Executive summary

Conventional wisdom maintains that, compared with their large- and mid-cap counterparts, small-cap active equity managers are more likely to outperform their market segment. At first pass, this “inefficient small-cap market” argument is appealing since greater opportunities could arise from greater dispersion of small-cap stock returns, more gradual information flows, and less thorough coverage by stock analysts.

Our research challenges this widely held belief on several fronts. We find that the typical small-cap fund’s outperformance is an artifact of a particular benchmarking methodology. When we correct for the mismatch between active funds and popular small-cap benchmarks, the typical small-cap fund’s outperformance disappears.

We also examine a related belief; i.e., because the small-cap stock market is inefficient, it’s possible to identify skilled managers who will repeatedly exploit those inefficiencies and generate persistent outperformance in the future. We demonstrate for prospective investors that the historical outperformance of the typical small-cap manager is fleeting. Our analysis indicates that the probability that past winners will repeat in the future is equivalent to a coin toss before costs (the same odds as if one picked small-cap funds at random). After costs, of course, the odds are less than 50-50.

A key portfolio implication of our research is that, contrary to the conventional wisdom, indexing is a powerful investment strategy in all market segments, including small-caps.
Small-cap active outperformance: Myth or reality?

The conventional wisdom: Pursue small-cap active equity funds

Conventional wisdom maintains that small-cap active equity funds have greater success in beating their respective benchmarks than their large-cap and mid-cap counterparts. This apparently widely held view leads some investors to index their large-cap and mid-cap equity exposure and to pursue active management in the small-cap universe.

Based on certain benchmarking methodologies, the historical performance of the “typical” small-cap active equity fund would appear to support the conventional wisdom. Figure 1 presents historical excess returns for the three small-cap style categories judged against their assigned Russell small-cap style indexes from 1984 through 2005. By this measure, the median outperformance of small-cap active funds—in particular that of small-cap growth funds—appears impressive. The median small-cap growth fund registered an economically and statistically significant 2.6% excess return over the Russell 2000 Growth Index before costs and a 1.0% excess return after costs.

Note: Prices of small-cap stocks often fluctuate more than large company stocks.

1 A complete description of our data and empirical methodology can be found in the Appendix.

We should note that, throughout this paper, we present pooled fund-weighted statistics since they are the most relevant for prospective small-cap active investors. As a result, our approach differs from certain studies (e.g., Carhart, 1997; Davis, 2001) that form equal-weighted portfolios of mutual funds before estimating risk-adjusted returns. This time-weighted portfolio approach treats the aggregate performance of small-cap funds each year as the random variable, so the aggregate performance of small-cap funds in, say, 1980 counts the same as their aggregate performance in 2005. Since the number of funds and the volume of assets managed are both growing over time as the mutual fund industry has exploded, an equal-weighted portfolio approach would not permit us to realistically characterize the typical small-cap manager’s performance.

In addition, it is important to recognize that our median fund-weighted data may not adequately characterize the collective historical experience of all small-cap active investors. To do so would require us to focus on the dollar-weighted performance of all small-cap funds, since the assets under management of any two small-cap active funds can differ widely (see also “A zero-sum game for active equity managers” on page 4).

2 In every style box, we find that the distributions of annual relative performance data are positively skewed and kurtotic. The skewed distributions imply that small-cap active growth investors have a higher historical probability of realizing more extreme positive relative returns than a normal distribution would dictate. For instance, using Russell benchmarks from 1984 through 2005, the average small-cap fund’s excess return is 2.72% per year before costs, while the median small-cap fund’s excess return registers a lower 1.72% per year. The outperformance distributions for small-cap active growth funds are the most skewed, especially during the years surrounding the peak in the U.S. equity market bubble (when some apparently hit the proverbial “home run”). Given the nonnormality of the small-cap outperformance distributions, median small-cap outperformance statistics are the most appropriate measure of central tendency and, hence, the best means of conveying the “typical” track record of small-cap active managers. Throughout the remainder of the paper, we focus on the median fund’s relative performance statistics.

3 We present performance data both before and after costs since certain high-balance investors may pay active management fees that are markedly below the industry average.
Some investors interpret the sizable outperformance results in Figure 1 as evidence of an inefficient small-cap equity market. At first pass, the “inefficient small-cap market” argument is appealing since greater opportunities could arise from the greater dispersion of small-cap stock returns, more gradual information flows, less thorough coverage by stock analysts, and higher concentration of fund managers possessing stock-selection skill. In such a world, skilled active managers should be able to repeatedly exploit these market differences and provide their investors with above-index returns over time.

Investors should be skeptical of the conventional wisdom

While greater security dispersion makes it possible to add greater value in the small-cap universe, simply having a greater opportunity does not guarantee that the average small-cap fund manager will beat the performance of the fund’s benchmark. Indeed, there are several potential explanations for the sizable Russell-based positive excess returns of the median small-cap active growth fund in Figure 1.

One potential explanation of the outperformance is that skilled small-cap fund managers are able to exploit opportunities and market inefficiencies at the expense of other small-cap active growth investors and/or active fund managers in other segments of the U.S. equity market. At face value, Figure 1 seems to violate the rules of the zero-sum game that characterize aggregate performance in any properly defined market segment.

But why would the zero-sum game not hold in the small-cap growth style box when, as we demonstrate on the next page, the zero-sum argument holds in the aggregate for active equity management? Do small-cap managers really exist in a proverbial Lake Wobegon, where most are above average?

Another potential explanation for the excess returns in Figure 1 could simply be mismeasurement. For instance, previous Vanguard research (Investment Counseling & Research, 2005), based on the evaluation of excess returns, has attributed the widely touted historical outperformance of small-cap active funds to benchmark mismatching and survivorship bias (see also “Index selection is critical when assigning benchmarks” on page 5). Richard M. Ennis and Michael D. Sebastian (2002), however, advocate judging the performance of small-cap active funds versus a combination of market indexes—which may better capture the considerable heterogeneity among small-cap portfolios—rather than a single style-box index.

This paper reexamines these propositions using a formal returns-based style analysis, MSCI-based benchmarks, and data from the CRSP Survivor-Bias-Free US Mutual Fund Database. In doing so, we demonstrate that the historical outperformance of the typical small-cap manager is both fleeting and extremely sensitive to alternative performance-measurement methodologies.

