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Mutual Fund Performance Evaluation with Active Peer Benchmarks

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Abstract

We propose a simple approach to account for commonalities in mutual fund strategies that relies solely on information on fund returns and investment objectives. Our approach augments commonly used factor models with an additional benchmark that represents an equal investment in all same-category funds, which we call an "Active Peer Benchmark," or APB. We find that APBs substantially reduce the average time-series correlation of residuals between individual funds within a group when added to a four-factor equity model (or to a seven-factor fixed-income model). Importantly, adding this APB significantly improves the selection of funds with future outperformance.

Keywords: G11, G23, mutual funds, performance measurement

1. Introduction

The open-end mutual fund industry is now the main venue through which retail investors participate in traded securities.[1] It is widely known that a growing number of their fund managers follow passive strategies, linking their investments to a particular index. The majority, however, still claim that they can add value

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[1] As of 2010, households hold 37.8% of total assets in financial assets. Of financial assets, 15% are held in pooled investment funds, not including holdings in retirement accounts or money market funds, while 18% are directly held in stocks and bonds. An additional 38.4% is held in retirement accounts, much of which is allocated to mutual funds (Board of Governors of the Federal Reserve System, 2010).

to investors by actively managing their portfolios. The basic question facing academics, regulators, and investors alike is whether active fund managers deliver superior performance to investors, as they claim, or just aggressively solicit additional funds when they are lucky, and downplay their poor performance when they are not. Consequently, the literature on active fund management has been expanding rapidly in its attempt to answer the same basic question: does active management produce persistent superior investment performance? Indeed, among U.S.-domiciled equity funds alone (investing in U.S. or world equities), active management accounts for $4.9 trillion in assets under management at the end of 2012 (Investment Company Institute, 2013).

The academic literature on evaluating active managers has evolved from simple Sharpe ratio comparisons to Jensen's alpha using a single risk factor, to the Fama and French (1993) three-factor model, to which Carhart (1997) added momentum as the fourth factor. Subsequently, the literature modeled α and β as time-varying with observed macroeconomic variables, as in Ferson and Schadt (1996), Christopherson, Ferson, and Glassman (1998), Ferson and Siegel (2003), and Avramov and Wermers (2006); or with Kalman filters, as in Mamaysky, Spiegel and Zhang (2008). This literature, in general, has added more exogenously determined risk factors to better model fund returns, relative to the original Jensen model. In addition, most of the research efforts have focused on U.S. domestic equity mutual funds, as empirical asset pricing research (e.g. Fama and French, 1993) has chiefly focused on exposing new priced factors in U.S. stocks.[2,3]

A pervasive problem with performance evaluation is the presence of similar strategies among funds, which produces correlated residuals from commonly used models and, therefore, reduces the power of such models to separate skilled from unskilled fund managers. For example, Grinblatt, Titman, and Wermers (1995) find that the majority of mutual fund managers use momentum as part of their stockpicking strategies, while Chen, Jegadeesh, and Wermers (2000) find that fund managers commonly prefer stocks with higher levels of liquidity. Jones and Shanken (2005) and Cohen, Coval, and Pastor (2005) recognize this issue, and develop approaches to exploit commonalities in fund returns to improve performance evaluation. However, these papers require fund portfolio holdings data or knowledge about the commonalities that may not be available in practice. In addition, portfolio holdings are disclosed infrequently for mutual funds (each calendar quarter, with a delay of 60 days), limiting their informativeness. For example, Kacperczyk, Sialm, and Zheng (2008) find a substantial "gap" between actual monthly returns of domestic equity funds and the hypothetical returns of their periodically reported portfolio holdings. Clearly, infrequent holdings data, when available, have important but limited usefulness in measuring commonality in strategies.

In this paper, we propose a simple and easily implementable approach to account for commonalities in

[2]Extensive literature reviews can be found in Fischer and Wermers (2012) and Wermers (2011).

[3]Another branch tries to attribute the performance to various types of decisions made by the manager: asset allocation, security selection, and high frequency market- or style-timing. Such analyses generally require data on fund holdings. Examples of papers that use holdings information are Daniel, Grinblatt, Titman, and Wermers (1997), Wermers (2000), and Jiang, Yao, and Yu (2007).

fund strategies that only uses information on fund returns and the investment objective of the fund (which may be obtained from a fund prospectus, by comparing recent portfolio holdings to holdings of common market benchmarks, or by measuring correlations between fund returns and common market benchmark returns). Our approach is to form an additional benchmark from the return on the group of funds to which a given fund belongs, since each fund manager chooses the peer group with which it intends to compete. By this selection, the fund signals the set of strategies from which it chooses, as well as the subgroup of stocks on which it implements these strategies–i.e., the fund signals how it will generate returns, both priced and unpriced by the risk model. We note that it is much simpler to account for commonalities using this reference group return, rather than trying to identify the potentially numerous exogenous factors that represent the many complex strategies that may be used by funds within a group. As such, there are some important and intuitive reasons for using this variable as an additional "factor."[4]

