The Performance of Separate Accounts and Collective Investment Trusts

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Abstract

Despite the size and importance of separately managed accounts and collective investment trusts, their characteristics and performance have not been studied in detail in the financial economics literature. In this paper, we show that, using the Fama-French-Carhart 4-factor model, 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 of those accounts. When the management-selected benchmark rather than either the single-index model that best fits the return pattern of the account or the Fama-French-Carhart 4-factor model 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 separately managed accounts. We examine and find a set of variables that explains (at a statistically significant level) both the cross section of alphas and the cross section of cash flows. In addition to the set of variables that have been used to explain those phenomena in mutual funds, a set of organizational variables such as limited liability and tax exposure are found to have a statistically significant impact on alphas and cash flows.
I. Introduction

In this paper we study pooled Separately Managed Accounts (SMA) and Collective Investment Trusts (CIT). These vehicles represent alternatives to mutual funds for investment by wealthy individuals and institutional investors, including pension plans and endowments. A separately managed account 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 separately managed account generally has a minimum initial investment which in almost all cases range from $100,000 to $25 million. Separately managed accounts are not regulated, although the manager is often a registered investment advisor subject to the Investment Advisor Act of 1940. 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 the study of 401(k) accounts estimated that these accounts had 61% of their assets invested in separate accounts and comingled accounts as opposed to 38% invested in mutual funds.

Collective Investment Trusts are co-mingled accounts offered by banks or trust companies for qualified pension plans, defined benefit plans, defined contribution plans, and certain government pension plans. 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 they are not required to disclose performance data. About 40% of pension plans hold collective investment trusts.
Despite the fact that SMAs and CITs are important investment vehicles, they have not been studied in detail in the literature of financial economics. In this paper we examine several aspects of their 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. The performance of separate accounts when properly measured is very close to that of index funds and better than a matched sample of mutual funds.

We also study the determinants of both cross-sectional differences in the returns 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, limited liability, size of the minimum initial purchase, and the existence of pending lawsuits. Statistically significant relationships are found.

SMAs and CITs supposedly have a cost advantage over mutual funds in that they have less required reporting, lower marketing costs, smaller support staffs to handle customer inquiries, and no independent boards. In addition, they have flexibility in fees, and portfolios can be customized to meet a client’s objectives.

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

\footnote{The primary studies of institutional products are Busse et al. (2010) and Petersen et al. (2011), both of which principally study predictability using pre-expense returns.}
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 that accounts represent 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.

Separate accounts, like hedge funds, often report data with a lag. This means that an account that suffers a loss can delay reporting in hopes that subsequent months’ returns are better. If there is no improvement, they may choose not to report. This can induce a bias, since returns in the last few months before they are dropped from the database are not observable. The effect of this will be discussed in detail later.

In addition, there may be a bias in favor of higher returns caused by self-selection of those managers who choose to start reporting. However, this is mitigated by the belief that to be considered by a new investor they need to be in one of the large databases.\(^2\)

This paper is organized as follows: In Section II we present some more information on our sample. In Section III we present the methodology used in measuring performance. In Section IV we examine performance. In Section V we compare the performance of SMAs and CITs with the performance of mutual funds. In Section VI we analyze the cross-sectional determinants of the performance of separate accounts. In Section VII we analyze the cross-

\(^2\) Morningstar does not allow separate accounts to enter the database with a history, so there is no backfill bias.
sectional determinants of cash flow to separate accounts. Our conclusions are presented in section VIII.

II. 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).

We then eliminated:

1. All accounts that were identified as index accounts, specialty accounts (e.g., REITs, tech funds, etc.) or were heavily invested in bonds or foreign securities (847 accounts).
2. Any accounts that started prior to January 2009 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. 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 was accurate (14 accounts). This left us with a combined sample of 2,627 accounts consisting of 2,277 pooled separately managed accounts and 350 collective investment trusts. 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

3 This 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.
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.4

Table 1, Panel A shows the distribution of minimum investment in an account for the combined SMAs and CITs and 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 1, the median mutual fund is more than 2 1/2 times larger than the median combined separate accounts (SMA's and CIT's). 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 very little difference. The mutual funds sample holds slightly more stocks, which is consistent with mutual funds being larger and the tendency of mutual funds to add additional stocks slowly as fund size grows (see Pollet and

4 We also selected as a comparison sample all institutional mutual funds. The results discussed in later sections were very similar with this sample.
Wilson (2008)). Even with the larger number of stocks held by mutual funds, the concentration in the top 10 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 the return series to estimate the expense ratios for the combined sample. If Morningstar does not receive data on both pre- and post-expense return, it calculates the return data it doesn't have using a representative fee from the firm supplying the data.\(^5\)

Some fees were reported quarterly and some monthly. In all cases we converted fees to annual fees. The data on fees are reported in Table 1. In validating the data, we did an extensive amount of data checking. On occasion 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.\(^6\) However, there are probably mistakes in the imputed expense ratios that fall within the parameters for elimination. Nevertheless, 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

\(^5\) If Morningstar doesn't have a representative fee, they use the maximum fee from the firm's schedule. However, if they don't have a representative fee they rarely have a fee schedule. Finally, if they don't have any fee data they leave the return series that is not reported blank.