In the section entitled How robust is small-cap outperformance? (which begins on page 6), we demonstrate that the small-cap outperformance is confined to Russell benchmarks and is concentrated among small-cap active growth funds in the years surrounding the peak of the U.S. equity market bubble. In fact, the Russell-specific outperformance of small-cap growth funds in Figure 1 is strongly associated with a “buy-past-winners” momentum factor that primarily reflects a Russell reconstitution effect. Using MSCI benchmarks, we show that the relative performance of the median small-cap fund manager is zero before costs and economically and statistically negative after costs. These results hold for both excess returns and style-analysis-based alphas.

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4 Kent Daniel et al. (1997) argue that stock-selection ability is strongest among small-cap growth fund managers. Malcolm Bakar et al. (2004) find that growth-oriented mutual fund managers possess security-selection ability in that they tend to purchase stocks that earn higher returns upon subsequent earnings announcements and to sell stocks that earn lower returns. See also Gregory C. Allen (2005).

5 Similar arguments are made for active equity investing in emerging markets. Unfortunately, data constraints at the present time limit our empirical analysis to actively managed U.S. small-cap mutual funds.
A zero-sum game for active equity managers

In the aggregate at any given time, active equity management is a zero-sum game before costs: 50% of actively managed dollars outperform the market-cap-weighted index return and 50% underperform. And since the average dollar invested in any market must receive its average dollar-weighted return, the presence of investment costs implies that the investor who holds the average actively managed dollar will realize below-index returns (Sharpe, 1991).

Of course, the dollars invested in all actively managed equity mutual funds could conceivably out- or underperform non-mutual-fund assets (e.g., pension funds, hedge funds, direct retail holdings). However, an empirical analysis of a very broad sample of active U.S. equity fund assets reveals that this is indeed not the case. Table 1 indicates that approximately 50% of all actively managed equity mutual fund dollars have yielded a positive excess return relative to the return of the total U.S. equity market. In the aggregate, the active equity mutual fund industry has yielded a slight positive annual excess return before costs.

Contrary to recent comments by Joanne M. Hill (2006) and others, the results in Table 1 empirically validate what other academic studies and years of practical experience suggest: Active equity management is a zero-sum game before costs and a negative-sum game after costs.

Table 1. A zero-sum game for all actively managed U.S. equity mutual fund dollars

<table>
<thead>
<tr>
<th>Benchmark</th>
<th>Number of fund-year observations</th>
<th>Dollar-weighted percentage of active U.S. equity funds with positive excess returns</th>
<th>Dollar-weighted mean excess return of active U.S. equity funds</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>Before costs</td>
<td>After costs</td>
</tr>
<tr>
<td>Russell 3000 benchmark (1984–2005)</td>
<td>16,522</td>
<td>49.2%</td>
<td>42.4%</td>
</tr>
<tr>
<td>MSCI 2500 benchmark (1992–2005)</td>
<td>13,812</td>
<td>48.6%</td>
<td>43.3%</td>
</tr>
</tbody>
</table>

Note: Statistics are dollar-weighted such that all mutual fund observations are weighted each year by each active fund’s dollars under management at the beginning of the calendar year. The values in the table reflect the annual time-series average of the dollar-weighted data. For further details on our active mutual fund sample, please refer to the Appendix.

Source: Authors’ calculations based on data from the CRSP Survivor-Bias-Free US Mutual Fund Database.

The performance data shown represent past performance, which is not a guarantee of future results. The performance of an index is not an exact representation of any particular investment, as you cannot invest directly in an index.
Index selection is critical when assigning benchmarks

Constructing an active equity fund’s customized benchmark requires a reliable and representative suite of equity market indexes. But what suite of indexes should investors consult?

There are at least four popular investable sets of equity market indexes available: Russell, Standard & Poor’s, Dow Jones Wilshire, and MSCI. For certain equity market segments (especially the small-cap universe), average return differentials among the various indexes can be sizable, as illustrated in Figure 2, due to differences in index weightings and the indexes’ rebalancing and reinvestment procedures (see Philips, 2006). Craig L. Israelsen (2006) demonstrates that the average return differential between the best- and worst-performing U.S. equity indexes is largest for small-cap growth indexes and is especially pronounced during the U.S. stock market’s volatile 1999–2001 period.

Russell indexes are often chosen in small-cap performance attribution studies because they have a long history in real time; however, there are significant disadvantages involved in using certain Russell small-cap indexes. As some have long recognized, Russell indexes suffer from a well-known reconstitution effect since Russell rebalances its indexes only periodically (Madhavan, 2006; see also the Appendix). Russell indexes also utilize fewer screening criteria to characterize the style and size attributes of individual stocks than competing benchmark indexes. These biases are most pronounced for the small-cap Russell 2000 Growth Index.

Other equity market indexes—such as those maintained by MSCI—more effectively measure style and market-cap exposures of actively managed portfolios. MSCI indexes were available to active small-cap managers in real time beginning only in 1999, although returns data were backfilled through mid-1992 using the real-time methodology.

Acknowledging that no set of benchmarks is without limitations, we have calculated style-based alphas using various sets of nonoverlapping benchmarks. In results unreported here, typical small-cap fund performance data using Standard & Poor’s indexes are similar to the MSCI-based results, while Dow Jones Wilshire-based benchmarks produce results that lie between the MSCI and Russell results. For that reason, we focus here on two sets of benchmarks—MSCI and Russell—to provide the historical range of small-cap fund performance.

Figure 2. Russell benchmarks have provided a significantly lower threshold for small-cap growth alpha

Average return differential between Russell and MSCI style benchmarks, July 31, 1992–December 31, 2005

Source: Authors’ calculations.

While excess returns as well as style-analysis-based alphas of the median small-cap growth manager have occasionally been very large in the past, our analysis further indicates that typical small-cap outperformance is unlikely to be replicated in the future. In the section entitled *Does small-cap alpha persist?* (which begins on page 12), we show that the historical probability of a small-cap active fund achieving positive alpha is equivalent to a coin toss before costs, even if the fund outperformed in the previous year. This lack of persistence suggests that outperformance is the product of luck more than manager skill, which makes small-cap manager selection a challenge.

The implication for portfolio construction is that—contrary to the conventional wisdom—indexing remains a powerful strategy for investing in small-cap stocks.

**How robust is small-cap outperformance?**

*Defining an active manager’s “value-added”*

An actively managed fund can add value, or alpha, over its strategic asset allocation through a combination of the manager’s security selection and tactical asset allocation, such as over- or underweighting size and value risk factors. For investors and analysts looking to quantify an active fund’s value-added from such strategies, they must first specify the fund’s benchmark. However, benchmark identification is more challenging than it first appears since an active fund’s strategic asset allocation may not necessarily correspond to the single style-box index that it is placed in by various database providers, such as Morningstar (see “A fund’s ‘alpha’ is defined by its benchmark” on pages 7 and 8).