First, let us take the point of view of the investor who has already decided on asset allocation, in terms of choosing the type of funds in which she would like to invest, but needs help in choosing the best funds within the reference group. Even the least sophisticated investor always has a fallback strategy of equally-weighting (or value-weighting) all funds in the group every period; this tradeable strategy is quite simple.[5] To deserve a higher (than proportionate) share of an investor's portfolio, the fund manager must convince the investor that the fund can be expected to deliver superior performance, relative to this naive strategy of investing in the entire group. Consequently, it is intuitive to use the group investment as a pre-determined benchmark for each fund that belongs to that group.[6] We claim that, by choosing the strategy and advertising herself as managing an active equity fund that benchmarks against, say, the Russell 1000 Growth index, the manager implicitly chooses from a set of strategies used by the set of active funds that benchmark themselves against this index. Thus, it is only natural to evaluate her performance using the portfolio of all funds that benchmark against the Russell 1000 Growth index, and that are available for investment at the same point-in-time. In effect, using the entire reference group to benchmark the individual funds for risk has an alternative investment interpretation: it focuses on identifying the best active strategies, among a set of correlated strategies, within a group that focuses on a similar universe of stocks.

Second, it may well be that many fund managers in a peer-group make similar security or sector bets, perhaps dynamically changing these bets over time. They may use similar models, have similar behavioral biases, or locate in the same geographical area (thus, analyzing similar local stocks, perhaps due to networking). Clearly, such similarities induce correlated errors across funds in the peer-group (after controlling for

[4]In this paper, we often refer to this active peer benchmark as an "additional factor" for simplicity in exposition. However, we do not imply that it is necessarily priced (this question is left for future research). In this paper, we use it only to improve the estimation of the parameters of interest.

[5]We only consider no-load funds, thus, the cost of rebalancing is low.

[6]It is notable that Lipper and Morningstar use simple peer-groups alone (without a formal model) in their assessments of fund performance. We propose that this peer adjustment should instead be added to known risk factors in a formal model, and demonstrate why this peer "factor" can improve ex-post performance evaluation–as well as the identification, ex ante, of future outperforming managers.

priced factors). In such a case, the peer-group return will capture these commonalities.[7] Then, extending the argument of Pastor and Stambaugh (2002) for augmenting a model with a passive factor, an active peer-group return can help to account for dynamically changing commonalities across funds. Thus, we can improve the estimation of alpha from a performance regression by including the peer-group return in order to reduce the common idiosyncratic noise.

Apart from the above benefits, as well as its simplicity and implementability, our approach offers additional advantages: it allows evaluation of the performance of any fund, and is not limited to equities. For instance, while risk models are well-developed for most of the mutual funds that we consider in this paper (i.e., for domestic equity and fixed-income categories), there are many asset classes where this is not so. In those asset classes, the active peer benchmark can be added to a model with factors that only modestly explain fund returns, or can even be used in a model as the only "factor." Moreover, the benchmark is a tradeable asset, unlike most of the risk factors in conventional factor models – for instance, one can easily invest equal amounts of one's wealth in many no-load mutual funds. As another example, one can invest in a fund-of-hedge-funds as an alternative to investing in one or two of the target hedge funds.

We label the average peer-group return an "Active Peer Benchmark," or APB–this benchmark return is measured gross of fund expense ratios to focus on fund manager skill rather than fund cost efficiency (which is largely out of the control of the fund's portfolio management team). To demonstrate the effect of using an APB, we use data on U.S. mutual funds specializing in equities, where there exists an ample literature identifying priced risk factors. We measure performance using the standard four-factor Carhart (1997) model, then compare this with measurements using the four-factor model augmented by the APB "factor."

We begin our analysis by documenting that the α of the APB factor itself, measured with the four-factor model, can be rather sizeable in magnitude (either positive or negative) and significant during subperiods of a few years, even though it is closer to zero (and, for most peer-groups, insignificant) over longer sample periods. This finding suggests that periodic measurements of a typical fund α contain a large group component, since the APB α is simply the average α of individual funds within that APB group. Next, we document a large correlation between the four-factor model residuals of pairs of individual funds within a particular peer-group. This further suggests strong commonalities in the behavior of fund managers that are not captured by the standard pricing model. Together, the above results indicate a strong need to account for these commonalities, and we argue that using the APB captures these in the most parsimonious way. That is, the high correlation of residuals within a peer-group is expected to overwhelm the loss of one degree of freedom by adding the APB factor to the standard four-factor model.

The first indication of the power of this approach becomes evident when we add the APB to standard

[7] In addition, if funds within a peer-group dynamically change their risk-factor exposures over time in a common way, the active peer-group return can help to control for this.

model specifications. Here, the within-group (individual fund pair) residual correlations are decreased by one-third to one-half of their prior levels, depending on the peer-group. Further, the coefficient on the APB factor is positive and significant for over half of the funds in every equity fund category, even after accounting for the standard four factors; this level is higher than the degree of significance of all the traditional factors, apart from the market return. Both of these results clearly indicate that the APB is a simple, yet powerful tool to control for (unknown) commonalities in behavior.

Central to our paper are our tests of whether the APB-augmented model better forecasts the ability of equity managers to generate alphas, compared to the standard models. Ex-ante, we have no clear prediction on that, as lower-variance estimation of alpha may actually imply lower predictability of future returns, if these superior abilities are non-existent, and the spurious estimated alpha is correctly removed by our procedure. On the other hand, if superior managers do exist, our procedure should improve their detection.