\(^6\) 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 8 times the average difference, or where either gross or net returns were plus or minus 200% per month.
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 1 except for the 90% breakpoint, CIT and SMA fees are lower than those for mutual funds. 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 1 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. Lower costs are frequently cited as a reason why institutions and high-net-worth individuals use SMAs or CITs rather than mutual funds that cater to these clients.

Another supposed advantage of SMAs is that they need less support staff to handle customer inquiries. Table 1 shows the median number of customers following any strategy is 12. However, since each individual account is customized, each account may require more attention by management.

III. Methodology

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

\[ R_i = \alpha_i + \sum_{j=1}^{J} \beta_{ij} I_{jt} + \epsilon_{it} \]

where

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

\[ \alpha_i = \text{the intercept; } \]

\[ \beta_{ij} = \text{the coefficient associated with factor } j; \]

\[ I_{jt} = \text{the indicator variable for factor } j \text{ at time } t; \]

\[ \epsilon_{it} = \text{the error term.} \]

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7 A few of the separate accounts were wrap accounts, and this accounts for the higher upper-end expenses.
\[ I_{ij} = \text{index } j \text{ of an appropriate set of indexes (each defined as the return on a zero-investment portfolio) for month } t; \]
\[ \beta_{ij} = \text{the sensitivity of account } i \text{ to index } j; \]
\[ \alpha_i = \text{the risk-adjusted return (using the included indexes) of account } i; \]
\[ \epsilon_{it} = \text{the residual return of account } i \text{ in month } t \text{ not explained by the model}. \]

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 two or more indexes. There were 22 remaining benchmarks selected by 2,249 accounts. Examination of these 22 benchmarks showed that for reporting summary statistics they could be grouped into nine categories, though all 22 indexes were retained for purposes of computing alpha. The nine categories of benchmarks used for reporting purposes are identified as large-cap, mid-cap and small-cap, with each group divided into growth, blend and value.

Thus the first performance measure used was simply the alpha from a regression of each account against the management-declared benchmark. For purposes of computing alpha against management's preferred benchmark, we used whatever management chose. However, for reporting purposes we aggregated the results into the nine categories described above plus another category for the 29 composite benchmarks that did not fit these nine categories.
For the second model we used the single index that best explained the behavior of each account. Four of the 22 indexes were essentially identical to one of the remaining 18 (e.g., S&P Midcap and Russell Midcap). Thus for the stepwise procedure we used 18 indexes. The best index was selected via a stepwise procedure from the 18 possible indexes. The alpha from this procedure was computed, and this alpha 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. 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. 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. While we will emphasize the Fama-French-Carhart model throughout the rest of the paper, 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.

IV. Performance

In Table 2 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 70 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.\(^8\) The average difference is 6.3 basis points per month or approximately 76 basis points per year. This difference is economically and statistically significant at the 0.01 level.\(^9\) Furthermore, the best-fit alpha is lower in 8 of the 10 categories.\(^10\)

When we examine individual categories we see that the biggest differences in alpha occur in the management benchmark growth categories, while only the mid-size blend and value categories have benchmark alphas below those produced by the best-fit index.

There is definitely a difference between the alphas produced by the benchmarks selected by management 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.

Why is there a difference in average alpha when it is computed using the manager's chosen benchmark and when it is computed using the index that best describes the return pattern? Obviously, if the manager's benchmark and the best-fit index are the same, there is no

\(^8\) It is interesting to note how infrequently managers change their benchmarks. For instance, in a one-year period only 27 out of 2,627 accounts changed their benchmarks.

\(^9\) All of the differences in alphas between models of performance reported in panel A of Table 2 are performed using a matched-pair \(t\) test for difference in means.

\(^10\) The fact that the management-preferred benchmark results in higher alphas has been documented by Angelidis et al (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.
difference in the computed alphas. Thus the difference comes about because the managers chose
to use a benchmark other than the one that best described the performance of the account they
managed.

Table 3 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 4 shows the alpha which
arises from the difference in classifications presented in Table 3.

For example, from Table 3 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
impact of this can be seen from Table 4. The average increase in alpha attributed to each of these
69 funds is 21 basis points per month.\(^{11}\)

Some clear patterns arise from Table 3. 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

\(^{11}\) Observations with less than five entries have been deleted in Table 4 to better examine
the factors influencing differential alpha. There are some minor values on the main diagonal that
have been zeroed out. These occur because the index the manager chooses and the best-fit index,
while in the same one of the nine cells, can be slightly different (e.g., Russell and S&P midcap
indexes).
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 3, 193 of the managers who chose a large stock-index had returns which looked like they were investing in smaller stocks.

Table 4 makes it clear that the choice of a benchmark by managers results in a higher alpha than that produced by the best-fit index. Note that almost all entries in this table are positive. In only six cells in this matrix are the alpha differentials negative, while in 20 cells they are positive. Managers are almost uniformly making choices that increase this alpha over using a more appropriate index. In addition, note in general that the further the manager's chosen benchmark is from the best-fit alpha, the greater the differential alpha. 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 is presented in the bottom row of Table 4. The numbers in this row represent the average increase in alpha associated with all accounts for which management has selected a different benchmark than the one shown in the column. This is computed by taking the sum of all differential alphas where the best-fit index differs from the management-declared benchmark and then dividing by the number of observations. We see that for nine of the benchmarks selected by management, eight show a higher alpha than they would show using the best-fit benchmark. The one category that shows a lower value is the mid-cap value account category. Many of these accounts should have been categorized as mid-cap blend.
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 one year period only 27 out of 2627 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 can most easily be seen by examining the row labeled “average” in Table 4. This row contains the increase in alpha in several categories by using the benchmark management has selected rather than the best-fit benchmark. For example, the first entry, 27.9 basis points per month, means that portfolio that management classified as large cap growth produced an excess monthly alpha of 27.9 basis points per month higher than if the best fit benchmarks were used.

