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The Performance of Separate Accounts and Collective Investment Trusts*

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Abstract. Despite the size and importance of separately managed accounts (SMAs) and collective investment trusts, their characteristics and performance have not been studied in detail. We show that separate account performance is similar to that of index funds and superior to that of actively managed mutual funds. Management supplies a benchmark for each separate account. When the management-selected benchmark is used to measure performance, performance is significantly overstated. Despite this, investors react to differences in performance from the management-preferred benchmark in choosing among SMAs. Finally we find variables that explain both the cross section of alphas and the cross section of cash flows.

JEL Classification: G11

1. Introduction

In this article we study pooled separately managed accounts (SMAs) and collective investment trusts (CITs). These vehicles represent alternatives to mutual funds for investment by wealthy individuals and institutional investors, including pension plans and endowments. A SMA is a portfolio of assets managed by a professional management firm. Unlike mutual funds, the securities held in the account are directly owned by the customer, the fees are negotiable, and the account can be customized to reflect the customer's tax or social concerns. Each individual SMA generally has a minimum initial investment which in almost all cases range from \$100,000 to \$25 million. SMAs are not only offered by large financial institutions like Morgan Stanley or Prudential but also by smaller institutions

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that manage money primarily for wealthy individuals or institutions. If the SMA is offered by a large financial institution that offers a wide range of financial products, the portfolio management is normally the institutional manager not the retail manager. Thus SMAs are institutional products offered to institutions and wealthy individuals. SMAs are not regulated, although the manager is often a registered investment advisor subject to the Investment Advisor Act of 1940. Thus SMAs are not required to publically report their returns. However, as we discuss below data does exist on pooled (by investment style) SMAs and it is this data that we use in this study. In 2007 *Money Management* estimated the amount invested in SMAs was $808 billion. In 2008 Reuters estimated that financial advisers with accounts over $2 million allocated 18% to SMAs compared to 28% to mutual funds. Deloitte (2011), in a study of 401(k) accounts, estimated that these accounts had 61% of their assets invested in separate accounts and co-mingled accounts as compared to 38% invested in mutual funds.

CITs are co-mingled accounts offered by banks or trust companies exclusively for qualified pension plans, defined benefit plans, defined contribution plans, and certain government pension plans. As such they only are offered to tax-exempt accounts. The pension account may be fully invested in a CIT, or the CIT may be one option in a defined contribution plan. Like SMAs, they are unregistered, but they are regulated by the Office of the Controller of the Currency. The implication of their being unregistered is that like SMAs they are not required to disclose performance data. About 40% of pension plans hold CITs. Powell (2013) reports that there is at least 1.6 trillion dollars invested in CITs. The Pension Protection Act of 2006 approved CITs as a default option for defined contribution pension plans which has led to growth of 13–18% per year (Powell 2013).

Despite the fact that SMAs and CITs are important investment vehicles, they have not been studied in detail in the literature of financial economics.[1] We know very little about why separate accounts exist or how they perform. They resemble mutual funds in several aspects, but there are important differences. Mutual funds have a much more complex structure. Separate accounts have a small number of investors, a larger minimum investment, smaller support staff, no legal requirement to publicly report returns, much less supervision by the SEC, no independent boards of directors, and the

[1] The primary studies of institutional products are Busse, Goyal, Wahal (2010) and Petersen *et al*. (2011), both of which principally study predictability using pre-expense returns.

ability to customize the holdings of individual investors to meet their needs. Furthermore, since each investor within a pooled separate account owns the securities in his individual separate account he directly bears the cost of transactions and the buying and selling decisions of other investors in a pooled separate account does not affect his transaction cost. This is not true for mutual funds where the purchases or sales of any investor affect the costs of all investors.

All of these differences should lead to lower costs and more freedom in making investment decisions. However, costs are probably raised by the need to give more individual attention to each client. We expect, and in fact find, that the freedom from regulation leads to lower costs to the investor. However, lower costs need not translate to higher return for the investor. Increased freedom from regulation leads to more flexibility of investment behavior. This flexibility and freedom from oversight by the regulators and boards of directors could increase or decrease performance. In this case we find that it leads to higher risk-adjusted returns. While we cannot make a general statement about regulations in this case, the size of the individual investor's commitment, a median of five million dollars, would suggest that they can impose appropriate behavior on management.

More specifically, we find that separate accounts do as well as index funds and considerably better than mutual funds. This result persists when measured over a large set of benchmarks chosen by the institutions themselves and benchmarks selected from the literature of financial economics. Separate accounts offered by management companies that have mutual funds with the same objective do not outperform the mutual funds with which they are matched. Rather, it is the independently managed separate accounts, and in particular those with management companies organized as partnerships, that have the best performance.

In this article we examine several other aspects of SMA and CIT performance. Almost all SMAs and CITs supply a benchmark against which they wish to be judged. We show that they choose benchmarks such that their performance is vastly overstated when compared with either the single-index benchmark that best describes their return behavior or the multi-factor models most often used in the literature.

We also study the determinants of both cross-sectional differences in the performance of pooled separate accounts and cross-sectional differences in cash flows to these accounts. The variables tested include, in addition to a set of variables that have been found to explain performance in mutual funds (e.g., expenses, turnover, and lagged performance), a set of organizational variables such as how income is distributed to the managers, limited liability, size of the minimum initial purchase, and the existence of pending lawsuits. Statistically significant relationships are found.

SMA and CIT data, like hedge fund data, are self-reported. Morningstar collects return and other data on both SMAs and CITs. SMA data are reported on a pooled basis; that is, the performance and characteristics are reported for the aggregate of all accounts with the same investment objective (e.g., large growth). Most follow standards set by the industry in how they aggregate return data, and thus return is usually reported by weighting account returns by the proportion each account represents of the aggregate. Like data on the returns of hedge funds, the return data on SMAs and CITs may be upward-biased. Morningstar retains data on SMAs or CITs up to the time the firm stops reporting, so that the major source of potential upward bias (survivorship) is eliminated. However, separate accounts, like hedge funds, often report data with a lag. Firms can stop reporting after a few months of bad returns which can induce a bias. The effect of this will be discussed in detail later.