In this paper, we adopt a conventional approach in inferring an active fund’s strategic asset allocation through a risk-model procedure known as returns-based style analysis. Style analysis (Sharpe, 1992) is a standard statistical method available to practitioners through various software programs (e.g., Zephyr StyleADVISOR) that infer an active fund’s effective investment style, or *customized benchmark*, by comparing the active fund’s returns with the returns of a series of nonoverlapping indexes that represent different investment styles of the U.S. equity market. Generally speaking, the more highly correlated a fund’s returns are with a given style index, the greater the weighting that the index is given in the customized benchmark.

Practitioners commonly define the excess return of an active fund versus its customized benchmark as the fund’s *style-adjusted alpha.* Through the remainder of the paper, we focus on style-adjusted alphas, although we do find that alternative relative-performance measures produce similar historical results for the median small-cap fund (again, see “A fund’s ‘alpha’ is defined by its benchmark”).

*Russell-based small-cap alpha is not consistent over time*

The strong performance of small-cap active growth funds displayed in Figure 1 is not consistent over time. To illustrate the period sensitivity of style-adjusted alphas, Figure 4 on page 9 presents the median small-cap fund alpha based on customized Russell benchmarks for five nonoverlapping four-year subperiods. The chart reveals that the “typical” outperformance of small-cap active growth managers based on Russell benchmarks is concentrated in the four-year period (1998–2001) that includes the peak of the U.S. equity market bubble and its subsequent collapse. In most other subperiods, the typical small-cap growth fund outperforms a Russell indexing strategy by a significantly lower amount. Moreover, the investor’s return in the median small-cap fund, as represented by net or after-cost return, trails the small-cap index return over certain four-year subsamples, such as the recent 2002–2005 period.

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 Naturally, the reliability of a fund’s estimated alpha is a direct function of the reliability of the risk-factor model (see, for instance, Louis K.C. Chan et al. [2006]).
A fund’s “alpha” is defined by its benchmark

Alpha—a ubiquitous term in investment circles—is simply a portfolio’s excess return versus its effective benchmark. But what should be an active fund's effective benchmark? Any answer to that question raises important philosophical issues regarding which investment risks active managers are to be rewarded for. Indeed, where does one draw the line between an active fund's performance evaluation and its performance attribution?

Among the spectrum of methods that may define an active fund's alpha, two common industry measures are the fund’s style-adjusted alpha, derived from the returns-based style analysis that is used in this paper, and the fund’s excess return relative to a style-box index. Excess return is a strict form of alpha since this framework assumes that the fund’s beta relative to a style-specific index is 1.

At the fund level, whether customized or single benchmarks are more appropriate in deriving a fund’s alpha depends critically on the investment philosophy and strategies of the active fund manager. Similar to the rigorous evaluation process that Vanguard’s Portfolio Review Group continuously conducts of its existing and prospective active fund managers, investors should consider several important questions when considering an active fund:

- Does the active portfolio consciously possess a size or style bias? If so, why?
- Is it an intentional decision of the managers, and have they been successful in the past?
- If the size and style tilts of an active fund are sufficiently stable, could an investor be potentially better served by selecting a lower-cost indexing strategy?

Answers to these questions may provide an investor with a clearer picture of the fund’s past (and future) investment philosophy.

Style-adjusted alphas, for instance, can correct for the tendency of some active funds to gradually “tilt” across various investment styles over time. However, such style tilts may actually reflect an intentional active position incurred by an active fund manager in an attempt to beat a style-box index.8 One could argue that excess returns would be the preferred measure of an active fund’s value-added for (a) those funds that explicitly try to add value through style tilts around their assigned style boxes, or (b) those funds that implicitly appear to do so because they are either “benchmark agnostic” or self-described “pure stock-pickers.” However, the common practice of classifying (some would say pigeonholing) active funds into one of nine equity-market style categories can distort the “typical” performance of active funds since the vast majority of active equity funds have an effective allocation exposure beyond their single style box. As illustrated in Table 2 on page 8, for instance, active funds that we classify as small-cap based on Russell indexes tend to have a mid-cap tilt (i.e., they are “smiddish”).9

In reality, the style-adjusted alpha and excess return of most small-cap funds in our research sample have been positively correlated historically because the total returns of the various style-box indexes have not varied widely. In Figure 3 on page 8, the historical correlation between annual alphas and excess returns is 97.25% for small-cap growth funds and 86.93% for small-cap value funds.

(Continued on page 8.)

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8 Conceivably, an investor could replicate a fund’s strategic allocation (as suggested by its customized benchmark) through an indexing strategy, but such a replication strategy would have to assume that the fund’s strategic asset allocation did not change in the future; i.e., the fund’s betas would have to remain stable over time.

9 It is also important to note that we observe considerable dispersion of the customized weights assigned across funds within any single style box, indicative of a wide range of manager factor tilts.
Given this tight average correlation, it is not surprising that median fund excess return and style-adjusted alpha are similar across all three small-cap fund categories in our research sample. For instance, the median small-cap growth fund’s before-cost excess return is 2.57%, while its median before-cost alpha is 1.81%. The tendency for the median small-cap value fund’s excess return to exceed the median fund’s alpha is, in part, a function of the strong performance of the mid-cap value index over the time period. Of course, observed differences between style-adjusted alphas and excess returns may be more pronounced for other active equity fund categories and during other time periods, depending on the relative performance of different style-box indexes.

Table 2. The typical small-cap fund’s strategic asset allocation extends well beyond a single style box

<table>
<thead>
<tr>
<th>Equity market style category</th>
<th>Mean estimated Russell customized benchmark weight</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Russell Large Cap Value Index</td>
</tr>
<tr>
<td>Small-cap value</td>
<td>5.4%</td>
</tr>
<tr>
<td>Small-cap blend</td>
<td>2.9%</td>
</tr>
<tr>
<td>Small-cap growth</td>
<td>1.0%</td>
</tr>
</tbody>
</table>

Note: The six nonoverlapping style benchmarks used to estimate customized Russell-based benchmark weights are as follows: Russell Top 200 Value, Russell Top 200 Growth, Russell Midcap Value, Russell Midcap Growth, Russell 2000 Value, and Russell 2000 Growth.
Source: Authors’ calculations.