Examining Table 3 column 1 shows that the best-fit index was smaller or less growth oriented than the growth index chosen by management. It is easy to see, from examining the row labeled average in table 4 that managers who used a growth benchmark, rather than a best fit benchmark, did better in each size category than those that used a blend or value benchmark. Similarly, those that used a blend benchmark did better compared to the best-fit benchmark than those that used a value benchmark. Similar statements are true with respect to size. By using a benchmark that overstates the size of the securities in the portfolio and the growth orientation, managers increase the reported alpha over more appropriate benchmarks.
Returning to Table 2, 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 difference between the four- and five-factor models for accounts where the manager has a declared benchmark is 0.0051 b.p. per month. This difference comes about because some of the accounts in our sample hold micro-cap stocks, often in large amounts. Thus the inclusion of a micro-cap index seems appropriate. The alpha from the five-factor model across all accounts is minus 24 basis points per year while it is minus 17 basis points for the four-factor model. In the following section we will compare these numbers with those found for our sample of mutual funds.\(^\text{12}\)

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 multiple-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

\(^{12}\) Both of the multi-index models produce alphas which are lower, at a statistically significant level (0.01) than either the manager preferred benchmark or the best-fit single index benchmark.
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 5 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 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. The return on the
small-minus-big (SMB) factor is positive in this period, which decreases the alphas for accounts
 tilted more towards large stocks and increases them for accounts tilted more toward small stocks
relative to what would be inferred from the benchmark. The differential betas on the high-minus-
low (HML) factor are positive for accounts designated as value, indicating that they have a lower
value tilt than that indicated by the multi-factor model. Likewise, the accounts designated as
growth are more value-tilted than would be indicated by the manager's benchmark. The factor
had a positive value in this period, increasing the alpha on growth accounts and decreasing it for
value accounts. 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 benchmark 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.

V. Comparison with Mutual Funds

Table 2, Panel B, shows the performance of our stratified sample of mutual funds. How does its performance compare to our sample of separate accounts? The average alpha from the four-factor model for mutual funds is $-77$ b.p. per year while it is $-94$ b.p. per year using the five-factor model. The expense ratio for the sample was 94 b.p. per year. The return is of the general order of magnitude found in other mutual fund studies, while the expense ratio is somewhat lower. The lower expense ratio is to be expected given the large size of initial investment required for the mutual funds in our sample.

For our separate account sample, we find that the average alpha from the four-factor model is $-17$ b.p. per year, while from the five-index model it is $-24$ b.p. per year. The differences in performance for separate accounts and mutual funds are between 60 and 70 b.p. per year, depending on the model used. These differences are statistically significant (at the 0.01 level) and economically significant.\footnote{Statistical significance for the difference in means was computed using a $t$ test of the difference in means for two samples with unequal variances.} Examining the difference in expense ratios still indicates that separate accounts managers outperform mutual fund managers by about 50 b.p. per year before expenses.\footnote{This was computed for the non-wrap accounts. Wrap account expenses include trading costs that are not included in expenses for mutual funds. Including wrap accounts would raise average expenses by 2 b.p.}

Is this a real difference or could the superior performance of separate accounts be explained by bias? To examine this we will explore all the potential biases. Potentially the most
serious source of bias, which is found in many data sources, is survivorship bias. This occurs when funds that do not survive (or in this case cease to report data to Morningstar) have their past records removed from the database. Fortunately, this is not a problem with Morningstar because during our sample period they maintained the history of funds that stopped reporting data.15

The size of the bias that would be present if accounts had their history removed can be determined by examining the history of accounts that stopped reporting. The average alpha for the funds that stopped reporting is −0.1226 per month or about −1.35% a year. The performance is even worse in the last year before they cease reporting. The alpha in the last year is −0.1777 per month or −2.3% per year, where a fund’s alpha is computed as the last year's average residual plus the fund’s overall alpha.

There is another potential source of upward bias. Since separate account managers supply data to Morningstar on a voluntary basis, the data could suffer from self-selected bias. After an account is started, if it is performing badly, it is not likely to supply data to Morningstar. If it does well it is likely to supply data. Morningstar does not allow accounts to enter with past data. Thus there is no bias within the Morningstar data. However, it does mean that our results might only apply to separate accounts supplying data to Morningstar and may not apply to the population of all separate accounts.