This article is organized as follows: In Section 2 we present some more information on our sample. In Section 3 we present the methodology used in measuring performance. In Section 4 we examine performance. In Section 5 we compare the performance of SMAs and CITs with the performance of mutual funds. In Section 6 we analyze the cross-sectional determinants of the performance of separate accounts. In Section 7 we analyze the cross-sectional determinants of cash flow to separate accounts. Our conclusions are presented in Section 8.

2. Sample

We initially selected all surviving and non-surviving accounts from the Morningstar Direct Database that were listed as United States Separate Accounts or United States Co-Mingled Investment Trusts between July 2000 and January 2009 and that were categorized as Equity Accounts (3,506 accounts). The Morningstar Direct separate account database has over 5,000 variables relating to returns, asset allocation, holdings, description of the management company and its clients and cash flow.

From our initial sample we eliminated:

(1) All accounts that were identified as index accounts, specialty accounts (e.g., REITs, tech funds, etc.) or that were heavily invested in bonds or foreign securities (847 accounts).
(2) Any accounts that started prior to January 2009 and that had less than 24 months of data (18 accounts).

We collected monthly gross return and net return data for this sample of funds from July 2000 to December 2010.[2] We eliminated funds where the return series was clearly implausible or where the relationship between gross and net return was implausible over long periods of time and therefore we could not identify which series was accurate (14 accounts). This left us with a combined sample of 2,627 accounts consisting of 2,277 pooled SMAs and 350 CITs. We refer to the total of these two samples as combined separate accounts.

We next drew a comparison sample of mutual funds. The principal characteristics of SMAs and CITs are that they are designed for institutional customers or high-net-worth individuals. Since only 442 of the 2,627 SMAs and CITs had minimum investment less than $1,000,000, we used all mutual funds listed on Morningstar that required a minimum investment of $1,000,000 or more as a comparison sample. Share classes and funds designed for institutional investors and high-net-worth individuals have lower fees and are likely to have better performance, and are thus the relevant alternative for these investors.[3]

Table I, Panel A shows the distribution of minimum investment in an account for the combined SMAs and CITs and for the mutual fund sample. The median minimum investment for the combined sample is $5 million, where the median for the mutual fund sample is $1 million. In addition, the minimum for the upper part of the distribution is much higher for the combined sample than for the mutual fund sample. As shown in Panel B, there is no difference in the median minimum investment for SMAs and CITs.

How does the combined separate account sample compare to the mutual fund sample on other characteristics? As shown in Table I, the median mutual fund is more than 2 1/2 times larger than the median combined separate accounts (SMAs and CITs). The difference in size is especially large for the lower part of the distribution, while for the largest accounts there is very little difference in size. Comparing SMAs to CITs shows that the median SMA is about three times larger than the CITs. When we look at the number of stocks held by the combined separate account sample and the mutual fund sample we see that despite being more than twice as large, the mutual fund sample holds only about 25% more stocks; this is consistent with mutual funds being larger and the tendency of mutual funds to add

[2] The early date was selected because it is the first date for which the Russell micro-cap index is available. The reason for employing the micro-cap index will be explained shortly.
[3] We also selected as a comparison sample all institutional mutual funds. The results discussed in later sections were very similar with this sample.

Table I. Characteristics of separate accounts and mutual funds

This table contains data on categories of separate accounts and a matched mutual fund sample. The aggregate size of an account represents the dollars invested in a particular account or mutual fund, while the number of customers in an account is the number of individuals and institutions that are in that account. The remaining columns are self-explanatory.

Panel B is parallel to Panel A except that we separate the combined separate accounts into CITs and SMAs.

Panel A, Part 1—Combined separate accounts

	Aggregate size of account (in thousands)	Number of customers in an account	Minimum investment (in thousands)	Number of stock holdings	% Assets in top ten (%)	Expense ratio (%)	Turnover (%)
Median (%)	152,410	12	5,000	63	28.8	0.81	60.6
10	3,090	2	100	32	16.2	0.44	22.5
25	25,000	4	1,000	43	22.2	0.61	35.8
75	692,000	45	10,000	97	35.9	0.98	95.6
90	2,091,200	187	25,000	164	44.0	1.53	145.1

Panel A, Part 2—Mutual funds

	Aggregate size of mutual fund (in thousands)	Minimum investment (in thousands)	Number of stock holdings	% Assets in top ten stocks (%)	Expense ratio (%)	Turnover (%)
Median (%)	403,703	1,000	79	26.3	0.93	85. 4
10	17,279	1,000	41	14.7	0.65	35.0
25	95,115	1,000	56	20.6	0.79	53.7
75	1,032.196	5,000	114	32.9	1.10	120.3
90	2,533,428	5,000	195	41.8	1.27	169.0

Panel B (medians)

Account	Aggregate size of account (in thousands)	Number of customer accounts in strategy	Minimum investment (in thousands)	Number of stock holdings	% Assets in top ten (%)	Expense ratio (%)	Turnover (%)
Separate account	162,430	12	5,000	62	28.8	0.82	60.0
CIT	55,697	14	5,000	79	29.1	0.72	73.2

additional stocks slowly as fund size grows (Pollet and Wilson 2008). Despite the larger number of stocks held by mutual funds, the concentration in the top ten stocks is similar for the combined separate account sample and the mutual fund sample.

Morningstar collects data on return both pre-expenses and post-expenses. We used the difference in these return series to calculate the expense ratios for the combined sample.[4] Some fees were reported quarterly and some monthly. The data on fees converted to an annual basis are reported in Table I. In validating the data, we found that occasionally the differential between pre- and post-expenses was so large and the numbers were such that there appeared to be an error in entering the data. Those entries were not included in the calculations.[5] However, there are probably mistakes in the imputed expense ratios that fall within the parameters for elimination. Since there is some arbitrariness in identifying and classifying mistakes in data, and since questionable observations tend to be in the tails, we reported the median expense ratio and points on the distribution rather than means, which are sensitive to tails and any misclassification. The expenses on the CITs and SMAs ranged from a low of 4 b.p. to a high of 3.77%. The median was 81 b.p. This is lower than that of our comparison sample of mutual funds where the median fee is 93 b.p. Using a chi-square test for the difference in medians, the difference is statistically significant at the 0.01 level. In addition, for all points on the distribution shown in Table I except for the 90% breakpoint, CIT and SMA fees are lower than those for mutual funds.[6] Trading costs are costs that lower returns but are not included in the expense ratio. If we use turnover as a proxy for trading costs, we see that median turnover and all points in the distribution shown in Table I are higher for mutual funds. The difference in medians is again statistically significant at the 0.01 level. Thus total expenses (expense ratio and trading costs) are higher for mutual funds.