Figure 3. Small-cap fund alphas and excess returns are highly correlated

**Small-cap growth funds: Alphas and excess returns**
Russell benchmarks, 1984–2005, gross returns

\[ R^2 = 94.57\%, \text{ correlation} = 97.25\%, \text{ number of fund-year observations} = 1,522 \]

**Small-cap value funds: Alphas and excess returns**
Russell benchmarks, 1984–2005, gross returns

\[ R^2 = 75.57\%, \text{ correlation} = 86.93\%, \text{ number of fund-year observations} = 663 \]

Note: A single outlier has been hidden from the small-cap growth chart for clarity.
Source: Authors’ calculations based on Russell benchmarks and data from the CRSP Survivor-Bias-Free US Mutual Fund Database.
The performance data shown represent past performance, which is not a guarantee of future results. The performance of an index is not an exact representation of any particular investment, as you cannot invest directly in an index.
What explains Russell small-cap growth alpha?

Even if one ignores the “home runs” hit by a minority of small-cap growth managers during the 1998–2001 period, the typical performance of small-cap active growth funds remains impressive. So what explains the median small-cap growth fund’s large and statistically significant alpha in the years surrounding the peak in the U.S. equity-market bubble? There are several possible explanations that could relate to manager skill.10

A favorable argument made by small-cap managers is that the years surrounding the bubble were a period of unprecedented security-level dispersion (de Silva et al., 2001) that rewarded their stock-picking skills by allowing them to differentiate themselves more significantly from the Russell 2000 Growth Index. However, since active managers trade with each other, this argument would not necessarily indicate that the median fund would do better over this short time period.

10 Another potential explanation relates to a measurement bias known as incubation bias. Richard M. Ennis and Michael D. Sebastian (2002) contend that backfill, incubation, and survivorship biases are most acute in the small-cap arena and hence will upwardly bias performance figures under any methodology. As we discuss in the Appendix, CRSP contains the private or semiprivate history of returns for the funds that later become public. Not surprisingly, Richard B. Evans (2004) finds that surviving incubated funds have higher risk-adjusted and total returns than nonsurviving incubated funds or other new funds. This so-called incubation bias—which we cannot systematically correct for—could be particularly pronounced in the small-cap growth space.
Another potential explanation may be that small-cap active growth funds, in particular, follow a momentum strategy by investing in stocks that recently performed well and that this strategy paid off handsomely during the 1999–2001 period. Figure 5 suggests that the impressive performance of small-cap active growth funds is correlated with a “buy-past-winners” momentum strategy, which in turn may be related to differences in benchmark construction among small-cap growth indexes (i.e., index-rebalancing guidelines).

**Figure 5. Russell small-cap growth alpha correlated with small-cap index differentials and momentum-based returns**

[Graph showing the relationship between Russell small-cap growth alpha and momentum-based returns from Dec. 1993 to Dec. 2005.]

The role of momentum

We examine how robust the Russell small-cap alpha estimates are compared with the momentum-based returns. To do so, we modify our style-analysis procedure by adding the returns of two small-cap momentum portfolios (a past-winners momentum portfolio and a past-losers momentum portfolio) to the existing set of six Russell style indexes in the returns-based benchmarking model.

When we recalculate the median Russell fund-weighted alphas “cleansed” of momentum factors, we find that the *style-adjusted alpha of the median small-cap growth fund declines markedly toward zero before costs* (see Table 3 on page 11). In other words, much of what appears to be alpha could be interpreted less generously as exposure to a risk factor, namely, momentum as represented by the past-winners index. The typical small-cap active growth fund in our research sample has had a statistically significant and positive beta on a momentum index created from a universe of small-cap stocks.

11 In a seminal article, Narasimhan Jegadeesh and Sheridan Titman (1993) document that a portfolio strategy of buying past winning stocks and shorting past losing stocks earns a statistically and economically significant alpha. Mark Grinblatt et al. (1995) analyze quarterly holdings of a small sample of active funds over an earlier sample period (1978–1984) and find that 77% of mutual funds engage in momentum strategies and that this behavior is most acute for aggressive growth funds. William J. Bernstein (2001) explicitly attributes the strong aggregate performance of active small-cap growth funds to the momentum factor.

12 See Kenneth R. French (2007) for details about the data and methodology used to construct a momentum portfolio. Here, we decompose the traditional momentum factor return (sometimes referred to as UMD for “up minus down”) into two parts for the small-cap universe: a past-winners portfolio and a past-losers portfolio. The monthly returns of the past-winners portfolio represent the top 30% of the highest-returning stocks on the NYSE, AMEX, and Nasdaq market exchanges over the past 2 through 12 months, less the returns on the middle 40%. The past-losers portfolio is constructed similarly, using the stocks whose returns rank in the bottom 30%. Note that the individual stocks that constitute the momentum portfolios change every month, often drastically. Active funds pursuing a traditional Jegadeesh-Titman momentum strategy would buy past winners (or overweight them relative to their benchmark) and sell past losers (or underweight them relative to their benchmark). In such an event, a fund’s coefficient on the past-winners (past-losers) momentum portfolio in Table 3 should be positive (negative), since its alpha would increase as returns on the past-winners (past-losers) portfolio increase (decrease).

13 In results unreported here, we also find that the performance of the median mid-cap growth fund under Russell benchmarks has had a statistically significant correlation with a buy-past-winners portfolio.
From the results in Table 3, we conclude that the typical active small-cap growth fund manager has benefited over time (either through accident or by design) from returns on a buy-past-winners momentum strategy. By artificially excluding momentum-based factors, the net alpha of a small-cap growth manager is significantly negative, thereby reversing the stellar Russell-based performance displayed in Figure 1.

Interpreting momentum

Table 3 reveals that the strong performance of the average small-cap growth fund based on Russell benchmarks becomes statistically negative after costs once we scrub the influence of momentum from fund-level returns. But how should investors interpret these “ex-momentum alphas”? Investors should interpret the momentum-based returns in Table 3 as primarily a reflection of aRussell reconstitution effect. For instance, we find that small-cap growth funds post economically and statistically significant positive alpha in those months surrounding the rebalancing of Russell small-cap indexes. This is important, for if the style-adjusted alpha of the median small-cap growth fund simply reflects a Russell reconstitution effect, then the median alphas should decline using small-cap indexes that rebalance more frequently, such as MSCI benchmarks (again, refer to “A fund’s ‘alpha’ is defined by its benchmark” on pages 7 and 8).

Interestingly, Table 3 reveals only one style box (small-cap value) where the average fund displays the pure contrarian behavior of buying past losers and selling past winners. That said, the regression coefficients of the median small-cap value fund are not statistically different from zero. Consistent with the findings of Mark Grinblatt et al. (1995), we find that the average active equity fund in the other eight style boxes only weakly sells past losers.