15 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 the data and examination of the number of funds with history that terminated earlier, it appears to be a recent phenomenon.
The third possible source of bias is likely present in our data. Data are reported to Morningstar with a lag of up to six months. If a fund has bad performance in a month or two, it might delay supplying data to Morningstar for up to the six-month period to see if results improve. If results are not satisfactory, it may stop reporting and one would not observe the last six-month results.\textsuperscript{16} 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 funds 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 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 60 b.p. to 70 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.\textsuperscript{17} First we assumed that in the six 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 six months after they stopped reporting before separate account performance

\begin{itemize}
\item \textsuperscript{16} 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 stop reporting was present for that sample.
\item \textsuperscript{17} Our population is all accounts in the Morningstar database. When an account disappears from the database we assume an investor no longer holds that account. Since data in Morningstar can be reported with a six month lag, six months of bad results may be missing before the investor realizes that the fund is no longer in the database.
\end{itemize}
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 4-factor model from -0.0141 to -0.0148, while for the 5-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 -28% a year for the 4-factor model or worse than -34.4% per year for the 5-factor model for differences to no longer be statistically significant. To put this in context, the average return on the market in a six-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 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 to −25 b.p. per year. In the absence of bias, separate accounts tend to produce performance slightly lower than index funds. Given the bias discussed above, it appears that separate accounts underperform index funds.

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 do to different objectives, mutual
funds and separate accounts were then grouped into the nine groups shown in Table 2 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.\textsuperscript{18} Thus along risk dimensions, mutual funds and separate accounts are virtually identical.

VI. Performance and Account Characteristics

One of the interesting issues in this study is what characterizes accounts that perform well and those that perform poorly. In our choice of potential variables, we will draw heavily from the mutual fund literature. One of the characteristics of better-performing mutual funds is that they have lower expenses (see Brown and Goetzmann (1995), Grinblatt and Titman (1992), Elton, Gruber and Blake (1996b) and Carhart (1997). Total expenses consist of two components: direct charges (expense ratios) and trading costs. We do not have a direct measure of trading costs. However, we do have a good proxy: turnover. Thus the first two variables we will examine are expense ratios and turnover. We expect similar results to the mutual fund literature, namely that higher expenses, whether direct charges or trading expenses, are negatively related to alpha. The third 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 a positive relationship between the size of the initial purchase and alpha.\textsuperscript{19}

\textsuperscript{18} 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.

\textsuperscript{19} Larger initial purchase also means lower expense ratios. The correlation between
The next two variables we examine measure 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 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. 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, Massa and Matos (2006) for mutual funds). Thus we would expect a positive sign for this variable.

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 earnings on existing assets. We would expect that large changes in assets are disruptive to performance and expenses and initial purchase size is negative but small.
would thus cause this variable to be negatively related to performance.

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.

The legal structure of the firm offering separate accounts might well have implications for the performance of separate accounts it manages. While there are data placing any firm managing separate accounts into one of six categories by organizational structure, these categories have two interesting dimensions: whether the income to the supervising firm is taxed as a corporation or as a partnership and whether the principals in the firm have limited liability or not. These choices can have major implications for the principals in the firm, and that, no doubt, affects the choice of structure for the firm managing the account. These same influences could also have implications for the type of investments the managers choose for any account and thus for the account’s returns.

If the principals in the firm are taxed as a partnership, the profits from running the business flow through directly to them and they may be more motivated to work harder and increase returns. Thus when we introduce a dummy variable to represent those accounts where profits flow directly to managers, we 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.\(^{20}\)

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 don't formulate any hypothesis about the difference in performance, but we do examine it.

There are three other discrete variables that might affect performance. The first is a pending lawsuit against the organization sponsoring the separate accounts. 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.\(^{21}\)

The next variable we examine is whether the account is a retail account, an institutional account, or both. While we do not have a strong theory, we would expect institutional accounts to be better run simply because they are bought by more knowledgeable investors with the help of a research staff. Finally, we examine the impact on alpha of the classification of an account as a separate account or a CIT.

Table 6 presents our results.\(^{22}\) 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.

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\(^{20}\) 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.

\(^{21}\) See Brown, Goetzmann, Liang and Schwarz (2011).

\(^{22}\) The sample sizes are much smaller since many separate accounts do not have data on all the variables. The principal variable missing data is 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.
However, the inclusion of dummies does increase the explanatory power and the magnitude of the significance of the variables.

Examining the expense variables, we see that they have the expected sign. Both higher turnover and higher expenses are associated with lower alpha. Both coefficients are highly significant, and the results are consistent with the mutual fund literature. The log of minimum initial purchase is positive and highly significant. This is consistent with more sophisticated investors selecting better-performing funds. The concentration measures are also significant. An increase in the percentage in the top 10 assets or a decrease in number of holdings leads to an increase in alpha. Both are highly significant and consistent with concentration improving performance. The two size variables and the cash flow variable discussed earlier are not included in Table 6. While all three variables had the expected sign, none of the three variables were close to significant. Thus there is no significant evidence for separate accounts that account size, the size of the family they belong to or changes in assets under management affect alpha.

The impact of the discrete variables on performance is shown in the top regression in Table 6. When we examine the form of the organization for the firms managing separate accounts, we study two aspects of the organizational structure: limited liability and taxed as a partnership or corporate entity. We hypothesized that limited liability would give management the ability to have more freedom and be more adventuresome in the assets they choose. Thus the coefficient on the dummy associated with limited liability should be positive and statistically significant, and it is.

We hypothesize that, if sponsoring firms are taxed as partnerships, it will lead to greater effort by the managers and a smaller and more sophisticated ownership structure. We use a
dummy variable for sponsors that are taxed on a flow-through basis. The coefficient of the dummy variables is positive and statistically significant at the 5% level.

The next set of variables we examined was the primary business of the sponsoring organization. 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.

Two other results were not significant and so the results are not reported in Table 6. We found no statistical significance difference in performance where a fund was a CIT or a managed account. Finally, we found no relationship between pending lawsuits and performance of the separate accounts.