Our results indicate that skills do exist, and that the APB-augmented model significantly improves the identification of outperforming equity funds in most peer-groups. For instance, using the four-factor model plus the equal-weighted return of funds that follow the Russell 1000 benchmark to rank individual funds over three-year lagged periods results in identifying top quartile funds (in that peer-group) with following-year four-factor (pre-expense) alphas that average 7 bps/month (84 bps/year). These funds also outperform bottom quartile funds (in that group) by 7 bps/month. Among our nine peer-groups, we find that four exhibit significantly positive following-year four-factor alphas for equal-weighted portfolios of top-quartile funds, ranked by the APB-augmented model, while, for eight of nine groups, these top-quartile funds significantly outperform bottom-quartile funds during the following year. No peer-groups exhibit negative alphas for top-quartile funds during the year following the ranking date. And, we find that our APB-augmented model selects top-quartile funds in the Russell 1000 benchmark group that outperform, on an equal-weighted basis, those top-quartile funds chosen by the standard four-factor model (also by 7 bps/month). In the Russell midcap category, top-quartile performance improves, relative to a four-factor model ranking, by an even more substantial margin (28 bps/month).

We further explore whether top-quartile funds may simply employ "leveraged" strategies that are common to the group to achieve their superior alphas. For instance, perhaps many funds within a peer group are skilled, but some managers employ these strategies more aggressively than others, perhaps due to lower career-concerns.[8] In this case, we would be less likely to conclude that high-alpha managers are more skilled than others with lower, but positive alphas. When we apply a model (to following-year returns) that adjusts for alpha that accrues from the use of common strategies (our "APB-adjusted alpha model"), our finding of superior skills of top-quartile managers (ranked by past APB-augmented model alpha t-statistic) remains, although it is somewhat reduced in magnitude. For instance, the equal-weighted portfolio of top-quartile

[8]Chevalier and Ellison (1999) find that career-concerned managers tend to take less risk, both idiosyncratic and systematic, than less career-concerned managers.

funds (chosen by their alpha t-statistic using the APB-augmented four-factor model) in the Russell 1000 group generates a statistically significant pre-expense alpha of 3 bps/month (36 bps/year) during the year following the ranking of funds (compared to the above-noted 7 bps/month total four-factor alpha). Further, top-quartile funds outperform bottom-quartile funds by roughly the same magnitude as measured by the APB-augmented model (without alpha adjustment). This finding indicates that superior funds (and inferior funds) continue to exist, after controlling for any alpha generated by common strategies.[9]

When we measure following-year performance using net-of-expense alphas (for funds ranked by their pre-expense alpha t-statistics from the APB-augmented four-factor model), we find that the APB-augmented four-factor model continues to outperform its baseline counterpart, although at a reduced level. Specifically, the following-year equal-weighted four-factor alpha (net of expenses) is positive and significant for top-quartile funds in two peer-groups. (This compares with statistically significant and positive alphas, pre-expense, for four of nine APB groups, using the same ranking methodology.) In the other seven groups, top-quartile funds have an insignificant alpha, but, in eight of nine groups, the difference in alphas between top- and bottom-quartile funds remain positive and statistically significant, and the magnitude of this difference is not unlike that of the above-mentioned pre-expense performance.

In robustness tests, we rank funds by their t-statistics of alphas using alternative models. Specifically, we implement a four-factor model, augmented by either (1) the passive "best fit" benchmark of Cremers and Petajisto (2009) (e.g., the Russell 1000 index for active funds that invest closest to this index) or (2) the liquidity factor of Pastor and Stambaugh (2003). We find that our APB-augmented model outperforms the rankings of these two alternative models in identifying top-quartile funds with persistent performance, indicating that an active peer benchmark captures incremental commonality in fund residuals. That is, the APB benchmark captures incremental commonality, relative to a passive, non-benchmark index (which Pastor and Stambaugh, 2002, show provides incremental power, relative to a standard four-factor model). In addition, the APB factor does not simply proxy for an omitted illiquidity factor that funds may load on, in common.

Our equal-weighted APB benchmark has a simple opportunity cost interpretation of an equal investment in each fund as an alternative to selecting a small number of active funds based on some ranking criteria. Also, an advantage of equal-weighting the APB benchmark, relative to value-weighting (or weighting on some other fund characteristic) is that, a priori, we would expect that equal-weighting would capture a common strategy with less noise than other weighting schemes. However, a potential drawback of this approach is that, if taken literally as an opportunity cost, it requires an equal investment in both very small and very large funds for an investor deciding to implement this simple strategy rather than choosing a few

[9]We also note that a reasonable interpretation is that the common group pre-expense alpha is truly zero (as indicated by studies such as Carhart, 1997), and that subtracting the (leveraged) exposure to the group efficiently corrects for short-period estimation error (i.e., where the group alpha is estimated to be non-zero). We thank the referee for this intuition.

active funds. For a retail investor, this may not be an issue, but it could present a greater difficulty for a larger institution that attempts to implement our procedure and decides to invest in the group as a whole rather than a particular active manager.[10]

Thus, for robustness, we implement a value-weighted APB benchmark for several of our baseline persistence tests. When we form the APB factor for each peer-group using value weights, we find that it continues to select top-quartile funds with qualitatively similar alphas, during the following year, as those selected above using the equal-weighted peer-group APB factor.