The ex-momentum alphas in Table 3 may also help address the questions raised by James L. Davis (2001, especially p. 25) and others about why the average historical alpha of small-cap value funds has been poor despite the value premium observed in common-stock returns. As Narasimhan Jegadeesh and Sheridan Titman (2001) discuss, it is unclear whether the returns from any momentum portfolio represent compensation for an anomalous equity risk factor (that may disappear through arbitrage in the future) or a behavioral inefficiency from delayed reactions to firm-specific information (which suggests that momentum-based profits may be a more enduring phenomenon).

Specifically, we first constructed a monthly time series of the difference between the average Russell-based gross fund alpha and the average MSCI-based gross fund alpha. For the sample period between June 1992 and December 2005, this time series was regressed on a number of factors as well as monthly dummy variables. In each of the three active small-cap categories, the monthly dummy variables for June and July are statistically and economically significant. Historically, the average small-cap fund has had more than a 1% higher return in the months of June and July with Russell benchmarks than with MSCI benchmarks. The actual regression results can be found in Table 7 in the Appendix.

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Table 3. Does momentum help explain Russell small-cap growth alpha?

<table>
<thead>
<tr>
<th>Equity market style category</th>
<th>Gross Russell fund-weighted alphas</th>
<th>Net Russell fund-weighted alphas</th>
<th>Median momentum exposure in fund-level regressions</th>
</tr>
</thead>
<tbody>
<tr>
<td>Small-cap value</td>
<td>1.44%</td>
<td>0.06%</td>
<td>0.06%</td>
</tr>
<tr>
<td>Small-cap blend</td>
<td>1.10</td>
<td>0.85</td>
<td>−0.44</td>
</tr>
<tr>
<td>Small-cap growth</td>
<td>1.81</td>
<td>0.04</td>
<td>0.29</td>
</tr>
</tbody>
</table>

Bold median alphas are statistically different from zero at the 5% significance level, as determined by a nonparametric sign test. Statistically significant median t-statistics on the fund-level momentum factors are bold.

Source: Authors’ calculations.
To test our hypothesis, we repeat our returns-based style analysis using MSCI indexes to create customized fund benchmarks. Table 4 presents the median style-adjusted alpha and excess return for the three small-cap active fund categories, using two alternative sets of equity indexes—MSCI and Russell—to generate customized benchmarks.

Table 4 reveals that the typical small-cap outperformance previously documented using Russell benchmarks is not robust with MSCI benchmarks. Indeed, the median small-cap alpha is statistically equivalent to zero before costs over the 1992–2005 period. After costs, the median small-cap active fund has underperformed an MSCI indexing strategy by approximately 1.5% per year on a risk-adjusted basis and by approximately 1.9% per year on an excess-return basis. The bottom half of Table 4 reveals that these conclusions hold for excess returns, too.

### Table 4. Small-cap alpha is not robust to other benchmarks

**Median fund-weighted alphas, alternative benchmarks, 1992–2005**

<table>
<thead>
<tr>
<th>Equity-market style category</th>
<th>Number of fund-year observations (Russell)</th>
<th>Number of fund-year observations (MSCI)</th>
<th>Gross style-adjusted alpha</th>
<th>Net style-adjusted alpha</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td></td>
<td>MSCI benchmarks</td>
<td>Russell benchmarks</td>
</tr>
<tr>
<td>Small-cap value</td>
<td>727</td>
<td>801</td>
<td>0.22%</td>
<td>1.58%</td>
</tr>
<tr>
<td>Small-cap blend</td>
<td>940</td>
<td>1,405</td>
<td>−0.21</td>
<td>1.12</td>
</tr>
<tr>
<td>Small-cap growth</td>
<td>1,593</td>
<td>1,654</td>
<td>−0.03</td>
<td>1.81</td>
</tr>
</tbody>
</table>

**Median fund-weighted excess returns, alternative benchmarks, 1992–2005**

<table>
<thead>
<tr>
<th>Equity-market style category</th>
<th>Number of fund-year observations (Russell)</th>
<th>Number of fund-year observations (MSCI)</th>
<th>Gross excess returns</th>
<th>Net excess returns</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td></td>
<td>MSCI benchmarks</td>
<td>Russell benchmarks</td>
</tr>
<tr>
<td>Small-cap value</td>
<td>627</td>
<td>695</td>
<td>−0.59%</td>
<td>0.90%</td>
</tr>
<tr>
<td>Small-cap blend</td>
<td>796</td>
<td>1,226</td>
<td>−0.47</td>
<td>1.47</td>
</tr>
<tr>
<td>Small-cap growth</td>
<td>1,351</td>
<td>1,407</td>
<td>−0.04</td>
<td>2.43</td>
</tr>
</tbody>
</table>

Note: Bold median alphas and excess returns are statistically different from zero at the 10% significance level, as determined by a nonparametric sign test.

Source: Authors’ calculations.

**Does small-cap alpha persist?**

We have demonstrated in Table 4 that, using several MSCI-based benchmarking methodologies, the relative performance of the typical small-cap fund manager is zero before costs and economically and statistically negative after costs.

A still-skeptical reader, of course, could argue that small-cap fund managers are skillful given the correlation between momentum-based returns and the typical outperformance of small-cap active growth funds using Russell benchmarks. Russ Wermers (1997), for instance, argues that the previous year’s best active funds intentionally invest on momentum (this year) more strongly than last year’s average fund.
But if the typical small-cap manager is more skillful than other investors in the small-cap market, then a majority of the same set of small-cap managers should earn positive alpha year after year. Since market efficiency ultimately relates to predictability in performance, small-cap alpha should persist regardless of the benchmark if the typical small-cap manager possesses genuine skill.

To address this luck-versus-skill debate, we calculate the positive-performance persistence rate for the three small-cap mutual fund universes: small-cap value funds, small-cap blend funds, and small-cap growth funds. Table 5 presents the historical probability that past MSCI-based style-adjusted alphas persist (both before and after costs) over a one-year manager evaluation window, to coincide with our one-year MSCI-based alpha estimates. If the average small-cap manager is skilled, then the odds of success for those small-cap funds with past positive gross alpha (or excess return) could be meaningfully higher than the odds of success for a small-cap active fund selected at random.