VII. 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. While the methodology we use is different from that used in the previous section, many of the variables we examine are the same.

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 fund. For cash flow we use the definition described earlier as the end-of-year asset value minus the quantity the beginning-of-year asset value times the rate of return for the year, all divided by the beginning of the year asset value.

The first two independent variables we examined are each measures of the lagged performance of each account. The first measure is based on the Fama French Carhart Four factor model and the second is based on the manager declared benchmark. The first measure was chosen because there is an extensive literature on mutual funds, which showed that cash flow is positively related to past performance measured by such models.\(^{23}\) We expect to see a similar relationship for separate accounts. The lagged performance measure we used was the monthly alpha annualized from our four-factor model (estimated over the two-year period preceding the cash flow) plus the sum of the monthly residuals for the year in question.\(^{24}\) Examining Table 7 shows that cash flow is positively related to past performance and the relationship is statistically significant at the 0.01 level.

The second independent variable we examined was the lagged alpha plus residuals employing the manager preferred benchmark. This was included to see if the manager preferred benchmark 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 orthoganolizing the MPB alpha to the four factor

\(^{23}\) For example, see Gruber (1996).

\(^{24}\) We also used the lagged 2-year alpha without adjustment for the one-year residuals; similar results were found.
alpha, we attribute any common effect of alpha on cash flow to the four factor model.

Examining Table 7 shows the cash flow is positively related to performance based on the manager preferred benchmark, 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 overstates performance, investors of private accounts pay attention to it in allocating investments.\textsuperscript{25}

The next variable we introduced was the natural logarithm of total assets managed by the firm using a given strategy (e.g. large growth). Alpha was not related to this variable, while 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.

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 7, cash flows are positively related to expenses though the relationship is not statistically significant. The positive sign is consistent with the results found in previous research.

\textsuperscript{25} 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 7 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 co-efficient of the unexplained cash flow on the MPB alpha had a t value of 2.23.
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. They also appear to lead a higher cash flow, though the results are not statistically significant.

Pending litigation is a dummy variable that is 1 if there is pending litigation. We find no effect on cash flows for this variable. 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. It seems that pending litigation does not affect cash flows.

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. When we included either the institutional or both as a dummy variable, the result was that neither was significant and both had coefficients close to zero. Retail focus comes in with a positive sign. Including a second dummy for another focus variable did not affect its magnitude. If any focus affects cash flow, it is a retail focus, though the results are not statistically significant.

The next variable we examined was 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 income is distributed as 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.
VIII. 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 paper we analyze a ten-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 the last few months of data when they disappear from the database. However given the small number of accounts that stop reporting during our sample period (thirty-one per year out of 2,617), this should not be a problem.

Performance can also be judged by using the benchmark which 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 paper 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 but 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 but 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.
Table 1 – Characteristics of Separate Accounts and Mutual Funds

Panel A, Part 1 – Combined Separate Accounts

<table>
<thead>
<tr>
<th>Aggregate Size of Account (in thousands)</th>
<th>Number of Customers in an Account</th>
<th>Minimum Investment (in thousands)</th>
<th>Number of Stock Holdings</th>
<th>% Assets in Top 10</th>
<th>Expense Ratio %</th>
<th>Turnover %</th>
</tr>
</thead>
<tbody>
<tr>
<td>Median 152,410</td>
<td>12</td>
<td>5,000</td>
<td>63</td>
<td>28.8%</td>
<td>0.81%</td>
<td>60.6%</td>
</tr>
<tr>
<td>10% 3,090</td>
<td>2</td>
<td>100</td>
<td>32</td>
<td>16.2%</td>
<td>0.44%</td>
<td>22.5%</td>
</tr>
<tr>
<td>25% 25,000</td>
<td>4</td>
<td>1,000</td>
<td>43</td>
<td>22.2%</td>
<td>0.61%</td>
<td>35.8%</td>
</tr>
<tr>
<td>75% 692,000</td>
<td>45</td>
<td>10,000</td>
<td>97</td>
<td>35.9%</td>
<td>0.98%</td>
<td>95.6%</td>
</tr>
<tr>
<td>90% 2,091,200</td>
<td>187</td>
<td>25,000</td>
<td>164</td>
<td>44.0%</td>
<td>1.53%</td>
<td>145.1%</td>
</tr>
</tbody>
</table>

Panel A, Part 2 – Mutual Funds

<table>
<thead>
<tr>
<th>Aggregate Size of Mutual Fund (in thousands)</th>
<th>Minimum Investment (in thousands)</th>
<th>Number of Stock Holdings</th>
<th>% Assets in Top 10</th>
<th>Expense Ratio %</th>
<th>Turnover %</th>
</tr>
</thead>
<tbody>
<tr>
<td>Median 403,703</td>
<td>1,000</td>
<td>79</td>
<td>26.3%</td>
<td>0.93%</td>
<td>85.4%</td>
</tr>
<tr>
<td>10% 17,279</td>
<td>1,000</td>
<td>41</td>
<td>14.7%</td>
<td>0.65%</td>
<td>35.0%</td>
</tr>
<tr>
<td>25% 95,115</td>
<td>1,000</td>
<td>56</td>
<td>20.6%</td>
<td>0.79%</td>
<td>53.7%</td>
</tr>
<tr>
<td>75% 1,032,196</td>
<td>5,000</td>
<td>114</td>
<td>32.9%</td>
<td>1.10%</td>
<td>120.3%</td>
</tr>
<tr>
<td>90% 2,533,428</td>
<td>5,000</td>
<td>195</td>
<td>41.8%</td>
<td>1.27%</td>
<td>169.0%</td>
</tr>
</tbody>
</table>

