00**	-0.80	0.32	0.78**	1.05**
	(0.09)	(0.01)	(0.15)	(0.56)	(0.03)	(0.01)
2	-0.10	0.37	-0.66	0.02	0.16	0.44
	(0.80)	(0.40)	(0.18)	(0.97)	(0.69)	(0.35)
3	-0.29	-0.03	-0.68	-0.07	-0.27	-0.09
	(0.43)	(0.95)	(0.19)	(0.89)	(0.48)	(0.84)
4	-0.46	0.04	-0.78*	-0.17	-0.29	0.21
	(0.22)	(0.93)	(0.07)	(0.70)	(0.48)	(0.68)
High	-0.75**	-0.20	-0.84*	-0.27	-0.68**	-0.22
	(0.01)	(0.61)	(0.06)	(0.54)	(0.04)	(0.61)
All	-0.20	0.24	-0.75*	-0.03	-0.06	0.28
	(0.55)	(0.56)	(0.09)	(0.95)	(0.87)	(0.52)
High-low	-1.33***	-1.19***	-0.02	-0.57	-1.45***	-1.26***
	(0.00)	(0.00)	(0.95)	(0.16)	(0.00)	(0.00)

This table presents annualized Carhart and MPB performances for quarterly rebalanced size-quintile portfolios from a sample of actively managed U.S. domestic equity SAs with either a clear quantitative or a clear fundamental investment approach from 1990/01 to 2015/12. Carhart performance for SA *i* in month *t* is the difference between its actual net 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*. ***, **, 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 8
Panel regressions of SA performance

	M1	M2	M3	M4	M5	M6	M7	M8
Log TA	-0.038***		-0.036***		-0.040***		-0.709***	
	(0.00)		(0.00)		(0.00)		(0.00)	
Log TA * Quant		-0.055		-0.049		-0.059*		-0.073
		(0.16)		(0.13)		(0.06)		(0.17)
Log TA * Fundamental		-0.186***		-0.177***		-0.185***		-0.401***
		(0.00)		(0.00)		(0.00)		(0.00)
Quant Dummy	-0.036	0.121	-0.033	0.107	-0.033	0.136	-0.113	-0.523***
	(0.32)	(0.26)	(0.25)	(0.28)	(0.24)	(0.16)	(0.51)	(0.00)
Fundamental Dummy	0.065***	0.430***	0.061***	0.408***	0.062***	0.424***	-0.016	-0.362**
	(0.00)	(0.00)	(0.01)	(0.00)	(0.00)	(0.00)	(0.90)	(0.01)
Industry Size	0.002	0.002	0.002	0.002	-	-	0.142*	0.099
	(0.94)	(0.93)	(0.94)	(0.93)			(0.05)	(0.18)
Net flow	0.009*	0.009	0.010*	0.009*	0.013***	0.012**	-0.138**	0.017
	(0.09)	(0.11)	(0.07)	(0.09)	(0.01)	(0.01)	(0.05)	(0.78)
Firm TA	-0.007	-0.008	-0.005	-0.005	-0.005	0.000	-0.066	-0.098**
	(0.41)	(0.37)	(0.56)	(0.57)	(0.52)	(0.98)	(0.14)	(0.03)
Lagged Alpha (1-year)	-0.023	-0.023	-0.023	-0.023	-0.023	-0.019	-0.489***	-0.438***
	(0.45)	(0.45)	(0.44)	(0.44)	(0.44)	(0.53)	(0.00)	(0.00)
Expense ratio (% TA p.a.)	-0.035***	-0.035***	-0.036***	-0.036***	-0.036***	-0.039***	-0.159***	-0.100*
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.05)
Log Min. investment	0.023**	0.019*	-0.018*	0.017	0.014	0.011	-0.069	-0.126**
	(0.04)	(0.09)	(0.10)	(0.12)	(0.14)	(0.23)	(0.27)	(0.04)
Age	-0.018*	-0.020**	-0.057**	-0.020**	-0.007	-0.010*	0.511***	0.282***
	(0.09)	(0.04)	(0.03)	(0.05)	(0.20)	(0.05)	(0.00)	(0.00)
Retail Dummy	-0.058**	-0.058**	0.022	-0.057**	-0.055**	-0.053**	-0.189	-0.281
	(0.03)	(0.02)	(0.42)	(0.03)	(0.02)	(0.03)	(0.33)	(0.15)
CIT Dummy	0.020	0.016	0.021	0.018	0.020	0.018	-0.154	-0.446
	(0.54)	(0.63)	(0.42)	(0.52)	(0.44)	(0.50)	(0.60)	(0.11)
p-Val: Log TA*Quant–Fund=0		0.01***		0.00***		0.01***		0.00***
Style-fixed effects	No	No	Yes	Yes	Yes	Yes	No	No
Time-fixed effects	No	No	No	No	Yes	Yes	No	No
Recursive demeaning (PST 2015)	No	No	No	No	No	No	Yes	Yes
Adjusted R^2	0.01	0.00	0.01	0.01	0.06	0.06	0.00	0.00
N	57,303	57,303	57,303	57,303	57,303	57,303	49,473	49,473