3. Methodology

The performance of any separate account was measured using several single- and multi-factor models. The general form is

$$R_{it} = \alpha_i + \sum_{j=1}^{J} \beta_{ij} I_{jt} + \varepsilon_{it}, \tag{1}$$

[4] If Morningstar does not receive data on both pre- and post-expense return, it calculates the return data it does not have using a representative fee from the firm supplying the data.

[5] Individual return observations (not accounts) were eliminated where net returns were higher than gross returns, where the difference between the two return series was more than eight times the average difference, or where either gross or net returns were plus or minus 200% per month.

[6] A few of the separate accounts were wrap accounts, and this accounts for the higher upper-end expenses.

where

R_{it} = the monthly excess return (over the riskless rate) on account i for month t;

I_{jt} = index j of an appropriate set of indexes (each defined as the return on a zero-investment portfolio) for month t;

β_{ij} = the sensitivity of account i to index j;

α_i = the risk-adjusted return (using the included indexes) of account i;

ε_{it} = the residual return of account i in month t not explained by the model.

The initial models used were single-index models. The first model compares the performance of each account with the benchmark that management selected as most relevant for that account. In our sample of 2,627 accounts, management supplied benchmarks for 2,319 accounts, or 88% of the sample. Management used 51 different benchmarks. Of the 51 benchmarks, 29 were selected in total by only 70 of the 2,319 accounts. These 29 benchmarks were primarily a composite of 2 or more indexes. There were 22 remaining benchmarks selected by 2,249 accounts. Examination of these 22 benchmarks showed that for reporting purposes they could be grouped into 9 categories, although all 22 indexes were retained for purposes of computing alpha. The 9 categories are large-cap, mid-cap and small-cap, with each group divided into growth, blend and value, the 29 benchmarks not so-classified are reported in the category "other."

For the second model we used the single index that best explained the behavior of each account. Three of the 22 indexes selected by managers were essentially identical to one of the others (e.g., S&P Midcap and Russell Midcap). Thus for the stepwise procedure we used nineteen indexes. The best index was selected via a stepwise procedure from the nineteen possible indexes and the alpha that was produced from the index is called the "best-fit alpha."

We next examined performance using a multi-index model. The base model used is the Fama–French model with the addition of the Carhart momentum factor. See Fama *et al.* 2010 and Carhart 1997. We regressed all of the Russell indexes against this model and found that the alpha on small and micro-cap growth indexes was significant. In addition, examining the composition of the accounts in our sample showed that many held a large portion of their portfolio in very small stocks. For these two reasons an additional variable was defined and added to the Fama–French–Carhart model. We defined a micro index as the orthogonalized value of the

Russell micro-cap index in excess return form.[7] While we will emphasize the Fama–French–Carhart model throughout the rest of the article, we will occasionally refer to the model that in addition to the four variables in the Fama–French–Carhart model adds the orthogonalized version of the Russell micro-cap index. We refer to these models as the four-factor model and five-factor model, respectively.

4. Performance

In Table II we examine the alphas from each of the models described earlier. The accounts are grouped for purposes of presentation into nine groups by the manager's preferred benchmark, and into a group labeled "other," combining the seventy funds that used indexes that could not be placed into any of the nine groups.

The first comparison to note is how much lower the best-fit alpha is than the alpha based on the benchmark the manager has selected. The average difference is 6.3 b.p. per month or approximately 76 b.p. per year. This difference is economically and statistically significant at the 0.01 level.[8] Furthermore, the best-fit alpha is lower in eight of the ten categories.[9]

Examining Panel B, we see that same phenomena in mutual funds. Mutual funds also select a benchmark that makes their performance better than the single index that best explains their return pattern. However, in this case the best-fit alpha is negative, indicating underperformance by mutual funds.

There is definitely a difference between the alphas produced by the benchmarks selected by management of separate accounts and the benchmarks selected by a best-fit criterion. Management has selected benchmarks that make their performance look good. We can gain more insight into this by examining differences in classification between the best-fit benchmarks and the benchmarks selected by managers and the impact on alpha for funds that are classified differently.

[7] The index was formulated by regressing the excess return of the Russell micro-cap index on the Fama–French–Carhart model and replacing the excess return on the index with the alpha plus the appropriate month's residual from this regression.

[8] All of the differences in alphas between models of performance reported in Panel A of Table II are performed using a matched-pair *t*-test for difference in means.

[9] The fact that the management-preferred benchmark results in higher alphas has been documented by Angelidis, Giamouridis, Tessaromatis (2013) for mutual funds. In what follows, we go further in explaining why this occurs. In addition, we examine the effect of the use of management-preferred benchmarks on flows into and out of separate accounts.

Table II. Separate account and open-end fund alphas

Panel A divides the sample of combined separate accounts into ten categories according to the manager-selected benchmark for each account. The row labeled "Overall Entire Sample" in Panel A includes, in addition to the separate accounts included in the row labeled "Overall Manager Preferred," the separate accounts for which no manager-selected benchmark was available. The second column in Panel A shows the number of separate accounts in each aggregate category of MPBs. The third column in Panel A shows the alphas for each category, where the alphas were computed using a single-index model based on the MPB. The fourth column in Panel A shows the alphas for each category, where the alphas were computed using a single-index model based on the index that best fit the return data for a given separate account. The alphas in the fifth column were computed using the familiar Fama–French–Carhart four-factor model. Finally, the alphas in the sixth column were computed using a five-factor model consisting of the Fama–French–Carhart four-factor model with an added micro-cap stock index, where the index was the residual excess return from regressing the excess return of a micro-cap stock index on the Fama–French–Carhart four-factor model.

Panel B divides a sample of open-end mutual funds with minimum investments of $1 million into Morningstar categories, and presents the number of funds in each category along with the alphas from the MPB, the best-fit benchmark, and the four-factor and five-factor models described above.