Panel B (medians)

<table>
<thead>
<tr>
<th>Separate Account</th>
<th>Aggregate Size of Strategy (in thousands)</th>
<th>Number of Customer Accounts in Strategy</th>
<th>Minimum Investment (in thousands)</th>
<th>Number of Stock Holdings</th>
<th>% Assets in Top 10</th>
<th>Expense Ratio %</th>
<th>Turnover %</th>
</tr>
</thead>
<tbody>
<tr>
<td>Separate Account</td>
<td>162,430</td>
<td>12</td>
<td>5,000</td>
<td>62</td>
<td>28.8%</td>
<td>0.82%</td>
<td>60.0%</td>
</tr>
<tr>
<td>CIT</td>
<td>55,697</td>
<td>14</td>
<td>5,000</td>
<td>79</td>
<td>29.1%</td>
<td>0.72%</td>
<td>73.2%</td>
</tr>
</tbody>
</table>

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.
### Table 2

#### Panel A, Separate Account Alphas

<table>
<thead>
<tr>
<th>Manager-Preferred Benchmark</th>
<th>Number of Funds</th>
<th>Manager-Preferred Benchmark Alpha</th>
<th>Best-Fit Alpha</th>
<th>4-Factor Model Alpha</th>
<th>5-Factor Model Alpha</th>
</tr>
</thead>
<tbody>
<tr>
<td>Large-Cap Growth</td>
<td>337</td>
<td>0.0898</td>
<td>-0.0335</td>
<td>-0.0577</td>
<td>-0.1019</td>
</tr>
<tr>
<td>Large-Cap Blend</td>
<td>677</td>
<td>0.0887</td>
<td>0.0087</td>
<td>-0.0389</td>
<td>-0.0351</td>
</tr>
<tr>
<td>Large-Cap Value</td>
<td>265</td>
<td>0.0871</td>
<td>0.0505</td>
<td>0.0048</td>
<td>0.0481</td>
</tr>
<tr>
<td>Mid-Cap Growth</td>
<td>182</td>
<td>0.0860</td>
<td>0.0125</td>
<td>0.0483</td>
<td>-0.0329</td>
</tr>
<tr>
<td>Mid-Cap Blend</td>
<td>154</td>
<td>0.0472</td>
<td>0.0527</td>
<td>0.1031</td>
<td>0.0308</td>
</tr>
<tr>
<td>Mid-Cap Value</td>
<td>110</td>
<td>0.0814</td>
<td>0.1021</td>
<td>0.1511</td>
<td>0.0971</td>
</tr>
<tr>
<td>Small-Cap Growth</td>
<td>186</td>
<td>0.1020</td>
<td>0.0332</td>
<td>-0.1112</td>
<td>-0.0633</td>
</tr>
<tr>
<td>Small-Cap Blend</td>
<td>185</td>
<td>0.1198</td>
<td>0.0713</td>
<td>-0.0532</td>
<td>-0.0355</td>
</tr>
<tr>
<td>Small-Cap Value</td>
<td>153</td>
<td>0.1687</td>
<td>0.1551</td>
<td>0.0637</td>
<td>0.0865</td>
</tr>
<tr>
<td>Other</td>
<td>70</td>
<td>0.0997</td>
<td>0.0156</td>
<td>-0.0649</td>
<td>0.0084</td>
</tr>
<tr>
<td>Overall Manager-Preferred</td>
<td>2319</td>
<td>0.0945</td>
<td>0.0318</td>
<td>-0.0123</td>
<td>-0.0174</td>
</tr>
</tbody>
</table>

| Overall Entire Sample       | 2627           | 0.0324                          | -0.0141        | -0.0202             |

#### Panel B, Open-end Fund Alphas

<table>
<thead>
<tr>
<th>Morningstar Category</th>
<th>Num. Funds</th>
<th>4-Factor Model Alpha</th>
<th>5-Factor Model Alpha</th>
</tr>
</thead>
<tbody>
<tr>
<td>US OE Large Growth</td>
<td>156</td>
<td>-0.0900</td>
<td>-0.1289</td>
</tr>
<tr>
<td>US OE Large Blend</td>
<td>112</td>
<td>-0.1203</td>
<td>-0.1127</td>
</tr>
<tr>
<td>US OE Large Value</td>
<td>80</td>
<td>-0.0395</td>
<td>0.0125</td>
</tr>
<tr>
<td>US OE Mid-Cap Growth</td>
<td>80</td>
<td>0.0128</td>
<td>-0.0790</td>
</tr>
<tr>
<td>US OE Mid-Cap Blend</td>
<td>33</td>
<td>0.0506</td>
<td>-0.0619</td>
</tr>
<tr>
<td>US OE Mid-Cap Value</td>
<td>36</td>
<td>0.1411</td>
<td>0.1005</td>
</tr>
<tr>
<td>US OE Small Growth</td>
<td>88</td>
<td>-0.2020</td>
<td>-0.1637</td>
</tr>
<tr>
<td>US OE Small Blend</td>
<td>39</td>
<td>-0.0264</td>
<td>-0.0145</td>
</tr>
<tr>
<td>US OE Small Value</td>
<td>27</td>
<td>-0.0080</td>
<td>0.0139</td>
</tr>
<tr>
<td>Overall Entire Sample</td>
<td>651</td>
<td>-0.0644</td>
<td>-0.0785</td>
</tr>
</tbody>
</table>