This table reports panel regressions of Separate account (SA) performance on their total assets. 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 9
Liquidity costs

	M1	M2	M3	M4	M5	M6	M7	M8	M9	M10
Log No Holdings * Quant					0.074*	0.081*			0.075*	0.081*
					(0.08)	(0.06)			(0.07)	(0.06)
Log No Holdings * Fundamental					-0.008	-0.013			-0.014	-0.020
					(0.86)	(0.78)			(0.77)	(0.67)
Log Ownership * Quant							-0.023	-0.028*	-0.020	-0.025
							(0.16)	(0.10)	(0.22)	(0.14)
Log Ownership * Fundamental							0.027	0.029*	0.029*	0.031*
							(0.11)	(0.09)	(0.09)	(0.08)
Change Log No Holdings * Q		-0.007		-0.007		-0.009*				-0.009*
		(0.15)		(0.17)		(0.07)				(0.08)
Change Log No Holdings * F		0.006		0.006		0.007				0.007
		(0.46)		(0.46)		(0.43)				(0.41)
Change Log Ownership * Q			0.010**	0.010**				0.012**		0.012**
			(0.02)	(0.03)				(0.01)		(0.02)
Change Log Ownership * F			-0.002	-0.002				-0.006		-0.006
			(0.73)	(0.73)				(0.40)		(0.39)
Log TA * Quant	-0.061	-0.060	-0.061	-0.060	-0.093	-0.095	-0.020	-0.011	-0.058	-0.051
	(0.26)	(0.27)	(0.26)	(0.27)	(0.14)	(0.13)	(0.75)	(0.85)	(0.43)	(0.49)
Log TA * Fundamental	-0.189***	-0.189***	-0.189***	-0.189***	-0.186***	-0.184***	-0.236***	-0.238***	-0.234***	-0.235***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Quant Dummy	0.201	0.200	0.203	0.202	0.081	0.067	0.018	-0.019	-0.080	-0.130
	(0.20)	(0.21)	(0.20)	(0.20)	(0.59)	(0.65)	(0.93)	(0.93)	(0.68)	(0.51)
Fundamental Dummy	0.437***	0.437***	0.437***	0.436***	0.447***	0.454***	0.572***	0.579***	0.598***	0.616***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Style-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R2	0.06	0.06	0.06	0.06	0.06	0.06	0.06	0.06	0.06	0.06
N	30,934	30,934	30,934	30,934	30,934	30,934	30,934	30,934	30,934	30,934

This table reports panel regressions of Separate account (SA) performance on their total assets and liquidity proxies following Pollet and Wilson (2008). 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 10
Hierarchy and Information Costs

