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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 self-identified, we find that fundamental SAs exhibit greater diseconomies of scale than quantitative SAs. Looking at liquidity costs, we find that quantitative SAs hold more diversified portfolios of higher liquidity stocks than fundamental SAs, thereby reducing their expected liquidity costs. 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 helps to explain the differences in diseconomies of scale.

I. 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.[1] Since that

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[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

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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. 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 (2021)) find a less economically significant relationship between size and performance than previously suggested.

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 different mechanisms for diseconomies of scale including liquidity (the increased trading and price impact costs associated with investing a larger pool of assets),[3] information processing (the increased difficulty of timely identification of 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 are involved in the investment process). The prior literature has suggested these three plausible (and plausibly interrelated) dimensions as the underlying economic mechanisms.[4]

In this article, we revisit the issue of diseconomies of scale, but contrast two different investment approaches, quantitative and fundamental, that likely differ on these dimensions. Using a database of separate accounts (SAs) from 1990 to 2018 as a laboratory, we test for differences in diseconomies of scale and differences in the channels across the two approaches.[5] To illustrate why fundamental strategies may exhibit different liquidity, information processing, and hierarchy 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

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

[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 (2020) 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]For example, Chen et al. (2004), Pollet and Wilson (2008), and Pastor et al. (2020).

[5]One important reason for using the separate account data, is the disclosure of the investment approach, quantitative or fundamental, by the manager, which is not available for mutual funds in the Morningstar database.

> 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.[6]

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 affect liquidity costs. For example, because the security selection process in a fundamental strategy is more time consuming, the investment response to inflows may be more likely to scale existing holdings as opposed to diversifying into new positions (e.g., Pollet and Wilson (2008)), increasing liquidity costs. At the same time, this slower decision-making process may also result in decreased turnover, possibly decreasing liquidity costs.

In contrast, consider 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.[7]

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, quant strategies may have lower hierarchy and information processing costs. These lower hierarchy/information processing costs may translate into more stocks held and less concentrated positions, consistent with lower liquidity costs, as a larger number of potential investments may be quickly analyzed and selected by the algorithm. At the same time, the rapid decision-making process may generate higher turnover, consistent with higher liquidity costs.

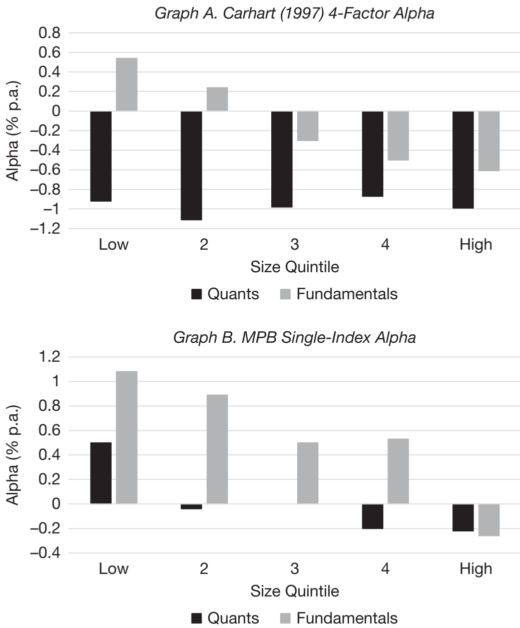
To begin our empirical analysis, we first examine whether or not diseconomies of scale differ across quant and fundamental SAs. Sorting SAs by the quintile of their total invested assets (TA), Figure 1 depicts a monotonically decreasing risk-adjusted performance for fundamental SAs with a statistically and economically

[6] *Source:* Morningstar Direct.
[7] *Source:* Morningstar Direct.

FIGURE 1

Alpha/Risk-Adjusted Annualized Performance by Lagged Size Quintile

Figure 1 shows the alphas of quarterly rebalanced size quintile portfolios of quantitative and fundamental US domestic separate accounts (SAs) in the period from Jan. 1990 to Dec. 2018. Alphas are denoted in % p.a. Black bar charts show quant SAs, gray bars show fundamental SAs. Graph A shows alphas measured against the "academic" Carhart (1997) 4-factor model. Graph B shows alphas measured against the manager preferred benchmark reported in Morningstar Direct.



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 flow, expense ratio, and manager ability 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,[8] the difference in diseconomies of scale is striking. To better understand the potential channels through which these two investment approaches differ, we

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

use the framework proposed by Pastor et al. (2020) – hereafter PST. PST models how fund size may affect performance as part of a system of interrelated investment constraints, that is, "mutual fund tradeoffs," across fund size, turnover, fees, and portfolio liquidity. They further decompose portfolio liquidity into stock liquidity (i.e., the 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). In modeling this relationship, they show that a fund faces greater diseconomies of scale if it trades a larger portion of the portfolio or holds a portfolio of less liquid securities.

Examining the tradeoffs among the different dimensions proposed by PST, we find that quantitative SAs hold more liquid portfolios consistent with the lower observed diseconomies of scale. The higher portfolio liquidity of quantitative SAs manifests both through holding higher liquidity stocks and more diverse portfolios. Decomposing portfolio diversification into its two components – coverage and balance – we find that quantitative SAs have 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. At the same time, quant SAs also have higher fund turnover than fundamental SAs. The lower observed diseconomies of scale for quant SAs suggests that the effects of this higher turnover are outweighed by the effects of portfolio liquidity.

While on average quantitative SAs exhibit greater portfolio liquidity, we also examine how portfolio liquidity changes as SA size increases for both quantitative and fundamental SAs. We find that diversification increases with increased size in a similar fashion for both investment strategies, but stock liquidity declines at a faster rate for quantitative SAs relative to fundamentals. 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. Overall, this analysis provides important evidence regarding the equilibrium tradeoffs that two distinct investment strategies, quant and fundamental, make in implementing their investment decisions.

As we discussed above, the overall differences in liquidity between quant and fundamental SAs may be indirect evidence of differences in the information processing and hierarchy costs. In thinking about how to more directly examine these potential costs, the industrial organization literature provides some insight. 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.

While the literature's sparse treatment of the information processing and hierarchy cost mechanisms attests to the difficulty in measuring these two dimensions empirically, using the insights of these papers 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).[9] If quant SA firms use hard information to a higher

[9]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

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degree and their investment decision process involves fewer or even no feedback loops, 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.