Panel A divides the sample of combined separate accounts into 10 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 manager-preferred benchmarks. As explained in the text, manager-preferred benchmarks are aggregated into 10 groups for reporting purposes. The third column in Panel A shows the alphas for each category, where the alphas were computed using the manager-preferred benchmark in a single-index model. 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 4-factor model. Finally, the alphas in the sixth column were computed using a 5-factor model consisting of the Fama-French-Carhart 4-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 4-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 4-factor and 5-factor models as described above.
Table 3

Number of Separate Accounts: Best-Fit Benchmarks and Manager-Preferred Benchmarks

<table>
<thead>
<tr>
<th>Best fit benchmark</th>
<th>Large-Cap</th>
<th>Manager Preferred benchmark</th>
<th>Small-Cap</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Growth</td>
<td>Blend</td>
<td>Value</td>
</tr>
<tr>
<td>Large-Cap Growth</td>
<td>199</td>
<td>56</td>
<td>1</td>
</tr>
<tr>
<td>Large-Cap Blend</td>
<td>69</td>
<td>448</td>
<td>50</td>
</tr>
<tr>
<td>Large-Cap Value</td>
<td>0</td>
<td>78</td>
<td>185</td>
</tr>
<tr>
<td>Mid-Cap Growth</td>
<td>50</td>
<td>27</td>
<td>0</td>
</tr>
<tr>
<td>Mid-Cap Blend</td>
<td>18</td>
<td>47</td>
<td>6</td>
</tr>
<tr>
<td>Mid-Cap Value</td>
<td>0</td>
<td>18</td>
<td>23</td>
</tr>
<tr>
<td>Small-Cap Growth</td>
<td>1</td>
<td>2</td>
<td>0</td>
</tr>
<tr>
<td>Small-Cap Blend</td>
<td>0</td>
<td>1</td>
<td>0</td>
</tr>
<tr>
<td>Small-Cap Value</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Total</td>
<td>337</td>
<td>677</td>
<td>265</td>
</tr>
</tbody>
</table>

There were 2,249 accounts analyzed.

For each manager-preferred benchmark, aggregated into 9 categories, this table shows the number of separate accounts that are best fit by each of nine benchmarks.
Table 4

Separate Accounts Differential Alphas

Manager-Preferred benchmark

<table>
<thead>
<tr>
<th>Best-Fit Benchmark</th>
<th>Large-Cap</th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Growth</td>
<td>Blend</td>
<td>Value</td>
<td>Growth</td>
<td>Blend</td>
<td>Value</td>
<td>Growth</td>
<td>Blend</td>
<td>Value</td>
<td>Growth</td>
<td>Blend</td>
<td>Value</td>
<td></td>
</tr>
<tr>
<td>Large-Cap Growth</td>
<td>------</td>
<td>0.0221</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td></td>
</tr>
<tr>
<td>Large-Cap Blend</td>
<td>0.2051</td>
<td>------</td>
<td>-0.0440</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td></td>
</tr>
<tr>
<td>Large-Cap Value</td>
<td>NA</td>
<td>0.1336</td>
<td>------</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td></td>
</tr>
<tr>
<td>Mid-Cap Growth</td>
<td>0.2993</td>
<td>0.1852</td>
<td>NA</td>
<td>------</td>
<td>-0.0392</td>
<td>NA</td>
<td>0.0427</td>
<td>-0.1694</td>
<td>NA</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Mid-Cap Blend</td>
<td>0.5063</td>
<td>0.4038</td>
<td>0.3560</td>
<td>0.3219</td>
<td>------</td>
<td>-0.0485</td>
<td>0.3012</td>
<td>0.0868</td>
<td>0.0462</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Mid-Cap Value</td>
<td>NA</td>
<td>0.4248</td>
<td>0.4038</td>
<td>NA</td>
<td>0.1944</td>
<td>------</td>
<td>NA</td>
<td>0.2517</td>
<td>0.0494</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Small-Cap Growth</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>------</td>
<td>-0.2351</td>
<td>NA</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Small-Cap Blend</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>0.3225</td>
<td>------</td>
<td>-0.0778</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Small-Cap Value</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>0.2337</td>
<td>------</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Average</td>
<td>0.279</td>
<td>0.192</td>
<td>0.117</td>
<td>0.322</td>
<td>0.059</td>
<td>-0.049</td>
<td>0.138</td>
<td>0.081</td>
<td>0.019</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

This table shows the difference in alpha when a manager chooses a benchmark index which is 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 chosen benchmark index.

"NA" indicates that there were five or fewer observations. The row labeled "Average" shows weighted averages of the numbers in the respective columns.