The results in Table 5 reveal that small-cap manager outperformance is fleeting. Indeed, the odds of a small-cap active fund achieving a positive future style-adjusted alpha in the next year are remarkably similar between past winners and past losers. For instance, the historical likelihood that any randomly selected small-cap value fund achieves positive alpha (before costs) in a given year is 51.8%, compared with a success rate of 50.4% for those small-cap value funds that had positive alpha the previous year. Overall, the historical probability of a small-cap active fund achieving positive alpha (or excess return) the following year is equivalent to a coin toss before costs, even if the fund had positive alpha in the previous year. We can further show that these conclusions are similar for excess returns.

18 Specifically, we adopt a conventional “contingency table” approach whereby we calculate the historical probability that a small-cap active fund with previous positive or negative alpha will earn positive or negative alpha in the future. A contingency table shows the frequency with which funds in a particular style box that posted a positive or negative style-adjusted alpha for a given three-year nonoverlapping interval also earned positive or negative alpha in the subsequent three-year period. If relative performance were random, then one would expect the cells in a fund starts to have no impact on the subsequent (nonoverlapping) period. If managers producing alpha in one period tend to repeat in the next, then they are said to exhibit positive performance.

19 While past positive performance may not assist in picking funds that will outperform in the future, it may help lower the odds of the active fund dying in the near future since investor cash flows tend to chase past performance.

---

Table 5. Small-cap alpha does not persist

Historical probability of small-cap fund outperformance, MSCI benchmarks, 1992–2005

<table>
<thead>
<tr>
<th>Outperformance measure</th>
<th>Fund selection criteria</th>
<th>Small-cap value</th>
<th>Small-cap blend</th>
<th>Small-cap growth</th>
<th>Small-cap value</th>
<th>Small-cap blend</th>
<th>Small-cap growth</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>Gross annual returns</td>
<td>Gross 3-year nonoverlapping returns</td>
<td>Net annual returns</td>
<td>Net 3-year nonoverlapping returns</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Style-adjusted alpha</td>
<td>Past winners only</td>
<td>50.4%</td>
<td>49.8%</td>
<td>50.8%</td>
<td>39.0%</td>
<td>45.6%</td>
<td>37.6%</td>
</tr>
<tr>
<td></td>
<td>Random selection</td>
<td>51.8</td>
<td>49.0</td>
<td>49.9</td>
<td>49.1</td>
<td>51.3</td>
<td>52.4</td>
</tr>
<tr>
<td></td>
<td>Difference</td>
<td>–1.4</td>
<td>0.8</td>
<td>0.8</td>
<td>–10.1</td>
<td>–5.7</td>
<td>–14.8</td>
</tr>
<tr>
<td>Style-adjusted alpha</td>
<td>Past winners only</td>
<td>44.0%</td>
<td>42.8%</td>
<td>47.2%</td>
<td>25.8%</td>
<td>30.2%</td>
<td>31.6%</td>
</tr>
<tr>
<td></td>
<td>Random selection</td>
<td>41.5</td>
<td>40.6</td>
<td>42.8</td>
<td>35.1</td>
<td>36.2</td>
<td>41.7</td>
</tr>
<tr>
<td></td>
<td>Difference</td>
<td>2.5</td>
<td>2.2</td>
<td>4.4</td>
<td>–9.3</td>
<td>–6.0</td>
<td>–10.1</td>
</tr>
</tbody>
</table>

Source: Authors’ calculations based on data from the CRSP Survivor-Bias-Free US Mutual Fund Database.
Indicative of fleeting past performance, Table 5 further shows that the success rates of past fund “winners” deteriorates significantly over longer time horizons. For instance, a small-cap active fund with positive alpha over the past three years has a significantly lower historical probability of achieving positive alpha over the subsequent three years than any randomly chosen small-cap fund. This lack of persistence is consistent with the interpretation that the typical small-cap active fund manager possesses more luck than skill. This interpretation would also be consistent with the findings of Mark Carhart (1997), who argues that top-performing funds are lucky in the sense that they happen to hold the previous year’s best-performing stocks, and that they subsequently fail to rebalance into new portfolios that repeat the previous year’s performance.

Our results contradict certain previous studies, in particular William N. Goetzmann and Roger G. Ibbotson (1994) and Edwin J. Elton et al. (1996), which find that a fund’s past alpha is predictive of future performance. These differences highlight the fundamental methodological shortcomings of previous studies, which excluded active funds that disappear in the future from their probability calculations. Our approach corrects for these deficiencies by classifying active funds that disappear in the subsequent year for reasons affiliated with poor past performance as “losers” that underperform through “death” (i.e., liquidation).20

Table 5 also indicates the important role of low costs when selecting an actively managed fund. The after-cost annual-persistence results from an active investor’s perspective are marginally better than those from an active small-cap manager’s perspective simply because costs are highly persistent.

Conclusions

This paper examines whether it is really easier to beat an index return in the small-cap market, as some investment professionals claim. We conclude that indexing is a powerful strategy among small-cap stocks, as it is in any market. Our empirical results are most closely aligned with those of Richard M. Ennis and Michael D. Sebastian (2002): Small-cap alpha is more myth than reality.

Specifically, we show that small-cap outperformance is overstated and fragile with regard to benchmark selection, time periods, and relative performance measures. Using Russell benchmarks, small-cap alpha is skewed upward by a minority of small-cap growth funds during the equity-market bubble, a period that magnified Russell benchmark deficiencies as well as any potential payoff from following a “buy-past-winners” momentum strategy. Using alternative benchmark methodologies, we show that the alpha of the median small-cap fund manager is zero before costs and economically and statistically negative after costs. Our paper is consistent with previous Vanguard research on the excess returns of small-cap mutual funds (Investment Counseling & Research, 2005).

Most important for investors, we find that small-cap outperformance is fleeting, regardless of methodology. We show that the historical probability of a small-cap active fund achieving positive alpha is equivalent to a coin toss before costs. Perhaps more remarkably, an investor’s odds of selecting a small-cap active fund that will outperform in the future do not meaningfully improve if the investor selects a small-cap fund that outperformed in the past. This lack of persistence is consistent with a reasonably efficient small-cap equity market, where the typical small-cap active fund manager possesses more luck than skill.

20 From the standpoint of an investor making real-time investment decisions, the exclusion of future missing funds induces survivorship bias in the mutual fund sample. Since it is well known that missing funds tend to have poor past performance, most previous studies overstate the likelihood that a fund’s positive alpha will persist in the future (Brown and Goetzmann, 1995; Malkiel, 1995).
Of course, the lack of outperformance persistence makes small-cap manager selection a challenge. In future research, we will examine factors beyond past performance that may help investors improve their odds of selecting above-average actively managed equity funds.