Finally, in further tests that are fully described in the Internet Appendix, we find that our APB approach also works well in identifying bond fund managers with persistent skills. We separately rank intermediate-term and long-term (1) government, (2) corporate, and (3) municipal bond funds (i.e., six categories) by their respective APB-augmented bond fund models. Similar to our equity fund results, we find that top quartile bond funds (ranked during a given three-year period) continue to outperform over the following year.

The use of APBs to augment standard regression models builds on Blake, Elton, and Gruber (BEG; 1999), who add a growth fund factor to augment equity performance models. Our paper builds on this intuition by separately defining a group factor for each peer-group, by demonstrating that this factor improves the ex-ante identification of skilled managers (relative to the four-factor model), and by determining *why* this factor improves this identification. Specifically, we show that our two versions of the augmented model lead us to conclude that skilled managers, within a given peer-group category, have both common talents (i.e., they produce alphas from common strategies) and idiosyncratic talents (i.e., they produce alphas, after controlling for common strategy alphas).

In another related paper, Busse and Irvine (2006) implement a Bayesian model that uses long histories of passive asset returns to improve the predictability (persistence) of fund performance. Using daily returns, Busse and Irvine add four different passive assets as factors to the standard four-factor model. Long-history average returns on the passive assets, along with the correlation of passive asset returns with fund returns, help to control for future returns that are due simply to fund tilts toward passive strategies (such as overweighting certain industries). Our paper suggests that adding a peer-group factor (the APB) is useful when long histories of passive assets are unavailable, or when the choice of particular passive assets is unclear. In addition, we find some evidence that the APB is incrementally useful even when passive asset returns are (first) added to a four-factor model.

This paper is organized as follows. Section 2 presents the intuition behind the choice of the group return as an explanatory variable and presents simple econometric arguments for doing so. Section 3 describes the

[10]Another potential advantage of value-weighting lies in the interpretation of the opportunity cost. A value-weighted portfolio of funds likely has an alpha closer to zero than an equal-weighted portfolio, as it is closer to the market portfolio of stocks. Thus, one may be able to interpret this opportunity cost as that of investing in active funds with skills just sufficient to match passive funds, net of fees.

data and the empirical methodology. Section 4 presents our results, while section 5 concludes.

2. Motivating Active Peer-Group Benchmarks (APB)

Consider an unsophisticated investor interested in investing in actively managed mutual funds. Assume that he has already obtained expert advice on asset allocation, which means that he has already determined the amounts he would like to invest in passive index funds and actively managed funds. Further, the investor has already decided the amount to invest in each actively managed style category. For simplicity, let us constrain ourselves to equities, and consider nine style categories of funds:

- large-capitalization: total, value, and growth
- mid-capitalization: total, value, and growth
- small-capitalization: total, value, and growth

Within each of the above categories, suppose that the investor hires an advisor to suggest the allocation to individual funds. It is clear to both parties that the investor can always save the advisor's fees by simply investing in a periodically rebalanced, equal-weighted (or value-weighted) portfolio of all the funds in the group. To justify the fee, the advisor must present an evaluation procedure that adds value over the default strategy.

For this task, we propose using the EW portfolio of all funds in a particular group as a benchmark for each individual fund in that group, since the investor has chosen an allocation to that active equity style category and the funds have chosen to compete in that category to attract the investor's capital. This "active peer-group benchmarking" is the cornerstone of our proposed performance evaluation strategy. The investor is advised to modify his naive strategy of investing in the APB, and to invest more in funds that generate positive excess risk-adjusted returns that significantly exceed those of the APB, while less in those that generate risk-adjusted returns that lie significantly below those of the APB.

The basic procedure we propose is to estimate the normal regression model α; however, instead of only the four standard factors (see e.g. Carhart, 1997, or Wermers, 2000), we propose adding the APB as a fifth "factor" to create an "APB-augmented four-factor model." To clarify, the return on the APB, for a particular month, is the EW-average (or, alternatively, the VW-average) across all funds that are available for investment in that category at the beginning of that month. To make the APB a realistic baseline investment, we include only no-load funds in our analyses to minimize any costs of investing and rebalancing among a potentially large group of funds in a particular category.

With funds in asset classes where risk-factors are poorly known (e.g., hedge funds), we might use the APB in a single-factor model to judge (relative) fund manager talents. However, when multiple risk factors are well-documented, as with U.S. equities, a preferred approach is to augment the standard multiple factor model (e.g., the four-factor model for equities) with the APB. With this approach, differential loadings on the different risk factors across funds within a category do not result in spurious regression alphas. For instance, a subgroup of large-capitalization growth managers may focus on extreme momentum strategies, while the entire group may follow a more muted momentum plus growth strategy. With only the APB factor, one may conclude that the funds focusing more strongly on momentum strategies are skilled; using an augmented four-factor model, one would not. Thus, an attempt should be made to use the APB in conjunction with well-defined risk-factors, whenever possible, when used to judge relative fund manager alphas in other asset classes.