Second, we look at the hard versus soft information content of the investment decisions made by quantitative versus 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 potentially proxies for the greater use of systematic or hard information by the manager. Across both models we employ (CAPM using the manager-preferred benchmark "MPB" 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, consistent with an unchanged quantitative model between managers playing an important role in the investment decision.

As a final step, we follow the theoretical framework proposed by PST to structure an empirical test of the role of differential liquidity costs (as well as proxies for information processing/hierarchy costs) in the observed differences in diseconomies of scale between quant and fundamental strategies. Controlling for manager skills via fixed effects, the baseline regression still shows evidence of higher diseconomies of scale for fundamental SAs. However, once we control for the PST proscribed liquidity measures and the broad proxies for information processing/hierarchy costs, diseconomies of scale between the two investment approaches are statistically indistinguishable. This is important because it provides a key insight: differences in diseconomies of scale associated with two very different investment approaches, quant and fundamental, are entirely explained by liquidity fund tradeoffs and information processing/hierarchy costs. This important insight can help guide future examination of diseconomies of scale in asset management. Instead of relying on a crude proxy, fund size, researchers should focus on the channels examined here. Additionally, differentiating between quant and fundamental investment approaches, a distinction which the prior literature often ignores, is important when examining fund tradeoffs.

Two recent papers analyze the performance of quantitative versus fundamental investment strategies. Harvey, Rattray, Sinclair, and Van Hemert (2017) examine the performance of discretionary (fundamental) versus systematic (quantitative) hedge funds from 1996 to 2014. They find that discretionary equity hedge funds do

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.

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 (2020) 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 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. Second, we empirically test the fund tradeoff equilibrium proposed by PST for each strategy. Consistent with anecdotal evidence that the two strategies are likely to differ in their trading implementation, we find unique fund tradeoff patterns for each style that are still consistent with the equilibrium tradeoffs proposed by PST. Moreover, we also find that accounting for the unique PST tradeoffs of quant and fundamental strategies helps, in part to explain the observed differences in diseconomies of scale. Third, we examine empirically the related issue of information processing and hierarchy costs and find faster information diffusion and greater use of hard information by quantitative strategies.

The paper proceeds as follows: Section II introduces our data set, explains how we measure performance and presents summary statistics. Section III examines performance and diseconomies of scale differences between quant and fundamental SAs. Section IV tests two possible channels for these differences, liquidity costs and hierarchy/information processing costs. Section V concludes.

II. Data and Performance Measurement

A. Data and Sample Construction

We obtain survivorship bias-free data on actively managed U.S. domestic equity SAs over the period of 1990 to 2018 from Morningstar Direct.[10] We recognize as "SAs" all separately managed accounts (SMAs) and collective investment trusts (CITs) following Elton et al. (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 et al. (2014) we exclude index SAs both by their names and by an R^2 greater than or equal to 99% from a performance regression against the SA's "best-fit benchmark," which we

[10]Elton, Gruber, and Blake (2014), who use a similar data set 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.

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identify by regressions of the SAs against a wide range of stock market indices.[11] We exclude "specialty" SAs both by their names and by stock market betas below 0.2 from the performance regression. Because our analysis 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.[12] 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 investment advisor level data. We also obtain quarterly SA level portfolio holdings in the subperiod from 2001 to 2018 for the majority of our sample SAs.

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 ($386 m vs. $740 m) 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 has an institutional focus (24.2%–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 flows of 9.93% for quants and 11.37% for fundamentals. We calculate quarterly implied percentage net flow (hereafter "flow") from quarterly TA and quarterly returns as in Sirri and Tufano (1998) following equation (2). This positive average flow attests to the growing economic importance of SAs over the past 29 years.

$$\text{(1)} \qquad \text{FLOW}_{i,q} = \frac{\text{TA}_{i,q} - \text{TA}_{i,q-1}\left(1 + R_{i,q}\right)}{\text{TA}_{i,q-1}}.$$

Panel C of Table 1 shows by-year market value-weighted summary statistics on the stock holdings of both 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 approaches invest in a very similar stock universe.

B. Performance

To measure risk-adjusted SA performance, we use two performance models: the CAPM vis-à-vis the manager-preferred benchmark (MPB; e.g., Jensen (1968),

[11] 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."

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

TABLE 1

Summary Statistics

Table 1 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 the 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.

				Percentile					
	N	Mean	SD	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 ($M)	322	12.20	14.70	0.05	0.25	5.00	20.00	25.00	1.30
No. of holdings (#)	350	155	151	32	72	113	194	301	3.48
Assets in top 10 Hldgs (%)	343	29	21	12	16	24	31	48	2.20
NET_FLOW (% p.a.)	348	9.93	29.16	−15.20	−4.35	7.60	21.19	40.24	−0.33
TURNOVER_RATIO (% p.a.)	311	110.33	76.16	26.67	64.39	90.78	131.77	239.53	1.43
No. of managers (#)	350	2.39	1.14	1.00	1.49	2.18	3.48	4.00	−0.11
AGE (years)	363	7.66	4.21	2.96	4.46	7.12	9.92	12.79	1.31
INSTITUTIONAL_FOCUS	88	24.2%							
RETAIL_FOCUS	18	5.0%							
INSTITUTION_AND_RETAIL_FOCUS	222	61.2%							
Panel B. Summary Statistics by SA (Fundamentals)									
TOTAL_ASSETS ($M)	1402	740.00	1390.00	12.50	56.40	211.00	765.00	1980.00	3.97
FIRM_ASSETS ($B)	1380	60.50	147.00	0.48	1.65	5.99	43.00	158.00	4.60
EXPENSE_RATIO (% p.a.)	1417	0.93	0.59	0.48	0.64	0.81	0.97	1.35	2.40
MINIMUM_INVESTMENT ($M)	1340	7.29	10.70	0.10	0.50	3.00	10.00	25.00	2.47
No. of holdings (#)	1408	62	40	30	38	53	76	101	4.30
Assets in top 10 Hldgs (%)	1378	34	13	20	25	32	40	50	1.57
NET_FLOW (% p.a.)	1386	11.37	22.14	−12.02	−2.38	8.55	22.87	39.25	0.71
TURNOVER_RATIO (% p.a.)	1293	53.71	41.52	16.81	25.95	41.75	69.31	105.99	2.23
No. of managers (#)	1389	2.10	1.01	1.00	1.00	2.00	3.00	3.65	0.34
AGE (years)	1417	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_AND_RETAIL_FOCUS	824	58.2%							

