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. We also 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 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. Separately managed accounts generally have minimum initial investments 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.[1] 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-index 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 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 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

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[1] 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.

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 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-sectional determinants of cash flow to separate accounts. Our conclusions are presented in section VIII.

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[2] Morningstar does not allow separate accounts to enter the database with a history, so there is no backfill bias.

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.[3] 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 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 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

[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.

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 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.

[4] We also selected as a comparison sample all institutional mutual funds. The results discussed in later sections were very similar with this 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 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

[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.

for the 90% breakpoint, CIT and SMA fees are lower than those for mutual funds.[7] 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-index models. The general form is

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

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*;

[7] A few of the separate accounts were wrap accounts, and this accounts for the higher upper-end expenses. Medians were tested because of potential errors in reporting expense ratios. These errors are likely to fall in the tails.

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 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 index. 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 orthoganalized 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.

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 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

[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.

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.[10]

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 a growth or value index.

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. From Table 3, 193 of the managers who chose a large stock-index had returns which looked like they were investing in

[10] 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).

smaller stocks. Finally, some managers who chose a small-stock index had returns that looked like they were investing in mid-cap 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 because of their tendency to choose benchmarks more appropriate for managers selecting large stocks and balanced portfolios.

Returning to Table 2, when we examine multi-index models compared to manager-selected benchmarks we see a large difference in alphas. As stated earlier, we employ two multi-index models. The first is the Fama-French-Carhart model. The second adds the excess return on the Russell micro-cap index (orthoganalized 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.[11]

Why do we find differences in alphas from a multi-index model with those from simply using the management-preferred benchmark? Note that any benchmark can be explained in part by a multi-index 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-index 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

[11] 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.

and the beta of the benchmark with the factor.

Table 5 shows the implicit manager-benchmark beta less the beta on the multi-index model for each index in the multi-index 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-index model. Likewise, the accounts designated as growth are more value-tilted than would be indicated by the manager's benchmark. The index 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-index 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-index 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.[12] 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.[13]

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

[12] Statistical significance for the difference in means was computed using a *t* test of the difference in means for two samples with unequal variances.

[13] 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.

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.[14]

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.

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

[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 the data and examination of the number of funds with history that terminated earlier, it appears to be a recent phenomenon.

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.[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 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.[16] 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 would performance have to be in the six months after they stopped reporting before separate accounts would not do statistically significantly better than mutual funds at the 0.01 level. Assuming that funds that

[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 stop reporting was present for that sample.

[16] 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.

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 -.002106. 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. 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.[17]

The next two variables we examine measure the concentration of the portfolio. These

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

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 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.[18]

[18] 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.

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.[19]

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.[20] 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.

Examining the expense variables, we see that they have the expected sign. Both higher

[19] See Brown, Goetzmann, Liang and Schwarz (2011).

[20] 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.

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 available on a yearly basis and since some of the variables determining cash flow are 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 independent variable examined is the lagged performance of each account. There is an extensive literature for mutual funds that shows that cash flow is positively related to past performance.[21] We expect to see a similar relationship for separate accounts. The lagged performance measure we used was the monthly alpha annualized from our four-index model (estimated over the two-year period preceding the cash flow) plus the sum of the monthly residuals for the year in question.[22] 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 next variable we introduced was the natural logarithm of total asset value. Alpha was not related to this variable, while here we find cash flow is negatively related to size at a statistically significant level. Why might this occur? Cash flow is computed as a percent of assets under management. It is extremely difficult for a very large firm to grow at the same percentage rate as a small firm.[23]

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

[21] For example, see Gruber (1996).

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

[23] Reformulating the cash flow variable as dollar cash flow reversed the sign of the relationship.

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 on mutual funds provided by Sirri and Tufano (1998) and Elton, Gruber and Blake (2003).

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.

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. In addition, partnership structure likely affects investment manager effort.

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.

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.

Table 1 – Characteristics of Separate Accounts and Mutual Funds

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 10	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 10 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

	Aggregate Size of Strategy (in thousands)	Number of Customer Accounts in Strategy	Minimum Investment (in thousands)	Number of Stock Holdings	% Assets in Top 10	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%

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

Manager-Preferred Benchmark	Number of. Funds	Manager-Preferred Benchmark Alpha	Best-Fit Alpha	4-Factor Model Alpha	5-Factor Model Alpha
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	2319	0.0945	0.0318	-0.0123	-0.0174
Overall Entire Sample	2627		0.0324	-0.0141	-0.0202

Panel B, Open-end Fund Alphas

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

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

Best fit benchmark	Manager Preferred benchmark								
	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