Aggregated MPB	Num. funds	MPB alpha	Best-fit alpha (out of 19 aggregated benchmarks)	Four-factor model alpha	Five-factor model alpha
Panel A: Separate account alphas					
Large-cap growth	337	0.0898	–0.0335	–0.0577	–0.1019
Large-cap blend	677	0.0887	0.0087	–0.0389	–0.0351
Large-cap value	265	0.0871	0.0505	0.0048	0.0481
Mid-cap growth	182	0.0860	0.0125	0.0483	–0.0329
Mid-cap blend	154	0.0472	0.0527	0.1031	0.0308
Mid-cap value	110	0.0814	0.1021	0.1511	0.0971
Small-cap growth	186	0.1020	0.0332	–0.1112	–0.0633
Small-cap blend	185	0.1198	0.0713	–0.0532	–0.0355
Small-cap value	153	0.1687	0.1551	0.0637	0.0865
Other	70	0.0997	0.0156	–0.0649	0.0086
Overall manager preferred	2,319	0.0945	0.0318	–0.0123	–0.0174
Overall entire sample	2,627	same as above	0.0324	–0.0141	–0.0202
Panel B: Open-end fund alphas					
Large-cap growth	110	0.0432	–0.0914	–0.0949	–0.1443
Large-cap blend	188	0.0361	–0.0569	–0.0816	–0.0793
Large-cap value	67	0.0270	–0.0145	–0.0410	0.0084
Mid-cap growth	57	0.0509	–0.0198	0.0307	–0.0662
Mid-cap blend	36	–0.1648	–0.1250	–0.0143	–0.1242
Mid-cap value	32	0.0230	0.0877	0.1417	0.0809
Small-cap growth	55	0.0353	–0.0496	–0.1991	–0.1420
Small-cap blend	58	0.0134	0.0320	–0.0800	–0.0725
Small-cap value	29	0.0564	0.0660	–0.0199	0.0042
Other	5	0.1005	–0.0565	–0.1085	–0.1502
Overall manager preferred	637	0.0250	–0.0373	–0.0655	–0.0798
Overall entire sample	651	same as above	–0.0403	–0.0644	–0.0785

Table III. Number of separate accounts: best-fit benchmarks and MPB

There were 2,249 accounts analyzed.

For each MPB, aggregated into nine categories, this table shows the number of separate accounts that are best fit by each of nine benchmarks.

Best-fit benchmark	MPB								
	Large-cap			Mid-cap			Small-cap		
	Growth	Blend	Value	Growth	Blend	Value	Growth	Blend	Value
Large-cap growth	199	56	1	1	1	0	0	0	0
Large-cap blend	69	448	50	0	2	1	0	1	0
Large-cap value	0	78	185	0	0	0	0	0	0
Mid-cap growth	50	27	0	139	24	0	57	6	0
Mid-cap blend	18	47	6	39	105	43	22	64	18
Mid-cap value	0	18	23	0	17	66	1	20	59
Small-cap growth	1	2	0	2	4	0	96	13	1
Small-cap blend	0	1	0	1	0	0	10	69	24
Small-cap value	0	0	0	0	1	0	0	12	51
Total	337	677	265	182	154	110	186	185	153

Table III shows the difference between the manager's choice and the benchmark that best explains the return pattern for the nine indexes. The manager's choices are shown in the columns and the indexes that best explain return are shown in the rows. Table IV shows the alpha which arises from the difference in classifications presented in Table III.

For example, from Table III we see that for 69 of the 337 managers who choose to be categorized as large-cap growth, the most representative benchmark was large-cap blend.

The average increase in alpha attributed to each of these 69 funds is 21 b.p. per month.

Some clear patterns arise from Table III. Note that the principal differences occur because of a different classification by size and different classification within the blend categories. Examining the large-cap blend category shows that, of the accounts categorized as large-cap blend by management, 92 behaved more like a mid-cap account, while 181 behaved more like a growth or value account. Across all managers who chose a blend benchmark, there were 279 cases where managers selected a blend benchmark where the return pattern was more like a value or growth account. A large part of this arose from managers selecting the S&P 500 index as their benchmark, when for 142 of these cases the return pattern was better described by either a growth or value index.

Table IV. Separate accounts differential alphas from the MPB minus the best-fit benchmark

This table shows the difference in alpha when a manager chooses a benchmark index different from the one that best fits the pattern of the separate account's returns.

A positive number indicates that the manager obtained a higher alpha with the manager-preferred benchmark than that obtained with the best-fit alpha.

	Growth	Blend	Value
Large-cap	0.279	0.192	0.117
Mid-cap	0.322	0.059	–0.049
Small-cap	0.138	0.081	0.019

When we examine the manager's choice of the size criteria we also find large differences between the manager's choice of an index and the best-fit index. For example, from Table III, 193 of the managers who chose a large stock-index had returns which looked like they were investing in smaller stocks.

The impact on average alpha of a manager classifying an account differently from what best explains his investment behavior is due to both the number of accounts misclassified and the differential alpha on the misclassified funds. The net result of this is shown in Table IV. Each of the nine entries shows how much higher the alpha associated with the manager benchmarks is than that associated with the best-fit benchmark. Note that eight of the nine categories are positive. In addition, the largest differences tend to be in the top row and left-most column. Management increases alpha by picking benchmarks that are much more oriented to growth and large size rather than the benchmark that is most appropriate for describing the return pattern on the separate account.

In summary, judicious choices of indexes by management resulted in high alphas. How can this be when managers change their benchmarks infrequently? For instance in a 1-year period only 27 out of 2,627 managers changed their benchmarks. If management changes its benchmarks infrequently how could they select benchmarks that on average make them appear as better investors than the benchmarks that more accurately describe their behavior? We believe that, based on the literature of financial economics, historical data or their experience, they are selecting benchmarks that are less heavily weighted on characteristics of securities that have historically done well. More specifically, they are selecting benchmarks that are composed of securities that are larger and more growth oriented than the securities in their portfolio. This is clearly demonstrated by the entries in Table IV.