Panel C. Market Value-Weighted Common Stock Holdings

	# SAs		% Holdings				# SAs		% Holdings		
Year	*Q*	*F*	Common	*Q* Only	*F* Only	Year	*Q*	*Q*	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						

Elton et al. (2014)) and the Carhart (1997) model.[13] The models are based on the following regressions (equation (2) and equation (3)):

$$\text{ER}_{i,t} = \alpha_i^{\text{MPB}} + \beta_i^{\text{MPB}} \text{ER}_{\text{MPB},t} + \varepsilon_{i,t}, \tag{2}$$

$$\text{ER}_{i,t} = \alpha_i^{\text{CARHART}} + \beta_i^{\text{MKT}} \text{ER}_{\text{MKT},t} + \beta_i^{\text{SMB}} \text{SMB}_t + \beta_i^{\text{HML}} \text{HML}_t + \beta_i^{\text{UMD}} \text{MOM}_t + \varepsilon_{i,t}, \tag{3}$$

[13]A previous version of the paper included the analysis with the traditional CAPM 1-Factor and Fama and French (1993) 3-Factor models with similar results.

where $\text{ER}_{i,t}$ 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, $\text{ER}_{\text{MKT},t}$ is the monthly market excess return, β_i^{MKT} is the SA's sensitivity to the market, $\text{ER}_{\text{MPB},t}$ 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 Carhart model, we use the common risk factors provided via Kenneth R. French's data library.[14] For the MBPs, we use 74 different self-stated benchmarks indices for which we obtain monthly returns from Morningstar Direct.[15] Using the MPB implicitly accounts for the fact that sophisticated investors may choose 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, $\alpha_{i,t}^{\text{OOS}}$, for each SA i in each month t. Specifically, the style benchmark return (equation (4a)) 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 ($F_{k,t}$).[16] The SAs out-of-sample performance in month t is the difference between the SAs excess return ($\text{ER}_{i,t}$) and the style benchmark return (equations (4a) and (4b)). To account for outliers and estimation errors in the rolling regressions, we winsorize the out-of-sample performance at the 1st and 99th percentiles.

$$\text{(4a)} \qquad \text{STYLE\_RETURN}_{i,t} = \sum_{k=1}^{K} \beta_{i,t-1}^{k} F_{k,t}.$$

$$\text{(4b)} \qquad \alpha_{i,t}^{\text{OOS}} = \text{ER}_{i,t} - \text{STYLE\_RETURN}_{i,t}.$$

Table 2 reports annualized average out-of-sample alphas as well as in-sample risk-factor loadings and R^2 statistics for both models, separately for quants (Panel A) and fundamentals (Panel B). "EW" denotes equal-weighted and "VW" denotes size-weighted results across SAs.[17]

Looking first at the 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 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

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

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

[16] Repeating the analysis with alternative sample window lengths of 12 and 36 months yields economically similar results.

[17] 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.

TABLE 2

Annualized Performance and Risk Factor Loadings

Table 2 presents annualized alpha/risk-adjusted performance and risk factor sensitivities from a sample of actively managed U.S. domestic equity SAs from Jan. 1990 to Dec. 2018. 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) 1-factor or the Carhart (1997) 4-factor model with 24-month rolling window regressions. ***, **, and * denote significantly different means from two-sided *t*-tests in means at the 1%, 5%, and 10% level, respectively. *p*-values are given in parentheses.

	MPB		Carhart	
	EW	VW	EW	VW
Panel A. Quants				
Alpha	0.040	−0.254	−0.954**	−0.884**
	(0.92)	(0.50)	(0.01)	(0.01)
MKT	0.987***	0.997***	0.997***	0.992***
	(0.00)	(0.00)	(0.00)	(0.00)
SMB			0.194***	0.077***
			(0.00)	(0.00)
HML			0.110***	0.117***
			(0.00)	(0.00)
MOM			0.065***	0.041***
			(0.00)	(0.00)
Adj. R^2	0.905	0.944	0.921	0.945
Panel B. Fundamentals				
Alpha	0.368	−0.153	−0.142	−0.485*
	(0.32)	(0.67)	(0.63)	(0.09)
MKT	0.947***	0.969***	0.959***	0.979***
	(0.00)	(0.00)	(0.00)	(0.00)
SMB			0.257***	0.149***
			(0.00)	(0.00)
HML			0.035***	−0.008*
			(0.00)	(0.08)
MOM			−0.004*	−0.002
			(0.09)	(0.42)
Adj. R^2	0.835	0.868	0.874	0.900

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 suggest 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.

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.

III. Differences in the Impact of Size on Performance

A. 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 Chen et al. (2004) in calculating the average performance of quarterly rebalanced size-quintile portfolios. Table 3 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.). Another indication that diseconomies of scale differ across quant and fundamental SAs.

TABLE 3

Annualized Performance by Lagged Size Quintile

Table 3 presents annualized Carhart and manager-preferred benchmark (MPB) alpha/risk-adjusted performance for quarterly rebalanced size-quintile portfolios (total assets, TA) from a sample of actively managed U.S. domestic equity SAs with either a quantitative or fundamental investment approach from Jan. 1990 to Dec. 2018. 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%, and 10% level, respectively. *p*-values are given in parentheses.

	All		Quants		Fundamentals	
TA_{t-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)

B. Panel Regressions of Future Performance

While the quintile sorting in Table 3 is compelling because of its simplicity, it is possible that this univariate result stems from other sources than differences in size. Therefore, Table 4 reports a wide range of panel regression approaches, where we explain quarterly future net Carhart model risk-adjusted performance ($a_{t+1,t+3}^{\text{OOS,CARHART}}$) with lagged SA size (ln(TA)), fundamental and quant investment style fixed effects[18], and various other SA and firm control variables (equation (5a)). Further, to separate the effects of size on performance for quant and fundamental SAs, we include interaction terms between size and indicator variables for quant and fundamental SAs (equations (5a) and (5b))). The different panel regressions include pooled regressions (columns 1, 2), style-fixed effects regressions (columns 3, 4),

TABLE 4

Panel Regressions of Performance

Table 4 reports panel regressions of SA alpha/risk-adjusted performance on SA size (ln(TA)) for of actively managed U.S. domestic equity SAs from Jan. 1990 to Dec. 2018. 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%, and 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.