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

Best-Fit Benchmark	**Manager-Preferred benchmark** Large-Cap			Mid-Cap			Small-Cap		
	Growth	Blend	Value	Growth	Blend	Value	Growth	Blend	Value
Large-Cap Growth	------	0.0221	NA	NA	NA	NA	NA	NA	NA
Large-Cap Blend	0.2051	------	-0.0440	NA	NA	NA	NA	NA	NA
Large-Cap Value	NA	0.1336	------	NA	NA	NA	NA	NA	NA
Mid-Cap Growth	0.2993	0.1852	NA	------	-0.0392	NA	0.0427	-0.1694	NA
Mid-Cap Blend	0.5063	0.4038	0.3560	0.3219	------	-0.0485	0.3012	0.0868	0.0462
Mid-Cap Value	NA	0.4248	0.4038	NA	0.1944	------	NA	0.2517	0.0494
Small-Cap Growth	NA	NA	NA	NA	NA	NA	------	-0.2351	NA
Small-Cap Blend	NA	NA	NA	NA	NA	NA	0.3225	------	-0.0778
Small-Cap Value	NA	NA	NA	NA	NA	NA	NA	0.2337	------
Average	0.279	0.192	0.117	0.322	0.059	-0.049	0.138	0.081	0.019

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)

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	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

Obs.	Adjusted R-Square	Intercept	Average Turnover	Assets in Top 10	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
1326	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)
1326	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)						

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)

	Intercept	Lagged Alpha	Log of Firm 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	-9.971	4.759	-4.412	27.596	7.006	5.413	73.614	-37.430	29.813	20.047
t-Value	(-0.165)	(4.529)	(-2.473)	(1.948)	(2.522)	(0.447)	(1.797)	(-4.075)	(2.942)	(3.155)

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 alpha is the annualized monthly alpha computed over the two years prior to the cash flow year plus the total residual in the year before the cash flow year.

t-values are shown in parentheses.

Bibliography

Berk, Jonathan and Green, Richard (2004). Mutual fund flows and performance in rational markets. *Journal of Political* Economy 112:1269-1295.

Brown, Stephen J. and Goetzmann, William N. (1995). Performance persistence. *Journal of Finance* 50:679-698.

Brown, Stephen J. Goetzmann, William N.; Liang, Bing; and Schwarz, Christopher. Trust and delegation. Social Science Research Network, (2011).

Busse, Jeffrey, Gleal, Amit and Wohal, Sunil. Performance and Persistence in Institutional Investment Management. *Finance 65* 765-790. (2010).

Carhart, Mark M. (1997). On persistence in mutual fund performance. *Journal of Finance* 52:57-82.

Deloitt. Inside the Structure of the Fine Contribution 401(k) Plans. *Reports of the Investment Company Institute*. 2011.

Elton, Edwin J.; Gruber, Martin J.; and Blake, Christopher R. (1996a). Survivorship bias and mutual fund performance. *Review of Financial Studies* 9:1097-1120.

Elton, Edwin J.; Gruber, Martin J.; and Blake, Christopher R. (1996b). The persistence of risk-adjusted mutual fund performance. *Journal of Business* 69:133-157.

Elton, Edwin J.; Gruber, Martin J.; and Blake, Christopher R. (2003). Incentive fees and mutual funds. *Journal of Finance* 58:779-804.

Elton, Edwin J.; Gruber, Martin J.; Rentzler, Joel (1987). Professionally managed publicly traded commodity funds. *Journal of Business*: 60:175-199.

Evans, Richard (2010). Mutual fund incubation. *Journal of Finance* 65:1581-1611.

Fama, Eugene F. and French, Ken R. (2010). Luck versus skill in the cross-section of mutual fund return. *Journal of Finance* 65:1915-1947.

Fama, Eugene F. and MacBeth, James D. (1973). Risk, return, and equilibrium: empirical tests. *Journal of Political Economy* 81:607-636.

Gaspar, Jose-Miguel; Massa, Massimo; and Matos, Pedro (2006). Favoritism in mutual fund families? Evidence on strategic cross-fund subsidization. *Journal of Finance* 61:73-104.

Bibliography (continued)

Grinblatt, Mark and Titman, Sheridan (1992). The persistence of mutual fund performance. *Journal of Finance* 47:1977-1984.

Gruber, Martin J. (1996). Another puzzle: the growth in actively managed mutual funds. *Journal of Finance* 51:783-810.

Petersen, James, Iachini, Michael and Lam, Winci. Identifying Characteristics to Predict Separately Managed Account Performance. *Financial Analysts Journal* 60*:* 40.

Peterson, Mitchell (2009). Estimating standard errors in finance panel data sets: comparing approaches. *Review of Financial Studies* 22:435-480.

Pollet, Joshua and Wilson, Mungo (2008). How does size affect mutual fund behavior? *Journal of Finance* 63:2941-2969.

Sirri, Eric and Tufano, Peter (1998). Costly search and mutual fund flows. *Journal of Finance* 53:1589-1622.