Returning to Table II, when we examine multi-factor models compared to manager-selected benchmarks we see a large difference in alphas. As stated earlier, we employ two multi-factor models. The first is the Fama–French–Carhart model. The second adds the excess return on the Russell micro-cap index (orthogonalized to the Fama–French–Carhart model) to the Fama–French–Carhart model. The alpha from the five-factor model across all accounts is −24 b.p. per year while it is −17 b.p. for the four-factor model. In the following section we will compare these numbers with those found for our sample of mutual funds.[10]

Why do we find differences in alphas from a multi-factor model with those from simply using the management-preferred benchmark? Note that any benchmark can be explained in part by a multi-factor model. When an account is regressed on a single benchmark to obtain alpha, the relative sensitivity to the various factors in the multi-factor model is determined by the sensitivity of the single index to each of the factors in the multi-factor model. When a multi-factor model is used directly, the relative sensitivity to the various factors is determined by whatever sensitivity best explains the return pattern of the accounts. Thus differences in the alphas computed from using the manager's benchmark and from using a multi-factor model are determined by the differences in the betas on the multi-factor model and the implicit betas when the benchmark is used. The implicit beta is the product of the account's beta with the benchmark and the beta of the benchmark with the factor.

Table V shows the implicit manager-benchmark beta less the beta on the multi-factor model for each index in the multi-factor model. All of the beta differentials on the market factor are negative, indicating that accounts have more market sensitivity than would be indicated by computing alpha using the manager's benchmark. Over this period the excess return on the market was positive, causing alphas to be higher when the manager's benchmark is used. Examining the SMB ("small-minus-big") factor shows that accounts that hold large stocks have more exposure to the SMB factor than that indicated by the manager's benchmark, while accounts designated as small have less exposure than that indicated by the manager's benchmark. The return on the SMB factor is positive in this period. Thus, the use of the manager's benchmark increases alpha for managers using a large-stock benchmark and decreases it for a manager using a small-stock benchmark.

[10] Both of the multi-index models produce alphas that are lower, at a statistically significant level (0.01), than either the manager-preferred benchmark or the best-fit single-index benchmark.

Table V. Differential betas (implicit benchmark betas minus four-factor betas)

This table shows the difference in implicit benchmark betas and betas obtained from the Fama–French–Carhart four-factor model.

Implicit benchmark betas are computed as the product of the beta of the fund returns on the MPB index and the beta of that benchmark index returns on the specified Fama–French–Carhart factor.

Manager-preferred benchmark	Number of funds	Market	Small-minus-big	High-minus-low	Momentum
Large-cap growth	337	–0.0489	–0.0895	–0.0797	–0.0605
Large-cap blend	677	–0.0061	–0.0836	–0.0100	–0.0171
Large-cap value	265	–0.0066	–0.0627	0.0690	0.0148
Mid-cap growth	182	–0.0629	–0.0241	–0.0636	–0.0778
Mid-cap blend	154	–0.0155	0.0125	0.0208	–0.0618
Mid-cap value	110	–0.0060	–0.0460	0.0665	0.0168
Small-cap growth	186	–0.0634	0.0758	–0.0165	–0.0566
Small-cap blend	185	–0.0327	0.0723	–0.0172	0.0074
Small-cap value	153	–0.0642	0.0395	0.1239	0.0113
Total funds	2,249				

The differential betas on the high-minus-low (HML) factor are positive for accounts designated as value and negative for accounts designated as growth. The HML factor is positive in this period, which means that the HML factor increases the alpha on growth accounts and decreases it for value accounts when the manager-preferred benchmark (MPB) is used. The differential beta on the momentum factor is large and negative for growth accounts, indicating that growth accounts follow more of a momentum strategy than their benchmark (which should be on average zero). Since the return on this factor is positive, growth accounts will have a higher alpha when their MPB index is used to compute alpha. For other types of accounts, the differential beta is small enough to have little impact on differential alpha. Aggregating across all four factors, the difference in betas leads to a larger alpha when the manager's benchmark is used to compute alphas. When the five-factor model is used, the pattern of alphas on the first four factors is the same, and the differential alpha on the fifth factor is small enough to have little influence on the overall differential alpha.

5. Comparison with Mutual Funds

Separate accounts exist alongside very similar mutual funds as options for wealthy investors and institutions. Separate accounts offer their customers the ability to customize their investment strategy and the ability to negotiate fees. Mutual funds have a Board of Directors and are subject to regulation. A Board of Directors makes sure that prospectuses are adhered to and monitor mutual fund profitability. The investors in these separate accounts and mutual funds requiring large investment are wealthy individuals or institutions. Does the cost of regulation overcome the benefits? To examine this we need to examine performance.

We have argued that separate accounts and mutual funds differ in several aspects. The most important are the cost and loss of flexibility due to regulations. We now examine performance to see if this makes a difference.

We did two comparisons of the performance of separate accounts to the performance of mutual funds. For our first comparison, we calculate the difference in performance between each separate account and a randomly selected with replacement mutual fund in the same Morningstar category.[11] When we make this comparison, we find that separate accounts outperform mutual funds by 57 b.p. per year using the four-factor model, and 62 b.p. per year using the five-factor model. These differences are both economically and statistically different at the 0.01 level.

Part of the difference is due to lower expense ratios of separate accounts. Part of the remaining difference is likely due to the lower turnover of separate accounts (and thus lower transaction costs). When we adjust for differences in expense ratios, the difference becomes 46 b.p. and 51 b.p.[12] However, there is still a substantial and statistically significant difference.

This suggests that the ability to customize accounts for investors adds value. Many of our funds are funds that are one share class of a fund with both retail and institutional classes. These funds have to cater their investment strategy to appeal to retail clients as well as wealthy clients. Wealthy clients are likely to take a longer view of performance, and this can lead to better performance. Also, if the board of directors and regulation add value, it is not sufficient to compensate for the greater flexibility of separate accounts. Shortly we will examine whether the results for separate accounts could be due to bias in the data.

Our second comparison used the 425 separate accounts where we could identify a mutual fund offered by the same management company and having the same Morningstar objective. For these funds the difference in performance is +3 b.p. per year for the four-factor model and −3 b.p. per

[11] Six were not classified, and for these we used the overall average.