Dependent: $a_{i,t+1,t+3}^{\text{OOS,CARHART}}$	1	2	3	4	5	6	7	8	9	10
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): $D^{\text{FUNDAMENTAL}}$		−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)
$D^{\text{FUNDAMENTAL}}$	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)
$\alpha_{i,t-11,t}^{\text{OOS,CARHART}}$	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	−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)
ln(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
Adj. 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

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

style- and time-fixed effects regressions (columns 5, 6), SA-fixed effects regressions (columns 7, 8)[19] and Zhu (2018) recursive demeaning two-stage least squares regressions to control for the endogeneity between size and performance (columns 9, 10). 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 account for both potential time-series and cross-sectional correlations.

$$
\begin{aligned}
\text{(5a)}\quad a_{i,t+1,t+3}^{\text{OOS,CARHART}} = {} & \varphi_1 \ln(\text{TA})_t \\
& + \varphi_2 D_i^{\text{FUNDAMENTAL}} + \varphi_3 D_i^{\text{QUANT}} + \varphi_4 \text{NET\_FLOW}_{i,t} + \varphi_5 \alpha_{i,t-11,t}^{\text{OOS,CARHART}} \\
& + \varphi_6 \text{EXPENSE\_RATIO}_{i,t} + \varphi_7 \ln(\text{MINIMUM\_INVESTMENT})_i \\
& + \varphi_8 \ln(\text{FIRM\_TA})_{i,t} + \varphi_9 \text{AGE}_{i,t} + \varphi_{10} D_{\text{i}}^{\text{RETAIL}} + \varphi_{11} D_i^{\text{CIT}} + \eta_{i,t+1,t+3}.
\end{aligned}
$$

$$
\begin{aligned}
\text{(5b)}\quad a_{i,t+1,t+3}^{\text{OOS,CARHART}} = {} & \varphi_{1a} \ln(\text{TA})_t : D_i^{\text{FUNDAMENTAL}} + \varphi_{1b} \ln(\text{TA})_t : D_i^{\text{QUANT}} \\
& + \varphi_2 D_i^{\text{FUNDAMENTAL}} + \varphi_3 D_i^{\text{QUANT}} + \varphi_4 \text{NET\_FLOW}_{i,t} + \varphi_5 \alpha_{i,t-11,\text{t}}^{\text{OOS,CARHART}} \\
& + \varphi_6 \text{EXPENSE\_RATIO}_{i,t} + \varphi_7 \ln(\text{MINIMUM\_INVESTMENT})_i \\
& + \varphi_8 \ln(\text{FIRM\_TA})_{i,t} + \varphi_9 \text{AGE}_{i,t} + \varphi_{10} D_i^{\text{RETAIL}} + \varphi_{11} D_i^{\text{CIT}} + \eta_{i,t+1,t+3}.
\end{aligned}
$$

The first column 1 reports an overall negative effect of ln(TA) on future performance, in line with the univariate sorting for all SAs in Table 3. 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 Table 2. Higher expense ratios are associated with lower future performance, in line with the previous literature.[20] 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)).

The second column 2 shows separate coefficients on ln(TA) for quant and fundamental SAs. Consistent with our previous result on the separate size quintile sorting in Table 3, the coefficient for fundamental SAs is negative and both statistically and economically significant. A one standard deviation increase in ln(TA) is associated with a decrease of future Carhart alpha of 0.832% per quarter. In contrast, the coefficient for quant SAs is statistically insignificant and the point estimate is close to zero. 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 (columns 3–6) does not change this finding materially.

While these specifications include a number of important controls, one important dimension they fail to account for is the skill of the manager. To address this, we include SA fixed effects in specifications 7 through 10. Considering

[19]We consider fixed effects via within group demeaning.

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

constant cross-sectional differences (7, 8)[21] and recursively demeaned cross-sectional differences between SAs (9, 10)[22] to account for potential endogeneity in the relationship between SA size and performance reveals that quant SAs also show diseconomies of scale but are 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 in the quant investment process.

IV. Diseconomies of Scale Channels

A. Fund Tradeoffs and Liquidity Costs

As discussed in the introduction, there are three related channels put forward by the literature to rationalize the existence of diseconomies of scale in active investment management: liquidity, hierarchy, and information processing costs. In this subsection, we follow the framework proposed by PST to consider potential tradeoffs between portfolio liquidity and turnover, expense ratio, and fund size and how those tradeoffs may differ for quant and fundamental SAs.

We follow the methodology laid out in PST to estimate "portfolio liquidity" as well as its components "stock liquidity" and "diversification," with further subcomponents "balance" and "coverage," from quarterly holdings data. We also use the holdings data to construct the "turnover" variable following the PST definition as the "dollar amount traded divided by [TA]." Note, that this turnover measure differs from the SEC turnover definition (the minimum of sales and purchases divided by TA) that is, intended to measure "discretionary" trading only and abstract from flow-related trading. In addition to capturing total turnover as assumed in the PST model, using holdings data to estimate the dollar volume of purchases and sales allows us to match the investment period for turnover variable to the other liquidity measures.[23]

Panel A of Table 5 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 approaches. Panel B of Table 5 mirrors PST's Table 4 by explaining the components of portfolio liquidity. Panel C of Table 5 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.

[21]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.

[22]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 et al. (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.

[23]Repeating the analysis with SEC turnover yields similar results.

TABLE 5

Separate Account Tradeoffs

Table 5 reports the results from panel regressions with the Pastor et al. (2020) – portfolio liquidity components as dependent variables in the period from Jan. 2001 to Dec. 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-by-quarter fixed effects (FEs) and cluster by separate account (SA). ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively.