References


APPENDIX

Active equity mutual fund research sample
We obtain monthly total returns for a broad sample of active, open-ended U.S. equity mutual funds from the CRSP Survivor-Bias-Free US Mutual Fund Database. The CRSP dataset includes records for nearly every mutual fund ever publicly available to investors, including funds currently “alive,” as well as funds now missing due to liquidation (i.e., “death”), closure, merger, or other event. The CRSP mutual fund returns are net of expenses. Following convention, we estimate gross returns by adding the monthly average of a fund’s annual expense ratio to a fund’s net returns.\(^{21}\)

We employ multiple filters on the CRSP Survivor-Bias-Free US Mutual Fund Database to construct our monthly sample of active equity funds. This filtering process eliminates balanced funds, sector funds, and international equity funds. Table 6 summarizes the major steps and the resultant distinct fund observations.

In our first step, we select funds with relevant classification codes in the CRSP database. Specifically, we select funds with the following Weisenberger objectives: G, LTG, MCG, GCI, IEQ, and SCG. Then, we include funds with the following ICDI fund objective: AG, GI, LG, or TR. Next, we select funds with the following Standard & Poor’s objectives: AGG, GMC, GRI, GRO, ING, and SCG. Finally, we include funds assigned the CS or MF policy. This process selects about 674,000 individual fund-month observations between January 1984 and December 2005.

In our second step, we combine the returns and expenses of multiple share classes on an asset-weighted basis to avoid duplicate return records. The aggregation of multiple share classes reduces our sample size by 52%, to 5,553 unique active funds. We also remove index funds from our active equity fund sample based upon keyword and manual inspection. We first delete any fund whose name contains the word “index” or an affiliated abbreviation (i.e., “idx,” “indx”). We also delete known index funds whose names do not include the word “index,” such as those from the fund families DFA and ProFunds. We also manually cross-check our active fund sample against the index fund universe listed in various releases of Morningstar’s Principia Pro CD-ROMs. Our empirical methodology in measuring the risk-adjusted fund performance and in assigning funds to one of nine equity styles also reduces the number of distinct-fund observations in our sample (see Steps 3 and 5 in Table 6).

In total, our research sample includes 899 active U.S. equity mutual funds and 40,233 distinct fund-month observations for the 1984–2005 period.\(^{22}\)

---

Table 6. Constructing the active U.S. equity mutual fund sample, 1984–2005

<table>
<thead>
<tr>
<th>Step</th>
<th>Action</th>
<th>Number of unique active funds</th>
<th>Number of distinct fund months</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Screen by fund classification code</td>
<td>11,518</td>
<td>674,079</td>
</tr>
<tr>
<td>2</td>
<td>Combine multiple share classes</td>
<td>5,553</td>
<td>367,533</td>
</tr>
<tr>
<td>3</td>
<td>Fund style box classification via regression. Exclude funds with &lt; 36 monthly observations</td>
<td>3,263</td>
<td>256,007</td>
</tr>
<tr>
<td>4</td>
<td>Purge index funds</td>
<td>2,955</td>
<td>202,372</td>
</tr>
<tr>
<td>5</td>
<td>Returns-based style analysis: custom benchmark. Exclude funds with (R^2&lt;60%)</td>
<td>2,714</td>
<td>184,990</td>
</tr>
<tr>
<td>6</td>
<td>Active U.S. equity mutual fund sample</td>
<td>2,714</td>
<td>184,990</td>
</tr>
<tr>
<td><strong>Final active U.S. small-cap equity mutual fund sample</strong></td>
<td><strong>899</strong></td>
<td><strong>40,233</strong></td>
<td></td>
</tr>
</tbody>
</table>

Source: Authors’ calculations based on data from the CRSP Survivor-Bias-Free US Mutual Fund Database.

\(^{21}\) Of course, reported expense ratios typically do not reflect explicit trading costs (i.e., broker commissions) and implicit trading costs (i.e., bid-ask spread and trading price impact), which can be substantial and can vary systematically across fund styles (Karceski et al., 2004).

\(^{22}\) Our monthly sample begins in January 1984 and terminates in December 2005 for two reasons. First, Edwin J. Elton et al. (2001, p. 2427) find that occasional differences in CRSP mutual fund returns and those reported by other sources (e.g., Morningstar) are most prevalent in the pre-1984 period and rather trivial thereafter. Second, the number of distinct funds in several style boxes is rather sparse before the mid-1980s. That said, our aggregate empirical results are robust under a longer sample; pre-1984 performance data would account for a small fraction of the total number of pooled observations in our research sample. The sample terminates in 2005 because 2006 data were not yet available when conducting our empirical analysis.
Empirical methodology
For every active fund, we must (1) classify its equity-market style category, (2) estimate its excess return and style-adjusted alpha, and (3) accumulate its monthly relative performance in an annual end-of-year value.

Estimating a fund’s investment style (nine-box classification)
We employ regression analysis to assign an active fund to one of nine equity-market style classifications (i.e., style boxes). Every month for every active fund, we run separate 60-month rolling regressions on 12 Russell style indexes, requiring at least 36 monthly observations over that 60-month rolling window for each fund. Each regression expresses a fund’s total returns (the dependent variable) as a linear function of the total return of a Russell equity index. Active funds are then classified into one of the nine Morningstar style boxes based upon the Russell style index that explains the highest percentage of the total variance in a fund’s total return over the previous 60 months. That is, an active fund is placed in the style box whose index produces the highest adjusted $R^2$.\(^{23}\) We repeat this classification procedure using MSCI style indexes.

Estimating a fund’s alpha
Following a common industry practice, we estimate an active fund’s alpha using returns-based style analysis. Every month for every active fund, we regress a fund’s total return on a set of six nonoverlapping benchmarks using constrained least squares over rolling 60-month windows.\(^ {24}\) This procedure estimates a customized benchmark for every active fund at every month. The specific regression is as seen below.

In this time-series regression, we constrain our customized benchmarks to have six benchmark weight parameters that are positive (no short sales) and that sum to 1.\(^ {25}\) The intercept (or alpha) from the customized benchmark regression is the excess return of the active fund that cannot be attributed to the benchmark returns (or the beta exposure).

We require active funds to have at least 36 months of returns history in our time-series calculations to ensure statistical reliability.\(^ {26}\) That said, requiring at least 24 months of data did not materially change the results reported in the paper. Finally, to ensure that our methodology produces reasonable alpha estimates, we exclude any fund in a given month that is assigned a customized benchmark with an $R^2$ below 60%.