2.1. The Econometric Model

In this section, we outline the econometric advantages of using the peer-group return, in addition to the traditional risk factors. We denote, by $R_{i,t}$, the actual reported return of fund i during month t. This return is net of the management fee (and trading costs), as is customary in fund reporting. Let $m_{i,t}$ be the periodic management fee (per dollar under management) that fund i charges at period t, and $r_{f,t}$ be the risk-free rate for the same period. Together, we can use these variables to define the gross excess return of fund i at time t:

$$r_{i,t} \equiv R_{i,t} + m_{i,t} - r_{f,t} \tag{1}$$

We define, by $r_{APB_i,t}$, the average gross excess return of the active peer-group of funds to which fund i belongs:[11]

$$r_{APB_i,t} \equiv \frac{1}{N_{APB_i}} \sum_{i=1}^{N_{APB_i}} r_{i,t} \ , \tag{2}$$

where N_{APB_i} equals the number of funds in the APB to which fund i belongs. Next, we discuss a simple model to illustrate the potential advantages of adding the APB to the traditional estimation of a model α.

2.1.1. Baseline Model

To illustrate the usefulness of the APB as an additional "factor," consider the common case where the asset-pricing model errors, $\epsilon_{i,t}$, are correlated across funds in a peer-group due to some commonality in investment strategies of the fund managers. Under such a scenario, Pastor and Stambaugh (PS; 2002) suggest increasing the precision of α by including the returns of carefully selected non-benchmark assets in the regression, regardless of whether these assets are priced by the benchmarks.[12] For instance, if it is known that a group of fund managers tend to concentrate on technology stocks, one might add the Nasdaq 100 total return as the non-benchmark asset to the four-factor model. The increased precision in the alpha

[11] Henceforth, all parameters with subscript APB indicate active peer-group averages of the corresponding fund-specific parameters.

[12] These non-benchmark assets must be carefully selected to be sufficiently correlated with the fund residual from the four-factor model.

from the "augmented four-factor model" comes from the correlation between the random components of the passive asset (Nasdaq 100) returns and the (technology) fund returns.

With our approach, it is easy to choose the non-benchmark asset. Specifically, the noise component of the APB and the individual fund return is likely to be positively correlated due to commonalities in idiosyncratic risk-taking, and the APB can be treated as a "zero skill" asset–that is, it can be viewed as a "passive" alternative for the investor.[13] Consequently, the estimation of individual fund alphas may be improved by adding the APB to the standard set of benchmarks, as per PS.

Formally, let us assume that the fund i errors have the following structure (here, we assume just one priced risk factor for simplicity):

$$r_{i,t} = \alpha_i + \beta_i f_t + \epsilon_{i,t}, \tag{3}$$

where

$$\epsilon_{i,t} = \rho_i L_t + \omega_{i,t},$$

L_t is a zero-mean random variable (an unpriced risk factor), and $\omega_{i,t}$ is an IID (across funds) error term. Note that we can obtain unbiased estimates of α_i directly with Equation (3) above; thus, our APB-augmented model is undertaken only to increase the precision of the estimator of α_i.

The APB return is:

$$r_{APB_i,t} = \alpha_{APB} + \beta_{APB} f_t + \epsilon_{APB,t}\ , \tag{4}$$

where

$$\epsilon_{APB,t} \equiv \rho_{APB} L_t + \omega_{APB,t},$$

or

$$L_t = \frac{\epsilon_{APB,t}}{\rho_{APB}} - \frac{\omega_{APB,t}}{\rho_{APB}}.$$

Substituting this expression for L_t into Equation (3)–the model for a single fund–we get:

$$r_{i,t} = \alpha_i + \beta_i f_t + \frac{\rho_i}{\rho_{APB}} \epsilon_{APB,t} + [\omega_{i,t} - \frac{\rho_i}{\rho_{APB}} \omega_{APB,t}]. \tag{5}$$

Equation (5) suggests adding the first-stage model residual for the APB, $\epsilon_{APB,t}$, to the standard asset-pricing model (Equation (3)) in a second stage will result in a lower-variance residual, $\omega_{i,t} - \frac{\rho_i}{\rho_{APB}} \omega_{APB,t}$. Of course, whether this translates into more precise regression parameter estimates, $\widehat{\alpha}_i$ and $\widehat{\beta}_i$, depends on whether a particular fund's residual, $\epsilon_{i,t}$, is sufficiently correlated with the APB residual, $\epsilon_{APB,t}$. A

[13]A reasonable prior is that groups of mutual funds have true alphas (pre-expense) of zero, rendering this interpretation of "no-skill" realistic. Strictly speaking, however, whether the APB exhibits alpha or not is irrelevant to our analysis, since our approach attempts to identify *subgroups* of funds within the peer-group that have the top skills.

sufficiently high (positive) correlation is necessary so that $\epsilon_{APB,t}$ does not act as a "nuisance parameter," using up a degree-of-freedom in the regression without decreasing the residual variance substantially. With a sufficiently positive correlation, we obtain more precise estimates of α_i and β_i for fund i (through a reduced estimated standard deviation of point estimates).