	Panel A. Portfolio Liquidity				*Panel B. Portfolio Liquidity Components*				*Panel C. Further SA Tradeoffs*			
	1	2	3	4	DIVERSIF.	COVERAGE	BALANCE	STOCK_LIQ.	EXPENSE_RATIO		TURNOVER_RATIO	
ln(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)
ln(TA): $D^{FUNDMENTAL}$	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_R.: 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_R.: 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_R.: 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_R: 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_LIQ.: 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_LIQ.: 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)					
DIVERSIF.: D^Q			0.255***					0.001		0.001		0.005
			(0.00)					(0.87)		(0.90)		(0.72)
DIVERSIF: 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
Adj. R^2	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

Fundamental SAs have lower portfolio liquidity on average, as indicated by the significantly negative coefficient on the respective dummy variable (Panel A). This is manifested, in part, through lower diversification, lower coverage, lower balance, and lower stock liquidity, at least relative to quants (Panel B). This average difference is a first indication, that the liquidity channel affects fundamentals more strongly.

Considering the dynamic relationship between liquidity and SAs size, the positive and significant coefficient on ln(TA) interacted with the fundamental indicator ($D^{\text{FUNDAMENTAL}}$), which shows that fundamental SAs increase portfolio liquidity as their size grows (Panel A). This is consistent with the tradeoff hypothesized by PST, as larger funds pursuing a more liquidity demanding strategy have to make larger trades, the equilibrium requires an increase in the liquidity of their portfolio. Quants, however, do not seem to face this tradeoff in overall portfolio liquidity – but in Panel B, we examine the components of overall portfolio liquidity, which gives us more insight into the quant tradeoffs. There we see that both quants and fundamentals increase diversification in reaction to growth, consistent with PST. Quants do this primarily by increasing coverage while fundamentals increase both 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 to equalize the average stock liquidity between the two. Moreover, the fact that the increase in coverage counteracts the decrease in stock liquidity is masked by the insignificant coefficient of quant size in Panel A, but is still consistent with the equilibrium described by PST. 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 (i.e., positive for balance but negative for coverage). 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 one aspect of the tradeoff hypothesized by PST, but only for fundamental SAs. Thus, there are strong "within portfolio liquidity tradeoffs" in quants, while fundamentals show strong "outside tradeoffs" between portfolio liquidity and the fund size. These differences may help to explain observed differences in scale diseconomies.

With respect to the other tradeoff variables, quants have lower expense ratios on average (Panel C), reinforcing the expense ratio differences observed in Table 1. Both quant and fundamental SAs 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 PST's 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 relationship or a weakly positive relation between portfolio liquidity, specifically 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.

TABLE 6

Speed of Information Diffusion Within SA Firms

Table 6 shows measures of information diffusion (ID) following Cici et al. (2017) within SA firms separately for i) firms majorly (>50%) managing quantitative separate accounts (SAs) versus fundamental SAs, ii) Initial Buys majorly made by quantitative versus fundamental SAs, and iii) Following Buys majorly made by quantitative versus fundamental SAs, in the period from Jan. 2001 to Dec. 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 H_0 that the difference is zero. *T*-statistics are reported in parentheses. ***, **, and * denote statistical significance on the 1%, 5%, and 10% level, respectively.

	Panel A. Quant Versus Fundamental Majority Firm			*Panel B. Quant Versus Fundamental Majority Initial Buyers*			*Panel C. Quant Versus 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)

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, examining 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. Accounting for these different tradeoffs may help to explain the differences in diseconomies of scale between the competing strategies.

B. Hierarchy and Information Processing Costs

While our discussion so far has focused on liquidity costs as the channel of interest in characterizing the differences in diseconomies of scale between quant and fundamental SAs, the tradeoffs observed in Table 5 may also reflect differences in the related channels of information processing and hierarchy costs. For example, lower coverage and lower balance indicate that fundamental SAs hold more concentrated positions in a smaller number of stocks. If the fundamental investment process incurs higher information processing costs, we would expect greater difficulty in identifying a large number of stocks to invest in. Similarly, the higher turnover for quant SAs suggests a faster decision-making process for purchasing and selling stocks. If the quant investment process is model-driven and automated thereby reducing hierarchy costs, we would expect more rapid decision-making consistent with the higher observed turnover.

While these observed tradeoffs are consistent with differences in information processing and hierarchy costs between quant and fundamental SAs, in this section, we examine more direct measures of these costs. While both the information processing and hierarchy cost mechanisms are discussed in the diseconomies of scale literature, there have been few empirical tests of these channels due to difficulty in measuring them. Following the insights of Radner and Van Zandt (1992), Radner (1993), Bolton and Dewatripont (1994), and Stein (2002) pointing to the efficient transfer of information through a firm as a key outcome of low information processing/hierarchy costs in a firm, we test for differences in these channels for quant and fundamental SAs in two ways.

As a first analysis of differences in hierarchy and information processing costs between quant and fundamental SAs, we follow a method proposed by Cici et al. (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, that is, the buy of a stock not held by any other SA at the time,[24] 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 (6) shows how ID speed is calculated for each initial buy.[25]

$$\text{(6)} \qquad \mathrm{ID}_{f,s,q} = \frac{I_{f,s,q} - 1}{I_{f,s,q} + J_{f,s,q} - 1}.$$

$I_{f,s,q}$ 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 follows 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 6 reports statistics for ID speed where Panel A shows mean ID speed separately for majority quant and majority fundamental firms.[26] Panel B shows

[24]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.

[25]Equation (1) from Cici et al. (2017), p. 151.

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

separate results for firms where the identified initial buys are majorly performed by quants (fundamentals), that is, 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), that is, 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, consistent with quant firms – and by extension quant SAs – exhibiting lower hierarchy and information processing costs.

As a second analysis, we examine the hard versus soft information content of the investment decisions made by quantitative versus fundamental asset managers through a factor analysis of their performance. While higher factor model R^2s and higher and more stable factor exposures may simply indicate that a given manager is more dogmatic about their investment approach, our use of these measures as potential proxies for hard information is consistent with evidence in and assumptions made by several papers in the literature. From a theory perspective, Abis (2020) models a possible equilibrium between fundamental (discretionary) and quantitative investors that incorporates learning. Her assumption about what distinguishes quant from fundamental investors is their ability to identify and invest according to factors: "Quantitative investors…have unlimited capacity for learning about idiosyncratic risk factors." If standard factor models incorporate common factor strategies, then we would expect, according to Abis' assumption, a higher correlation between quant strategy returns and factor models, or equivalently, higher R^2s for a factor model regression of quant strategy returns.