[12] This was computed for non-wrap accounts. Wrap account expenses include trading costs which are not included in expenses for mutual funds. Including wrap accounts would raise average expenses by 2 b.p.

year for the five-factor model. These differences are not economically or statistically different. Examining the separate accounts that were offered by any manager that offered mutual funds shows inferior performance related to the population of separate accounts. This means that the superior performance was importantly coming from boutique firms that cater only to large wealthy institutions or investors. Examining the organizational structure of these firms shows that they are much more likely to be partnerships with a greater stake in performance. This may explain part of the difference in performance.

Returning to our first comparison, we examine whether the superior performance of separate accounts could be explained by bias.[13] To examine this we will explore all the potential biases. The Morningstar database over the period we studied had neither survivorship nor back-fill bias.[14] However, since separate account managers supply data to Morningstar on a voluntary basis, the data could suffer from self-selection bias. After an account is started, if it is performing badly, it may choose not to supply data to Morningstar. Since some bad-performance managers may never supply data to Morningstar, our results might apply only to separate accounts supplying data to Morningstar and may not apply to the population of all separate accounts.

There is a final source of bias that may be present in our data. Data are reported to Morningstar with a lag of up to 6 months. If a fund has bad performance in a month or 2, it might delay supplying data to Morningstar for up to 6 months to see if results improve. If results are not satisfactory, it may stop reporting and one would not observe the last 6-month results.[15] This means that the returns we see could be upward-biased.

This might not be as serious a bias as it first appears, for two reasons. First, the number of funds that stopped reporting is not large. On average, 39 separate accounts a year stop reporting in our sample of 2,627 separate accounts. Second, it is important for an account to be included in the database because the database is used by investors choosing among

[13] See Elton, Gruber and Blake 1996 (1996a and b), Gruber 1996 and Evans 2010 for a description of bias in mutual funds.

[14] There is some evidence that Morningstar has recently changed its policy and is now removing past data on an account if a manager of that account requests them to do so. Based on several telephone conversations with Morningstar analysts in charge of this data, and examination of the number of funds with history that terminated earlier, it appears to be a recent phenomenon.

[15] Elton, Gruber, and Rentzler (1987) were able to obtain data on commodity funds after they stopped reporting and found that our conjecture of negative returns after they stopped reporting was present for that sample.

account managers. Thus a manager with a few months of bad performance has to balance the cost of revealing that bad performance against the cost of not being included in the database.

Returning to the comparison with mutual funds, separate accounts have alphas after expenses 57–62 b.p. higher than mutual funds. Are these differences real, or could they be due to the bias caused by funds that stopped reporting? To examine if this potential source of bias could explain our results, we tried two experiments. First we assumed that in the 6 months after they stopped reporting, the separate accounts earned an alpha equal to the alpha they earned in the last year before they stopped reporting. Second, we asked how bad performance would have to be in the 6 months after they stopped reporting before separate account performance would not be statistically significantly better than mutual funds at the 0.01 level. Assuming that funds that stopped reporting had 6 months of unobserved data equal to the past year before they stopped reporting changes the average alpha on the four-factor model from −0.0141 to −0.0148, while for the five-factor model the change was from −0.0202 to −0.0211. Under this assumption, mean performance of separate accounts changes only slightly and the difference from mutual funds remains significant at the 0.01 level.

The second question we asked was how large did the yearly alpha on separate accounts that disappeared have to be before the differences in performance between separate accounts and mutual funds are no longer significant at the 0.01 level. The average alpha for separate accounts would have to be on average worse than −26% a year for the four-factor model or worse than −32.3% per year for the five-factor model for differences to no longer be statistically significant. To put this in context, the average return on the market in a 6-month period after the separate accounts stopped reporting was 2% per year.

How does the performance of combined separate accounts compare to index funds? A performance of between −17 b.p. and −24 b.p. per year is consistent with, but slightly below, the performance of institutional index funds. The performance of the lowest cost institutional index funds (depending on the index chosen) tends to be in the range of −3 b.p. to −25 b.p. per year. In the absence of bias, separate accounts tend to produce performance slightly lower than index funds. The underperformance may be further increased by the bias discussed above.

In addition to alpha we also examined the risk of mutual funds compared to separate accounts. For each sample we computed both the standard deviation of total returns and the standard deviation of residuals. To control for risk differences due to different objectives, mutual funds, and separate accounts were then grouped into the nine groups shown in Table II and then an overall standard deviation was computed. Total risk of separate accounts was 2% less than mutual funds and residual risk was 6% higher. These differences are not economically meaningful and not statistically significant.[16] Thus along risk dimensions, mutual funds, and separate accounts are virtually identical.

6. Performance and Account Characteristics

An interesting issue is whether we can find characteristics that differentiate between separate accounts that perform well and those that perform poorly. In doing so we employ some variables that have been used to explain performance in the mutual funds literature and some that have not been used. Table VI presents our results.[17] Two regressions are presented, one with dummies for the descriptive variables and one without. Examining the two regressions shows that the inclusion of dummies does not affect the sign or whether any of the non-dummy variables are significant. However, the inclusion of dummies does increase the explanatory power and the magnitude of the significance of the variables.

We start our discussions with the standard variables used to explain performance differences for mutual funds: expense ratios, turnover (as a proxy for trading costs) and fund or family size. We expect expense ratios and turnover to be negatively related to alpha, just as they are in mutual fund studies. We find results consistent with the mutual fund literature. Firms that charge more have lower returns, and the coefficients associated with both variables are statistically significant at the 0.01 level.

The next set of variables we examine measures size: the log of assets in a single SMA or CIT, and the log of assets across all accounts in the managing firm with the same objective. Berk and Green (2004) argue that successful mutual funds grow, and when the fund grows, superior performance disappears. If this hypothesis held for separate accounts, we would expect to see a negative relationship between assets in a single separate account and alpha. Separate accounts that are members of large families have access to more research, and this should improve performance. (See Gasper *et al*. (2006) for mutual funds.) This may also be true when there is a larger investment in a

[16] The coefficient of determination for separate accounts with a four-index model is 0.91, close to what we find for actively managed mutual funds.

[17] The sample sizes are much smaller since many separate accounts do not have data on all the variables. The principal variable missing data are turnover. Re-estimating the regressions without this variable (and thus having a much larger sample) does not affect the sign or significance of the other variables and their magnitude is virtually unchanged.