	M1	M2	M3	M4
Assets per Inv.-Prof. * Quant		0.017**		0.019**
		(0.02)		(0.01)
Assets per Inv.-Prof. * Fundamental		-0.015		-0.014
		(0.11)		(0.11)
Inv.-Prof. Ratio * Quant			0.007	0.016
			(0.53)	(0.16)
Inv.-Prof. Ratio * Fundamental			0.009	0.006
			(0.58)	(0.72)
Log TA * Quant	-0.099	-0.113*	-0.101*	-0.121**
	(0.10)	(0.06)	(0.09)	(0.05)
Log TA * Fundamental	-0.188***	-0.178***	-0.187***	-0.179***
	(0.00)	(0.00)	(0.00)	(0.00)
Quant Dummy	0.321*	0.340*	0.311*	0.319*
	(0.08)	(0.06)	(0.09)	(0.08)
Fundamental Dummy	0.460***	0.447***	0.443***	0.438***
	(0.00)	(0.00)	(0.00)	(0.00)
Controls	Yes	Yes	Yes	Yes
Style-fixed effects	Yes	Yes	Yes	Yes
Time-fixed effects	Yes	Yes	Yes	Yes
Adjusted R2	0.06	0.06	0.06	0.06
N	20,202	20,202	20,202	20,202

This table reports panel regressions of Separate account (SA) performance on their total assets and proxies for hierarchy and information processing costs. 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 11
Liquidity, Hierarchy and Information Processing Costs

	M1	M2	M3	M4	M5	M6	M7	M8	M9	M10
Assets per Inv-.Prof * Q		0.014**		0.016**	0.015**	0.015**	0.016**	0.016**	0.015**	0.015**
		(0.04)		(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.04)
Assets per Inv-.Prof * F		-0.017*		-0.017*	-0.017*	-0.017*	-0.017*	-0.016*	-0.016*	-0.016
		(0.08)		(0.08)	(0.08)	(0.08)	(0.09)	(0.09)	(0.09)	(0.10)
Inv-.Prof. Ratio * Q			0.009	0.018	0.019	0.019	0.019	0.018	0.020*	0.019*
			(0.38)	(0.12)	(0.10)	(0.10)	(0.11)	(0.11)	(0.09)	(0.09)
Inv-.Prof. Ratio * F			0.007	0.004	0.004	0.004	0.002	0.002	0.002	0.002
			(0.67)	(0.82)	(0.81)	(0.81)	(0.90)	(0.92)	(0.90)	(0.92)
Log No. Holdings * Q					0.047	0.054			0.053	0.062
					(0.32)	(0.27)			(0.27)	(0.22)
Log No. Holdings * F					-0.013	-0.016			-0.020	-0.025
					(0.84)	(0.81)			(0.75)	(0.70)
Log Ownership * Q							0.014	0.010	0.013	0.009
							(0.52)	(0.65)	(0.53)	(0.67)
Log Ownership * F							0.022	0.027	0.024	0.029
							(0.22)	(0.14)	(0.18)	(0.12)
Change holdings * Q						-0.010				-0.010
						(0.22)				(0.21)
Change holdings * F						0.003				0.003
						(0.78)				(0.74)
Change Ownership * Q								0.010*		0.010*
								(0.08)		(0.08)
Change Ownership * F								-0.015		-0.016
								(0.11)		(0.11)
Log TA * Quant	-0.139*	-0.149*	-0.143*	-0.159**	-0.172**	-0.172**	-0.184**	-0.178**	-0.198**	-0.192*
	(0.08)	(0.06)	(0.07)	(0.05)	(0.05)	(0.05)	(0.04)	(0.04)	(0.04)	(0.05)
Log TA * Fundamental	-0.241***	-0.229***	-0.241***	-0.230***	-0.227***	-0.226***	-0.269***	-0.276***	-0.267***	-0.274***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Quant Dummy	0.550**	0.555**	0.538**	0.536**	0.432*	0.414*	0.651**	0.622**	0.531**	0.477*
	(0.03)	(0.03)	(0.04)	(0.04)	(0.06)	(0.07)	(0.03)	(0.04)	(0.04)	(0.07)
Fundamental Dummy	0.579***	0.566***	0.566***	0.560***	0.580***	0.582***	0.678***	0.702***	0.718***	0.752***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Style-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R2	0.06	0.06	0.06	0.06	0.06	0.06	0.06	0.06	0.06	0.06
N	17,948	17,948	17,948	17,948	17,948	17,948	17,948	17,948	17,948	17,948

This table reports panel regressions of Separate account (SA) performance on their total assets and proxies for liquidty, hierarchy and information processing costs. 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.