Empirically, Akbas, Armstrong, Sorescu, and Subrahmanyam (2016) examine how increased flows to quant strategies relate to market efficiency. To identify flows from quant funds, they regress mutual fund returns on the returns of a multifactor simulated quant strategy, classifying those funds with the highest loadings (top 10%) on this multifactor portfolio as quant funds. As a further test of whether or not they are picking up "quant funds," they suggest that "A relevant issue is whether the loadings of mutual fund returns on quant returns exhibit stability over time, which would shed light on whether funds follow an intertemporally stable quant 'style.'" To address this, they examine the stability of each quant fund's multifactor loading over time, concluding that their sample likely represents quant strategies in part because "…the coefficient estimate 36 months forward is on average about 89.8% … of the initial coefficient estimate, indicating reasonable intertemporal stability."

Finally, Beggs, Brograard, and Hill-Kleespie (2021) examine how variation in quantitative investing relates to market stability over time. They follow Abis (2020) in classifying mutual funds as quantitative through a textual analysis of mutual fund prospectuses. In analyzing the factor exposures of quant mutual funds, they find their strategies exhibit "significantly greater exposure to risk factors suggesting that they respond to similar signals in their investment processes." While all three of these papers focus on mutual funds in their analysis, their common interpretation that quants exhibit higher factor model R^2s and factor loadings in addition to more stable factor loading exposures supports the use of similar tests to assess the use of hard versus soft information by quantitative and fundamental SAs.[27]

Additionally, one may expect that the differential use of hard and soft information by quants and fundamentals may also show in the implementation of their strategies. Specifically, we expect that quant investment strategies, based on systematic signals, to show higher consistency in their style and risk factor loadings compared to fundamental strategies. The latter relies more on qualitative signals and qualitative assessment of quantitative signals, both of which may not show as systematic signals in quant data.

In Table 7, we report the differences in quant and fundamental factor loadings. We examine the average differences for the full sample in Panel A

TABLE 7

Differences in Risk Factor Loadings

Table 7 presents risk factor loadings and R^2 statistics for the full sample (Panel A) and changes in risk factor loadings and R^2 statistics around manager changes (Panel B) from a sample of actively managed U.S. domestic equity separate accounts (SAs) with either a quantitative or a fundamental investment approach from Jan. 1990 to Dec. 2018. In Panel A, the risk factor loadings and R^2 statistics are measured over monthly rolling 24-month windows using either the manager-preferred benchmark (MPB) 1-factor model or the Carhart (1997) 4-factor model. In Panel B, the risk factor loadings and R^2 statistics around the manager changes ($t = 0$) are measured over the previous ($t-12$ to $t-1$) and the following ($t+1$ to $t+12$) year using either the MPB single-index model or the Carhart (1997) 4-factor model. ***, **, * indicate significances at the 1%, 5%, and 10% level, respectively, for differences in means or differences ((standard deviations)) from two-sided t-tests ((Levene's robust test for equality of variances)).

Panel A. Full Sample

	Quants			Fundamentals			Differences	
	N	Mean	SD	*N*	Mean	SD	Mean	SD
MKT (MPB)	41,359	0.99	0.12	207,105	0.95	0.17	0.04***	−0.05***
MKT (CARHART)	54,098	1	0.12	241,955	0.96	0.16	0.05***	−0.03***
SMB	54,098	0.19	0.38	241,955	0.26	0.37	−0.06***	0.01***
HML	54,098	0.11	0.26	241,955	0.03	0.32	0.08***	−0.06***
MOM	54,098	0.07	0.14	241,955	0	0.17	0.07***	−0.02***
Adj. R^2 (Carhart)	54,098	0.93	0.09	241,955	0.87	0.11	0.05***	−0.02***
Adj. R^2 (MPB)	41,359	0.91	0.12	207,087	0.83	0.15	0.08***	−0.03***

Panel B. Manager Changes

	Diff-in-Quants	Diff-in-Fundamentals	Diff-in-Diffs
| MKT (MPB) beta diff |	0.087	0.121	−0.034*
| MKT (CARHART) beta diff |	0.125	0.209	−0.083***
| SMB beta diff |	0.13	0.301	−0.171***
| HML beta diff |	0.214	0.322	−0.108***
| MOM beta diff |	0.125	0.27	−0.144***
| Adj. R^2 CARHART diff |	0.045	0.095	−0.05***
| Adj. R^2 MPB diff |	0.018	0.068	−0.049***
# Changes	97	382	
# Differences in betas (Carhart)	73	301	
# Differences in betas (MPB)	54	247	

[27] One important aspect of our analysis is clarifying what we mean by hard versus soft information. While a common distinction is that hard information is quantitative, while soft information is not, Liberti and Petersen (2019) point out that even given the same set of information, two agents with different approaches to processing that information could be categorized as using soft or hard information because "soft information can, at least partially, be transformed into hard information …" Even given the same information set, if a quant manager transforms soft information into hard (e.g., textual analysis) or automates decision-making based on given information, these different forms of 'hardening' information would be classified as the use of "hard" information, even though fundamental managers might be making decisions with a similar information set.

and the differences around managerial changes in Panel B. For the full sample, we see higher performance model R^2 statistics and lower factor beta standard deviations for quants than for fundamentals for both factor models we employ. This suggests that quants rely more heavily on factor-based strategies and that their strategy, as measured by deviation in the factors, is more consistent over time.

While the full sample results are suggestive, they may represent individual manager preferences as opposed to systematic characteristics of the two types of strategies. To control for this potential endogeneity, Panel B looks at how changes in the management teams of the SAs affect changes in the factor loadings 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.[28] For each of these management changes ($t = 0$), we analyze the absolute differences in factor exposures 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 7 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 are 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 a more stable investment process relying more on hard information, which is less costly to process and communicate.

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 R^2 statistics from both performance regression models (e.g., Amihud and Goyenko (2013)) around the managerial change. Again, the differences are higher for fundamentals than for quants, as indicated by negative differences-in-differences, and statistically significant. Overall, the results in Table 7 are consistent with the hypothesis that quant SAs rely more on hard information, indicative of lower information processing and hierarchy costs.