Note that our proxy ($\epsilon_{APB,t}$) for the commonality in residuals (L_t) is correlated with the Equation (5) model residual through $\omega_{APB,t}$, therefore, it is an imperfect proxy, as defined by Wooldridge (2002). Wooldridge (2002, p.64) suggests that, unless the proxy is highly correlated with the other regressors, it is worthwhile in a mean-squared error sense to introduce it: even though it generates an inconsistent estimate, it reduces the error. In our case, $\epsilon_{APB,t}$ is uncorrelated with f_t, by construction, thus, it makes sense to introduce it.

We have performed numerous simulations to evaluate the error in the estimate of α_i with and without the use of the APB in various factor models. In all cases, the mean-squared-error of the estimate of α_i without the APB factor was significantly larger. This leads us to believe that the introduction of $\epsilon_{APB,t}$ improves the estimation of α_i. Note, also, that the intercept from Equation (5) can be interpreted as an "absolute" skill level of fund i, since we do not subtract the intercept of the peer-group. Some of this absolute level could be common among funds. Our next section presents a model that adjusts for common alphas within a peer-group.

2.1.2. APB-Adjusted Alpha Model

A slight variation on the above correlated errors model provides further insight. Suppose that all funds in a particular peer-group generate alphas through the same strategy, except that some fund managers leverage this strategy more than others. Such differences in "aggressiveness" of investment strategy can be motivated by differential risk-aversion among fund managers, which can arise because of the career concerns of fund managers discussed by Chevalier and Ellison (1999). In such a case, we would observe differential alphas that are merely a leveraging of the common peer-group alpha, and not due to unique individual fund manager skills.

We introduce a variant of Equation (5) that helps us to determine whether unique fund manager skills exist. We call this version the "APB-adjusted alpha model":

$$r_{i,t} = a_i + \beta_i f_t + \frac{\rho_i}{\rho_{APB}} \left(\alpha_{APB} + \epsilon_{APB,t}\right) + [\omega_{i,t} - \frac{\rho_i}{\rho_{APB}} \omega_{APB,t}]. \tag{6}$$

Note that we add the APB alpha to its residual as the additional "factor" in Equation (6), compared to Equation (5), and that the "APB-adjusted alpha," a_i, equals the "unadjusted alpha" of Equation (5), α_i, minus $\frac{\rho_i}{\rho_{APB}} \alpha_{APB}$. If, for example, fund i merely generates a return that is a "k-leveraged" APB return plus (uncorrelated) noise, $r_{i,t} = k r_{APB_i,t} + \epsilon_{i,t}$, then Equation (6) will assign the manager a zero alpha.

Intuitively, if an investor can simply buy the APB and leverage it, there is no need to engage in a costly search for managers to achieve the same end. Another interpretation, in such a case, is that the fund actually has zero (pre-expense) alpha, since studies such as Carhart (1997) indicate that true long-run alphas equal zero, before expenses, on average across large groups of funds (such as each of our peer-groups, and, thus, for our APB return time-series). Under this interpretation, the above APB-adjusted alpha is the active-benchmark analog to the Pastor and Stambaugh (2002) passive-benchmark approach (we discuss this in more detail when we present our results).

To summarize, our econometric prediction is that our APB-augmented model, Equation (5), will result in a lower-variance estimate of individual fund alphas. We will now proceed to test this prediction.

3. Data and Empirical Models

We obtain monthly NAV returns, distributions reinvested, as well as annual expense ratios for the universe of U.S. mutual funds from the CRSP Mutual Fund Database for the period January 1980 to December 2010. We include only no-load mutual fund shareclasses in our study, in order to minimize the costs of trading mutual funds for an investor attempting to mimic our strategy. In addition, we include only one shareclass from each mutual fund if more than one is no-load. In cases where a single fund has two no-load shareclasses, we arbitrarily select one of those shareclasses for our sample. When that shareclass no longer reports returns, it is replaced with another shareclass, if available. We also add back 1/12 of the most-recently reported annual expense ratio for a given shareclass to its monthly net return in order to focus on fund manager skills prior to expenses, which are generally set by advisory companies. When we conduct our tests of persistence of performance, which attempt to create an investable strategy, we will discuss results both gross and net of expenses.

3.1. Fund Categorization

Mutual fund advisors choose and disclose a passive benchmark against which to compare each fund's performance, in their prospectus and in other public disclosures (e.g., websites and newspaper advertisements). While this revealed preference may be a good indication of their chosen peer-group, the free choice also induces some substantial principal-agent problems. Since there appears to be no large penalty for choosing an inappropriate benchmark, other than the potential of increased tracking error (which, as per del Guercio and Tkac, 1999, retail investors pay little attention to, compared to institutional investors), mutual fund managers are incentivized to choose easy-to-beat benchmarks. For instance, a mid-cap value manager may choose the S&P 500 as a benchmark, in order to capitalize (at least, in expectation) on the small-cap and value premia documented by Fama and French (1992, 1993).