Annual individual fund alpha
Similar to previous academic studies, we focus on evaluating an active fund’s performance over a one-year horizon. Shorter investment horizons (e.g., monthly) can be noisy, and it takes time for investors to evaluate the (perceived) skill of an active manager. Conversely, longer investment horizons (e.g., five or ten years) require longer fund track records that magnify a form of survivorship bias (known as omission bias) that overstates active fund performance.

$$r_{\text{fund}} = \alpha + \sum_{i} w_t LCV_i + \sum_{i} w_t LCG_i + \sum_{i} w_t MCV_i + \sum_{i} w_t MCG_i + \sum_{i} w_t SCV_i + \sum_{i} w_t SCG_i + \epsilon_t$$

Customized benchmark

\(^{23}\) For tractability, active funds that regress most significantly on the three total market benchmarks (i.e., “total market,” “total growth,” and “total value”) are placed in the related large-cap style box (i.e., “large-cap blend,” “large-cap growth,” or “large-cap value”) given the highest correlation between the total market and large-cap benchmarks.

\(^{24}\) The six nonoverlapping style benchmarks used to estimate customized Russell-based alphas are as follows: Russell Top 200 Value, Russell Top 200 Growth, Russell Midcap Value, Russell Midcap Growth, Russell 2000 Value, and Russell 2000 Growth. The six nonoverlapping style benchmarks used to estimate customized MSCI-based alphas are as follows: MSCI US Large Cap Value, MSCI US Large Cap Growth, MSCI US Mid Cap Value, MSCI US Mid Cap Growth, MSCI US Small Cap Value, and MSCI US Small Cap Growth.

\(^{25}\) Broadly speaking, the style benchmark that is assigned the highest customized benchmark weight in the returns-based style analysis is the style that receives the highest $R^2$ in the above single-benchmark regression procedure.

\(^{26}\) Incidentally, Morningstar’s classification system is also based on a trailing three-year window in evaluating fund characteristics and performance.
Similar to AIMR (Association for Investment Management and Research) performance guidelines, our style-adjusted alphas are defined as the cumulative geometric excess return of an active fund over its dynamic customized benchmark, $\alpha_{i,t}^{1\text{yr}}$, such that:

$$\alpha_{i,t}^{1\text{yr}} = \left(\prod_{n=t}^{t+12} (1 + R_{i,t}) - 1\right) - \left(\prod_{n=t}^{t+12} (1 + R_{i,t}^{\text{CBM}}) - 1\right)$$

where $R_{i,t}$ is the monthly total return of fund $i$ at time $t$, aggregated over the previous 12 months, and $R_{i,t}^{\text{CBM}}$ is the customized benchmark return estimated for fund $i$ at time $t$. Annual excess returns are calculated in similar fashion, although the fund’s assigned style-box index is used, rather than the customized (“blended”) benchmark. We calculate end-of-calendar-year alphas and excess returns for both net and gross returns for every active fund in the research sample. Focusing on nonoverlapping end-of-year values preserves the statistical independence of a fund’s performance over time.

Potential data biases
While the CRSP Mutual Fund Database includes both alive and dead U.S. equity funds, data-reporting procedures and our empirical methodology could introduce other biases that may have the same effect as survivorship bias when measuring active fund performance. We have identified four potential sources of bias: (1) multiple share class bias, (2) incubation bias, (3) frequency omission bias, and (4) rolling omission bias.\(^{27}\)

Multiple share class bias
According to the CRSP Mutual Fund Database guide, new share classes of funds are permitted to inherit their entire return history, duplicating the return histories of successful funds. By convention, we avoid this bias by combining multiple share classes on an asset-weighted basis.

Incubation bias
The CRSP database contains the private or semi-private history of returns for funds that later become public. Not surprisingly, Richard B. Evans (2004) finds that surviving incubated funds have higher risk-adjusted and total returns than nonsurviving incubated funds or other new funds. We cannot systematically control for incubation bias in our study.

Frequency omission bias
Our focus on monthly fund returns may also induce an omission bias, as some funds listed in the CRSP database report annual returns or none at all. While Edwin J. Elton et al. (2001) report that this frequency-omission bias is significant for funds with less than $15$ million in total net assets, we find that this is not a significant issue from 1984 to 2004. To further substantiate this claim, we examine active equity funds by testing the statistical significance of the mean return difference between funds that report monthly and funds that report annually. A paired $t$-test reveals that the average return differential between the two fund groups is not statistically significant at the 10% level.

\(^{27}\) Fund mergers, another potential source of survivorship bias, do not appear to systematically affect the returns of active funds in the CRSP database (Elton et al., 2001, p. 2425).
Rolling omission bias
The requirement of 36 monthly observations for our returns-based style analysis could potentially bias fund performance measures by excluding funds listed in the CRSP database that have less than 36 months of return history. On average, 39% of the funds in our sample have less than 36 monthly return observations in a given month. Of these excluded funds, 47% of the funds have less than 36 monthly observations because they ceased reporting within that three-year period. The remaining 53% had less than 36 monthly observations because they were new funds that had not yet accumulated a three-year track record.

Broadly speaking, one would expect the omitted dead funds to upwardly bias performance measures (through conventional survivorship bias), while the omitted new funds would downwardly bias the performance measures (by reducing the higher returns associated with incubation bias). Since the mix of omitted-dead and omitted-new funds was roughly equal in each style box, it is likely that the influences of new- and dead-fund exclusions offset each other such that the rolling omission bias does not meaningfully affect our empirical results. Indeed, a paired t-test reveals that the average monthly return differential over time between our included fund sample and those excluded funds with less than 36 months of history is statistically insignificant.

Empirical evidence of the Russell reconstitution effect in the small-cap fund universe

Table 7. The reconstitution effect of Russell benchmarks

The dependent variable is the difference between the average monthly Russell gross fund alpha and the MSCI alpha, July 1992–December 2005

<table>
<thead>
<tr>
<th>Active small-cap fund category</th>
<th>OLS regression</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Small-cap minus large-cap (SMB)</td>
</tr>
<tr>
<td></td>
<td>Coefficient</td>
</tr>
<tr>
<td>Small-cap value</td>
<td>(0.01)</td>
</tr>
<tr>
<td>Small-cap blend</td>
<td>(0.02)</td>
</tr>
<tr>
<td>Small-cap growth</td>
<td>(0.08)</td>
</tr>
</tbody>
</table>

Source: Authors’ calculations.
Regressions include Fama-French SMB, HML, and small-cap momentum factors. Statistically significant regression coefficients at the 10% level are highlighted and bold.
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