Table VI. Alpha cross-sectionally regressed on explanatory variables

This table shows the results from cross-sectional regressions of the separate account Fama–French–Carhart four-factor alphas on two sets of explanatory variables.

The first set includes a series of dummy variables; the second set does not.

t-values are shown in parentheses.

Obs.	Adjusted R-square	Intercept	Average turnover	Assets in top ten	Number of holdings	Average expenses	Log of min. initial purchase	Bank adviser dummy	Broker adviser dummy	Consultant adviser dummy	Independent adviser dummy	Limited liability dummy	Partnership dummy
1,326	0.0733	–0.2179	–0.0003	0.0018	–0.0002	–0.6267	0.0121	–0.0430	–0.0643	–0.0340	0.0161	0.0612	0.0235
		(–3.078)	(–3.170)	(3.2158)	(–3.044)	(–4.467)	(3.321)	(–1.385)	(–1.716)	(–0.568)	(1.005)	(3.499)	(1.821)
1,326	0.0600	–0.1187	–0.0003	0.0020	–0.0002	–0.6248	0.0105						
		(–1.884)	(–3.4074)	(3.5348)	(–3.251)	(–4.429)	(2.919)						

single strategy. Thus we would expect a positive sign for this variable. While both variables have the hypothesized sign, the t-values are very close to 0 and the results are not repeated in Table VI. The impact of these two variables is much smaller than their counterparts in the mutual fund literature. We also tested a number of variables not found in the mutual fund literature. The next variable we examine is log of initial purchase. Larger initial commitments are likely to involve greater diligence on the part of the investor and are more likely to be only accessible to institutions or very wealthy individuals who may employ professional guidance or be more sophisticated and thus better able to select superior funds. Thus we would expect, and we find, a significant positive relationship between the size of the initial purchase and alpha.[18]

We examine two measures of the concentration of the portfolio. These variables are the percentage of the portfolio in the top ten securities and the number of securities held long. Although both are measures of concentration, they measure different aspects of concentration and are weakly negatively correlated. A positive coefficient for percentage of securities in top ten holdings and a negative coefficient for number of securities held long would indicate that a manager places larger amounts in the securities he or she is most optimistic about. If concentration is a useful strategy, we would expect a positive relationship with percentage in top ten securities and negative with number of securities held long. The results are consistent with this and highly significant.

Our next variable is the absolute value of the cash flow into or out of an account. This is measured as the absolute value of total net assets at t minus the quantity of total net assets at $t-1$ times the return over the year, all divided by total net assets at $t-1$. Thus, it measures the absolute value of the percentage change in total net assets not accounted for by return on existing assets. We would expect that large changes in assets are disruptive to performance and would thus cause this variable to be negatively related to performance. We find no significance for this variable, and do not report it.

In addition to the quantitative data discussed above, Morningstar reports a number of descriptive variables. These include indicators of the type of legal organization (e.g., corporation or partnership), the type of business supervising the account (e.g., bank), whether there is pending litigation against the firm, whether the product is primarily an institutional or retail product, and whether or not the account is a CIT or SMA.

[18] Larger initial purchase also means lower expense ratios. The correlation between expenses and initial purchase size is negative but small.

The legal structure of the firm offering separate accounts might well have implications for the performance of separate accounts it manages. We study two aspects of legal structure: whether the management company is organized as a partnership, and whether it has limited liability.

Separate accounts that are organized as a partnership have the profits from running the business flow through directly to the partners, and they may be more motivated to work harder and increase returns. We introduce a dummy variable to indicate partnership and expect the sign to be positive. Similarly, when the firm has limited liability we would expect that this allows investment managers to select from a wider range of investment alternatives and this might improve performance. Here we introduce a dummy variable for limited liability, and we expect it to enter a regression with a positive sign.[19] Both variables have the expected sign, with limited liability highly significant.

The next discrete variable we examine is the type of sponsoring organization. Separate accounts may be run by banks, brokers, consultants, and independent investment advisors. We have no priors as to which type of sponsor is superior, so we do not formulate any hypothesis about the difference in performance, but we do examine it. We used individual dummies for banks, brokers, consultants, and independent investment advisors. The null was firms that signified they were "other." By far the bulk of the accounts were managed by independent investment advisors. They also had the largest positive impact on alpha, though the impact was not statistically significant. All of the other categories had negative dummy variable coefficients, with only the broker dummy variable being close to statistically significant.

The final discrete variable is a pending lawsuit against the organization sponsoring the separate accounts.[20] We would expect that separate accounts that had a lawsuit outstanding would have, in general, poor governance and would perform worse than funds that had no lawsuits outstanding. Although others have found pending lawsuits to be important, we find no evidence of this for separate accounts.[21]

[19] Note that there are forms of organizations that are taxed as partnerships but have limited liability. Thus the dummy variables take on different values and they are not redundant.

[20] We also examined whether type of account (retail or institutional or both) or whether classification as CIT or separate account is important. Neither variable was close to significant.

[21] See Brown *et al.* (2012).

7. Cash Flow Determinants

In the last section we reviewed the determinants of alpha in a cross section of the funds in our sample. In this section we examine cash flow to see if we can establish the variables that affect cash flow.

Since the cash flow variable is only available on a yearly basis and since some of the variables determining cash flow are only available on a yearly basis, we performed yearly cross-sectional regressions and used the standard Fama–MacBeth (1973) methodology to determine the significance of the independent variables across our yearly cross-sectional regressions.

The dependent variable for each cross-sectional regression was the annual cash flow for that year for each separate account. For cash flow we use the definition described earlier as the end-of-year asset value minus the quantity of the beginning-of-year asset value times the rate of return for the year, all divided by the beginning-of-year asset value.