Sensoy (2009) shows how this principal-agent problem manifests itself in the U.S. domestic equity mutual fund industry. He finds that, among funds self-identifying with a particular S&P or Russell passive benchmark, 31.2% have a better match with a different Russell or S&P benchmark, measured by regression R^2 of fund monthly return on benchmark return. He also finds that fund advisors have a strong incentive to strategically chose their passive benchmarks: fund investors tend to direct their flows toward funds that beat their self-chosen benchmarks, relative to funds that beat a better-fitting Sensoy "corrected benchmark."[14]

To help minimize the perils of this self-choice agency issue, we assign objective passive benchmarks to each equity mutual fund, each calendar quarter, using the "best fit" benchmark assigned by Cremers and Petajisto (CP; 2009) in the first step of computing the CP "active share" measure.[15] We obtain the best fit benchmarks for most domestic equity mutual funds during the January 1980 to December 2010 period from Martijn Cremers and Antti Petajisto.[16] To obtain fund categories with larger numbers of funds–which serves to reduce the noise in the active peer-group benchmark return–we map these "primary benchmarks" to a smaller set of "major benchmarks." Sensoy (2009) finds that the vast majority of U.S. equity mutual funds define their benchmarks on size and value/growth dimensions; industry performance monitors, such as Morningstar, also define styles in these two dimensions. Therefore, we have mapped the primary CP benchmarks to nine different major benchmarks defined in these two dimensions. Later in this paper, for robustness, we will report our baseline tests, using the primary CP benchmarks rather than the major benchmarks. The main disadvantage of the primary benchmarks is some of them contain very few funds during several of the early years of our sample period. The appendix discusses the approach used by CP to create the best-fit benchmarks, as well as summary statistics on both the primary and major benchmarks.

Our final set of nine best-fit benchmarks are:

	Value	*Core*	*Growth*
Large-Capitalization	Russell 1000 Value	Russell 1000	Russell 1000 Growth
Mid-Capitalization	Russell Midcap Value	Russell Midcap	Russell Midcap Growth
Small-Capitalization	Russell 2000 Value	Russell 2000	Russell 2000 Growth

Appendix Table A.3 provides a census of funds in each of these nine categories over three-year periods. To be included in a particular three-year period, a fund must have at least 30 non-missing monthly returns during this period (which, as we describe in the next section, are required to compute three-year alphas). To qualify as a non-null "group," it must consist of at least five funds following the same best-fit benchmark, each having at least 30 non-missing returns during a particular three-year period. Mutual funds following the three Russell 1000 indexes and the Russell 2000 Growth index have at least five qualifying funds during

[14]In that sense, investors following a better-fitting benchmark would be more likely to experience persistent performance partly due to avoiding investing with the crowd, and the diseconomies-of-scale of fund performance that result, as modeled by Berk and Green (2004).

[15]These best fit benchmarks are very similar to Sensoy's "corrected benchmarks."

[16]We note that assigning best fit indexes requires portfolio holdings data, but the econometrician can use relatively infrequent holdings data to classify funds (e.g., once per year or once per three years). Thus, our approach retains its advantages in simplicity over approaches that require frequent (e.g., quarterly) holdings data. In addition, as the Appendix indicates, one can alternatively choose "best-fit" benchmarks by maximizing the return correlations with funds.

every three-year time period covered by our study, from 1980 to 2010. The other five indexes qualify as groups during the majority of three-year time periods.

3.2. Models

3.2.1. Baseline Model

We use the Carhart four-factor model as our baseline performance evaluation model, against which we test our alternative specification that augments the model with our active peer-group benchmark (APB). The four-factor model applied to fund i is

$$r_{i,t} = \alpha_i + \beta_{i,rmrf} r_{rmrf,t} + \beta_{i,smb} r_{smb,t} + \beta_{i,hml} r_{hml,t} + \beta_{i,umd} r_{umd,t} + e_{i,t} \ , \qquad (7)$$

where $r_{i,t}$ is the fund i monthly NAV return, plus 1/12 times its annual expense ratio, minus T-bills, and $r_{rmrf,t}$, $r_{smb,t}$, $r_{hml,t}$, and $r_{umd,t}$ are the monthly return on the CRSP value-weighted portfolio (NYSE/AMEX/Nasdaq) minus T-bills, and the size, book-to-market, and momentum factor monthly returns (available via Ken French's website). We interpret α_i from this model (its true value, not its estimated value) as the proper measure of fund manager "skill". We run this regression over three-year periods, as described in later sections of this paper, on funds having at least 30 months of NAV returns and having expense ratio data available during that three-year period.

We also run the same regression, over the same three-year period, using the return of the equal-weighted active peer-group that fund i belongs to at the end of the given three-year period, $r_{APB_i,t}$ in place of the above single-fund return, $r_{i,t}$ (later in the paper, for robustness, we replace with the value-weighted peer-group return). This regression yields estimates of α_{APB_i} and $\epsilon_{APB_i,t}$.

3.2.2. Augmented Model

Our alternative specification adds the first-stage four-factor regression residuals for the APB, $\epsilon_{APB_i,t}$, to the four-factor model for fund i. In this second stage, we apply the following model to each individual mutual fund, i:

$$r_{i,t} = \alpha_i + \beta_{i,rmrf} r_{rmrf,t} + \beta_{i,smb} r_{smb,t} + \beta_{i,hml} r_{hml,t} + \beta_{i,umd} r_{umd,t} + \lambda_i \epsilon_{APB_i,t} + \epsilon_{i,t} \ . \qquad (8)$$

As stated above, the regression of Equation (8) helps to control for commonalities in idiosyncratic risk-taking by funds within the same APB group.