The entities in the row labeled "Average" show how much higher the alpha is when measured by each manager's preferred benchmark compared with the best-fit benchmark.
## Table 5

### Differential Betas

*(Implicit Benchmark Betas Minus Four-Factor Betas)*

<table>
<thead>
<tr>
<th>Manager Preferred Benchmark</th>
<th>Number of Funds</th>
<th>Market</th>
<th>Small-Minus-Big</th>
<th>High-Minus-Low</th>
<th>Momentum</th>
</tr>
</thead>
<tbody>
<tr>
<td>Large-Cap Growth</td>
<td>337</td>
<td>-0.0489</td>
<td>-0.0895</td>
<td>-0.0797</td>
<td>-0.0605</td>
</tr>
<tr>
<td>Large-Cap Blend</td>
<td>677</td>
<td>-0.0061</td>
<td>-0.0836</td>
<td>-0.0100</td>
<td>-0.0171</td>
</tr>
<tr>
<td>Large-Cap Value</td>
<td>265</td>
<td>-0.0066</td>
<td>-0.0627</td>
<td>0.0690</td>
<td>0.0148</td>
</tr>
<tr>
<td>Mid-Cap Growth</td>
<td>182</td>
<td>-0.0629</td>
<td>-0.0241</td>
<td>-0.0636</td>
<td>-0.0778</td>
</tr>
<tr>
<td>Mid-Cap Blend</td>
<td>154</td>
<td>-0.0155</td>
<td>0.0125</td>
<td>0.0208</td>
<td>-0.0618</td>
</tr>
<tr>
<td>Mid-Cap Value</td>
<td>110</td>
<td>-0.0060</td>
<td>-0.0460</td>
<td>0.0665</td>
<td>0.0168</td>
</tr>
<tr>
<td>Small-Cap Growth</td>
<td>186</td>
<td>-0.0634</td>
<td>0.0758</td>
<td>-0.0165</td>
<td>-0.0566</td>
</tr>
<tr>
<td>Small-Cap Blend</td>
<td>185</td>
<td>-0.0327</td>
<td>0.0723</td>
<td>-0.0172</td>
<td>0.0074</td>
</tr>
<tr>
<td>Small-Cap Value</td>
<td>153</td>
<td>-0.0642</td>
<td>0.0395</td>
<td>0.1239</td>
<td>0.0113</td>
</tr>
</tbody>
</table>

Total Funds 2249

This table shows the difference in implicit benchmark betas and betas obtained from the Fama-French-Carhart 4-factor model.

Implicit benchmark betas are computed as the product of the beta of the fund returns on the manager-preferred benchmark index and the beta of that benchmark index returns on the specified Fama-French-Carhart factor.
Table 6

Alpha Cross-Sectionally Regressed on Explanatory Variables

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>1326</td>
<td>0.0733</td>
<td>-0.2179</td>
<td>0.0003</td>
<td>0.0018</td>
<td>-0.0002</td>
<td>-0.6267</td>
<td>0.0121</td>
<td>-0.0430</td>
<td>-0.0643</td>
<td>-0.0340</td>
<td>0.0161</td>
<td>0.0612</td>
<td>0.0235</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>(-3.078)</td>
<td>(-3.170)</td>
<td>(-3.044)</td>
<td>(-4.467)</td>
<td>(3.321)</td>
<td>(-1.385)</td>
<td>(-1.716)</td>
<td>(-0.568)</td>
<td>(1.005)</td>
<td>(3.499)</td>
<td>(1.821)</td>
</tr>
<tr>
<td>1326</td>
<td>0.0600</td>
<td>-0.1187</td>
<td>0.0003</td>
<td>0.0020</td>
<td>-0.0002</td>
<td>-0.6248</td>
<td>0.0105</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>(-1.884)</td>
<td>(-3.4074)</td>
<td>(-3.251)</td>
<td>(-4.429)</td>
<td>(2.919)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

This table shows the results from cross-sectional regressions of the separate account Fama-French-Carhart 4-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.
Table 7

Separate Account Cash Flow Regressed on Explanatory Variables
(Averages and \( t \)-Values of Nine Annual Cross-Sectional Regressions)

<table>
<thead>
<tr>
<th></th>
<th>Lagged Intercept</th>
<th>Lagged 4-Factor Alpha</th>
<th>Lagged MPB Alpha</th>
<th>Log of Strategy Total</th>
<th>Log of Average</th>
<th>Log of Min. Initial</th>
<th>Pending Dummy</th>
<th>Retail Dummy</th>
<th>Product Dummy</th>
<th>Trust Dummy</th>
<th>Limited Dummy</th>
<th>Partnership Dummy</th>
</tr>
</thead>
<tbody>
<tr>
<td>Average</td>
<td>−90.645</td>
<td>3.159</td>
<td>2.235</td>
<td>4.226</td>
<td>20.712</td>
<td>0.019</td>
<td>−4.993</td>
<td>86.545</td>
<td>−43.510</td>
<td>34.033</td>
<td>27.849</td>
<td></td>
</tr>
<tr>
<td>( t )-Value</td>
<td>−1.087</td>
<td>2.951</td>
<td>2.520</td>
<td>2.354</td>
<td>1.157</td>
<td>0.006</td>
<td>−0.357</td>
<td>1.582</td>
<td>−6.356</td>
<td>3.097</td>
<td>3.799</td>
<td></td>
</tr>
</tbody>
</table>

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 4-factor alphas are annualized and obtained by taking the 2-year 4-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 1-factor alphas on the 4-factor alphas, where the single factor is the management-preferred benchmark index.
Bibliography


Bibliography (continued)