The first two independent variables we examined are each measures of the lagged performance of each account. The first lagged performance measure we used was the monthly alpha annualized from our four-factor model (estimated over the 2-year period preceding the cash flow) plus the sum of the monthly residuals for the year in question.[22] Examining Table VII shows that cash flow is positively related to past performance and the relationship is statistically significant at the 0.01 level. Similar results have been found in the mutual fund literature.[23]

The second performance variable we examined was the lagged alpha plus residuals employing the MPB. This was included to see if the MPB impacted cash flow beyond the influence due to the more traditional four-factor model. For each year, all MPB alphas were orthogonalized to the four-index alpha by using the residuals from a cross-sectional regression. By orthogonalizing the MPB alpha to the four-factor alpha, we attribute any common effect of alpha on cash flow to the four-factor model. Examining Table VII shows the cash flow is positively related to performance based on the MPB, even after other influences, and in particular the influence of the Fama–French–Carhart model, have been removed. This is important because despite the fact that the MPB

[22] We also used the lagged 2-year alpha without adjustment for the 1-year residuals; similar results were found for similar results for mutual funds.

[23] This follows since the literature on mutual funds shows that future performance is related to past performance. Cash flows are also related to past performance. See Brown and Goetzmann 1995, Elton *et. al*. 1996a and b, Gruber 1996 and Grinblatt and Titman 1992.

Table VII. Separate account cash flow regressed on explanatory variables (averages and *t*-values of nine annual cross-sectional regressions)

This table shows the averages and t-values across a set of nine annual cross-sectional regressions of cash flow on a set of explanatory variables.

Lagged four-factor alphas are annualized and obtained by taking the 2-year four-factor monthly alpha ending in the year prior to evaluation and adding the average monthly residual during the prior year.

Lagged orthogonalized MPB alphas are the cross-sectional residuals each year from a regression of the one-factor alphas on the four-factor alphas, where the single factor is the management-preferred benchmark index.

	Intercept	Lagged Four-factor alpha	Lagged orthogonalized MPB alpha	Log of strategy total assets	Average expenses	Log of min. initial purchase	Pending litigation dummy	Retail product dummy	Collective investment trust dummy	Limited liability dummy	Partnership dummy
Average	−90.645	3.159	2.235	4.226	20.712	0.019	−4.993	86.545	−43.510	34.033	27.849
t-Value	−1.087	2.951	2.520	2.354	1.157	0.006	−0.357	1.582	−6.356	3.097	3.799

overstates performance, investors of private accounts pay attention to it in allocating investments.[24]

The next variable we introduced was the natural logarithm of total assets managed by the firm using a given strategy (e.g., large growth). While alpha was not related to this variable, here we find cash flow is positively related to size at a statistically significant level. This indicates that firms with a larger amount of assets following any strategy are more successful in attracting new funds, probably because of promotional effort.

As discussed in the last section, expenses are negatively related to performance. Thus we would expect that higher expenses lead to lower cash flows. However, investor expenses also represent the investment managers' profit and provide funds for marketing effort. Thus higher expense funds provide the investment manager with a greater incentive to aggressively pursue new business and the revenue to do so. These two factors work in opposite directions. As shown in Table VII, cash flows are positively related to expenses, though the relationship is not statistically significant. The

[24] Performance relative to the manager-preferred benchmark are the data normally reported to the customer. A second method was employed to examine the impact on cash flows of the performance from the one-index MPB model. The equation in Table VII was re-run without the residuals of the MPB benchmark present. The unexplained cash flows (residuals) from this model were regressed in cross section against their alphas of the single-index MPB model. The results were consistent with those reported above. The coefficient of the unexplained cash flow on the MPB alpha had a *t*-value of 2.23.

positive sign is consistent with the results found in previous research on mutual funds provided by Sirri and Tufano (1998) and Elton, Gruber, and Blake (2003).

We next examined the effect of the minimum initial purchase on cash flows. We previously saw that larger minimum initial purchases lead to better returns. Although they have the expected sign, the results are not close to statistically significant.

Pending litigation is a dummy variable that is 1 if there is pending litigation. Pending litigation could come about because the investment manager is pushing the limit on types of investments or because of practices that could harm the investor. We find no effect on cash flows for this variable.

The next variable we examined was whether cash flows to combined separate accounts were affected by which customers they were appealing to. There are three possibilities: a retail focus, an institutional focus, or both. The results are not statistically significant when we include dummies for any of the variables and combinations of variables.

The next variable we examines whether the combined separate account was a CIT. This variable is highly negatively significant, implying that CITs get fewer cash flows than SMAs.

The last two variables measure corporate structure: first, whether it has limited liability, and second, whether it is a partnership. Both affect cash flows positively and significantly at better than the 1% level. As shown earlier, both of these are positively related to alpha. Thus, they are useful indicators of good performance and should affect cash flows.

8. Conclusion

Despite the size and importance of separate accounts, there have been very few studies of separate accounts in the literature. The principal reason for this is the lack of data on separate accounts. In this article we analyze a 10-year span of data on 2,627 separate accounts. We find that separate accounts perform no better and perhaps worse than index funds but can be more attractive than a matched sample of mutual funds. This is true when performance is judged by the four-factor Fama–French–Carhart model or by a five-factor model that adds a micro-stock index. A caution is in order, for while our sample is corrected for survivorship bias, there may still be some bias due to accounts not reporting data over the last few months when they disappear from the database. However given the small number of accounts that stop reporting during our sample period (31 per year out of 2,627), this should not be a problem.

Performance can also be judged by using the benchmark that management selects as most appropriate for each account. It is clear that management exhibits some ability to select benchmarks which make their performance look good. When using the management-selected benchmark, separate account performance looks much better than when an index that best fits the return on the account or the four- or five-index model are used.

In a later section of this article we show account performance is related to a number of variables. Expenses, whether measured directly via the expense ratio or indirectly through turnover, negatively affect performance. Concentration, the size of the initial purchase and the managing firm organized as a limited liability entity or where cash flows are distributed as a partnership positively affect performance. It is especially interesting that firms that are organized so that managers have a direct stake in the profits have higher alphas.

Finally, like mutual funds, past performance positively impacts cash flows into the separate account. Furthermore, cash flows are higher for SMAs, separate accounts with larger minimum initial purchase and for those cases where the managing firms have limited liability and where income is distributed as a partnership. Larger separate accounts have a smaller percentage increase in net assets.

Perhaps more importantly, we show that performance measured from the management-preferred benchmark impacts cash flows, even after the impact of performance measured from the Fama–French–Carhart models, has been removed. Despite the fact that the use of the management-preferred benchmark overstates performance relative to more reasonable models, investors take it into consideration when making investment decisions.

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