[28]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.

C. Diseconomies of Scale Controlling for Channels

Given the evidence that quantitative and fundamental strategies and firms face different liquidity costs and information processing/hierarchy costs, we revisit our examination of the diseconomies of scale between quant and fundamental SAs controlling for these effects.

First, to test the potential role of liquidity costs, we follow PST's proposed equilibrium framework to structure our analysis. PST models each SA's net alpha (α) as

$$\alpha = s - q(A) - f, \tag{7}$$

where s is the manager's level of skill, $q(A)$ is the proportional trading cost as a function of total assets A and f is the total expense ratio. The proportional trading cost function

$$q(A) = C(A,T,L)/A \tag{8}$$

characterizes total trading costs $C(A,T,L)$ as the following functional form of total assets A, turnover T, and portfolio liquidity L:

$$C(A,T,L) = \theta A^{\gamma} T^{\lambda} L^{-\varphi}. \tag{9}$$

Defining the benchmark-adjusted net return as $r = \alpha + \varepsilon$ and adding back expenses, f, we can combine equations (7)–(9) to give us the following equation for benchmark-adjusted gross return:

$$r + f = s - \theta A^{\gamma} T^{\lambda} L^{-\varphi} + \varepsilon. \tag{10}$$

As a final step, we define the log of assets, turnover, and portfolio liquidity, $a = \ln(A)$, $t = \ln(T)$ and $l = \ln(L)$, and using a Taylor expansion around $(a, t, l) = 0$, we arrive at the following equation:

$$r + f \approx s - \theta(1 + (\gamma - 1)a + \lambda t - \varphi l) + \varepsilon. \tag{11}$$

Additionally, as discussed in Section IV.A, we also follow PST in further decomposing portfolio liquidity, L, into its components of stock liquidity, coverage, and balance:

$$\ln(L) = l = \ln(\text{STOCK\_LIQUIDITY}) + \ln(\text{COVERAGE}) + \ln(\text{BALANCE}). \tag{12}$$

Equations (11) and (12) form the basis of our test of PST. Equation (11) identifies the predictions of the PST model to test. Namely, benchmark-adjusted gross returns decrease with turnover, consistent with higher trading costs, and increase with portfolio liquidity, consistent with lower trading costs. The equations also prescribe the regression framework for the test, which is reported in Table 8. Specifically, we regress benchmark-adjusted gross returns on manager fixed effects s, and the natural log of total assets, turnover, portfolio liquidity, or alternatively, the components of portfolio liquidity. Recognizing the evidence in Table 5 that the PST tradeoffs among fund size, turnover, and portfolio liquidity are different for quantitative and fundamental SAs, we interact these variables with the respective

TABLE 8

Panel Regressions of Performance with PST Liquidity Components, Family Characteristics, and Manager-SA Fixed-Effects

Table 8 reports panel regressions of separate account (SA) gross alpha/risk-adjusted performance on SA size (ln(TA)), Pastor et al. (2020) portfolio liquidity components and SA and family characteristics for of actively managed U.S. domestic equity SAs from Jan. 2001 to Dec. 2018. Carhart gross 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%, and 10% levels, respectively. *p*-values are reported in parentheses.

	1	2	3	4
$\ln(TA)$: D^{QUANT}	−0.105***	−0.111***	−0.124***	−0.121***
	(0.00)	(0.00)	(0.00)	(0.00)
$\ln(TA)$: $D^{FUNDAMENTAL}$	−0.227***	−0.226***	−0.238***	−0.208***
	(0.00)	(0.00)	(0.00)	(0.00)
p-Value: $\ln(TA)$: D^Q – $\ln(TA)$: D^F = 0	0.049**	0.068*	0.072*	0.164
ln(PST_TURNOVER_R.): D^Q		−0.016***	−0.019***	−0.018***
		(0.00)	(0.00)	(0.00)
ln(PST_TURNOVER_R.): D^F		−0.014*	−0.013*	−0.014*
		(0.06)	(0.08)	(0.06)
ln(PORTFOLIO_LIQUIDITY): D^Q		0.003		
		(0.50)		
ln(PORTFOLIO_LIQUIDITY): D^F		0.010*		
		(0.08)		
ln(STOCK_LIQUIDITY): D^Q			0.025***	0.028***
			(0.00)	(0.00)
ln(STOCK_LIQUIDITY): D^F			−0.017	−0.013
			(0.18)	(0.27)
ln(BALANCE): D^Q			−0.016**	−0.015**
			(0.01)	(0.02)
ln(BALANCE): D^F			0.029***	0.030***
			(0.01)	(0.00)
ln(COVERAGE): D^Q			0.029***	0.033***
			(0.00)	(0.00)
ln(COVERAGE): D^F			0.022	0.021
			(0.20)	(0.24)
ln(NO_OF_QUANT_MGRS)				−0.011
				(0.77)
ln(NO_OF_FUNDAMENTAL_MGRS)				−0.063***
				(0.00)
PERCENT_FIRM_TA_QUANT				−0.025
				(0.45)
PERCENT_FIRM_TA_FUNDAMENTAL				−0.093***
				(0.00)
Manager-SA FE	Yes	Yes	Yes	Yes
Other SA and Firm Controls	Yes	Yes	Yes	Yes
Adj. R^2	0.03	0.03	0.03	0.03
N	100,435	100,435	100,435	100,435

dummies to allow for potentially different equilibria for the two strategies. Because SAs may have multiple managers, we also reconfigure the panel regression data to a manager-SA-date observation level but then weight the observations by the inverse of the number of managers, so as to retain the SA-date weighting from Table 4. Additionally, we also include the set of control variables from Table 4.[29] All variables are standardized to unit standard deviation to ease coefficient comparisons. Standard errors are clustered on the dimensions of SA and date.

[29]Expense ratio is not included as an independent variable in Table 8 as the dependent variable is converted to gross alpha.

The first column 1 shows the regression results without the PST controls. Consistent with the results from columns 8 and 10 in Table 4, both quant and fundamental strategies exhibit diseconomies of scale, but the difference is statistically significantly higher in fundamental strategies. The coefficient difference is 0.122 and statistically significant as indicated by the respective p-value.

In the second column 2, we include the PST tradeoff variables turnover and portfolio liquidity, but we allow for the quant and fundamental strategy loadings on these variables to differ. Consistent with the PST predictions, turnover is statistically significantly negatively related while the point estimates for portfolio liquidity are positive, but only the coefficient on the fundamental investment strategy is statistically different from zero. Importantly, including these PST tradeoff variables reduces the difference in diseconomies of scale coefficients between the two strategies and reduces, but does not eliminate, the statistical significance of this difference.

In the third column 3, we replace the PST portfolio liquidity variable with its underlying components: stock liquidity, balance, and coverage. The results are consistent with the evidence in Table 5 that different investment strategies may arrive at different equilibria regarding these tradeoffs. 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 these additional PST components further reduces both the difference point estimates and p-value of the difference in diseconomies of scale. It is important to note that while including the PST fund liquidity proxies narrows the difference in scale diseconomies coefficients between quant and fundamental SAs, it does not replace them. The fund tradeoff model suggested by PST is an equilibrium between these various fund tradeoff dimensions, not a set of superior proxies for scale diseconomies.

Finally, in the last column 4, 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. However, once again drawing on the insights of the industrial organization literature cited previously, we would expect these costs to manifest themselves at an organization-wide level. To account for this we first control for the size of the overall organization (FIRM_TA) and then calculate the number of quant and fundamental managers at the rest of the firm (excluding the SA datapoint of interest in the regression set-up) and the percentage of firm assets invested in quant and fundamental strategies (once again excluding the SA of interest). By measuring these two dimensions, managers and assets, excluding the SA of interest, the effect, if any, on the performance of a given SA is more likely to proxy for organization-wide conditions like information processing or hierarchy costs.

Looking at the results in the last column, we see that SAs in firms with a larger number of fundamental managers or a higher fraction of the firm's TA invested in fundamental strategies, are more likely to underperform. This is consistent with greater hierarchy and information processing costs at such firms. The number of quant managers or the percentage of firm TA invested in quant SAs, however, is statistically unrelated to performance. We also see that including them further decreases the difference in scale diseconomies coefficients to a statistically insignificant 0.087. It is interesting to note as well, that this further decrease is driven largely by the change in the diseconomies of scale coefficient for fundamental SAs, not quant. 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.

V. 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 article, we investigate differences in diseconomies of scale associated with different investment strategies: quantitative versus fundamental. We find that quant strategies are less plagued by diseconomies of scale compared to fundamental strategies. In exploring how these two investment styles differ from one another, we examine how these different strategies differ both in terms of liquidity costs and information processing/hierarchy costs.

With respect to liquidity costs, we utilize the "mutual fund tradeoffs" framework by PST and find that such equilibrium tradeoffs are different for quants compared to fundamentals. Further, with respect to information processing and hierarchy costs, we find that quant investment firms exhibit higher speed of information diffusion and that quant SAs' investment strategies are more highly correlated with factor models and their factor loadings are more stable around management changes, both consistent with lower information processing and hierarchy costs in quant SAs. Finally, we relate such differences in the channels to the differences in diseconomies of scale between quant and fundamental SAs and find that the channels indeed help in decreasing the difference.

While our results provide important insights into the economic mechanisms underlying diseconomies of scale in asset management, they also have broader implications for the industry. Given the equilibrium suggested by PST, the lower diseconomies of scale for quant strategies could translate into greater assets under management. Consistent with this idea, quant investment strategies in both the institutional (i.e., SA) and retail (i.e., exchange-traded fund) segments have experienced substantial growth. At the same time, PST point out that a fund's scale is captured by the product of the fund's assets and how actively the portfolio strategy is implemented. The higher R^2 of quant SAs relative to their manager-preferred benchmark or a multifactor benchmark suggests that quant managers are less active in implementing their strategy. Overall, the total assets under management in the industry might increase, but holding manager skill fixed across both investment strategy types, fund investors would not necessarily benefit. How a shift in assets away from fundamental and toward quant strategies affects competition among investment advisors, the structure of the investment industry and overall market liquidity are questions that we leave to future work.

Appendix A. List of Manager-Preferred Benchmarks (MPBs)

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

Appendix B. First-Stage Zhu Results

First stages from Zhu (2018) – columns 9 and 10 of Table 4. [a]Stock–Yogo critical value for 10% maximum IV size is 16.38 in column 9 and 7.03 in column 10. ***, **, and * indicate significance at the 10%, 5%, and 1% levels, respectively.

	For Column 9	For Column 10	
	Forward Demeaned TA	Forward Demeaned Quant TA	Forward Demeaned Fundamental TA
ln(TA)	0.395*** (0.00)		
ln(TA): D^{QUANT}		2.446*** (0.00)	0.222*** (0.00)
ln(TA): $D^{FUNDAMENTAL}$		0.030** (0.03)	2.006*** (0.00)
D^{QUANT}	0.067*** (0.00)	−7.651*** (0.00)	−0.585*** (0.00)
$D^{FUNDAMENTAL}$	−0.133*** (0.00)	−0.050* (0.07)	−4.356*** (0.00)
ln(FIRM_TA)	0.001 (0.80)	−0.013*** (0.00)	0.003 (0.20)
$\alpha_{i,t-11,t}^{OOS,CARHART}$	−0.025*** (0.00)	−0.014*** (0.00)	−0.015*** (0.00)
NET_FLOW	0.060*** (0.00)	0.023*** (0.00)	0.047*** (0.00)
AGE	0.297*** (0.00)	0.067*** (0.00)	0.242*** (0.00)
EXPENSE_RATIO	−0.059*** (0.00)	−0.018*** (0.00)	−0.048*** (0.00)
ln(MINIMUM_INVEST.)	−0.072*** (0.00)	−0.005* (0.09)	−0.063*** (0.00)
D^{CIT}	0.327*** (0.00)	0.227*** (0.00)	0.239*** (0.00)
D^{RETAIL}	0.220*** (0.00)	0.048*** (0.00)	0.184*** (0.00)
Adj. R^2	0.27	0.19	0.29
N	86,987	86,987	86,987
		p-Values	
Anderson Canon. Corr. LM	<0.01	<0.01	<0.01
Cragg–Donald Wald F^a	<0.01	<0.01	<0.01
Anderson–Rubin Wald F	<0.01	<0.01	<0.01

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