We also apply an "APB-adjusted alpha" version of this augmented model,

$$r_{i,t} = a_i + \beta_{i,rmrf} r_{rmrf,t} + \beta_{i,smb} r_{smb,t} + \beta_{i,hml} r_{hml,t} + \beta_{i,umd} r_{umd,t} + \lambda_i (\alpha_{APB} + \epsilon_{APB_i,t}) + \epsilon_{i,t} \ . \qquad (9)$$

If the source of a fund's performance comes from unique manager skills that are uncorrelated with the manager's active peer-group's average skills, then alpha will be identical under both of the above models (i.e., $\lambda_i = 0$). On the other hand, if the source of a fund's performance comes entirely from co-movement related effects (represented by $\lambda_i \alpha_{APB}$), then $a_i = 0$, and we would not expend the search costs to identify this fund, in lieu of the active peer-group benchmark.

Suppose, however, that a subgroup of a peer-group of funds were able to outperform the APB by using a strategy common to that subgroup, but not used by any other fund in the peer-group (i.e., the model residuals for the subgroup are uncorrelated with the average residuals of the remaining funds in the APB group). In such a case, the APB-adjusted alpha model of Equation (9) would provide an alpha, a_i, that deviates from that of the non-adjusted augmented model of Equation (8) only according to the proportion of the APB that is represented by such outperforming funds.[17] In this case, we would expect the alpha adjustment model to identify the skilled subgroup of managers.

In some of the analysis to follow, we present a simplified model based only on the APB:

$$r_{i,t} = \alpha_i^{APB} + \lambda_i^{APB} r_{APB_i,t} + \varepsilon_{i,t}. \tag{10}$$

We do not promulgate using this model for U.S. equity funds, in lieu of the four-factor model or its counterpart augmented with the APB. However, it is instructive to determine how well the APB, alone, performs in a scenario (i.e., domestic equity funds) where the benchmarks are "tried and true," to gain insights into how it may perform when the proper benchmarks are not fully known (e.g., among more exotic fund groups, as well as in more complex investments, such as pension funds, private equity, or hedge funds).

4. Results

4.1. Performance of Active-Peer Group Benchmarks (APBs)

Most of the extant literature on mutual fund performance has focused on equity funds. A priori, we know that the explanatory power of the standard four-factor model is very high, thus, we would expect that adding an orthogonal factor will only make a small contribution to the explanatory power of the model. Although the addition of a mean-zero orthogonal factor, $\epsilon_{APB_i,t}$ (the residual from a first-stage regression of the APB on the four-factors of Carhart, 1997), will not change $\widehat{\alpha}$ rankings, it can dramatically change the statistical significance of estimates, $t_{\widehat{\alpha}}$, by removing the additional common idiosyncratic volatility to which these funds are exposed in varying degrees.

[17] More precisely, $\epsilon_{APB_i,t}$ will reflect the contribution of the idiosyncratic risk of the "skilled" subgroup to that of the entire APB group. The loading, λ_i, of the skilled fund managers on the APB factor will reflect this contribution, and it will adjust a_i in Equation (9) commensurately.

We first ask a very simple question: do fund groups, on average, exhibit abnormal returns after controlling for the four standard risk factors? To address this question, we run four factor regressions of the APB, for each group of funds, over three-year periods from 1980 to 2009. Table 1 shows that all equity APBs exhibit significant α's during at least some three-year periods, and some exhibit them during more than half of the subperiods. While some APBs exhibit positive and significant alphas over the entire 1980-2010 period, their values are much closer to zero than those of many three-year periods.

Moreover, the estimates can be quite sizably positive or negative, depending upon the period. For example, the active peer-group benchmark for funds in the Russell 1000 Growth group exhibits a statistically significant four-factor alpha of 0.55%/month during 1998-2000, and a significant alpha of -0.25%/month during 2001-2003. Since individual fund performance may be time-varying, as documented by Avramov and Wermers (2006), these time-varying APB alphas may be due to commonalities in time-varying true fund performance within an APB group. However, time-varying estimated APB alphas may also be due to common estimation error in three-year alphas. Whether common noise or common time-varying skills (or both), the large number of statistically significant three-year alphas indicates a significant amount of commonality in residuals among funds within each group, which can be controlled through the augmented model of Equation (8).

4.2. Correlation Between APB Residuals

It is important to note that the APB alphas across groups, shown in Table 1, tend to be of the same sign during a particular three-year period. This indicates that there may be commonality in idiosyncratic risk-taking among funds belonging to different APB groups.

Accordingly, we compute across-group correlations between equal-weighted APB residuals from the four-factor regression. Under the null of uncorrelated (idiosyncratic) fund strategies across different groups, we expect to find correlations that are not significantly different from zero. To test this, we compute correlations between APB groups over the 30-year period from 1980 to 2009. To allow for unstable regression loadings over time, we compute, for each of the 10 non-overlapping three-year periods, the four-factor residuals for each APB. Then, we splice these residuals into a 30-year record for each APB. Finally, we compute a Pearson correlation between the residuals of each pair of APB residual time-series.[18]

Panel A of Table 2 shows substantial evidence of across-group commonality in idiosyncratic risk-taking, as we can reject the null of no correlation between APB residuals quite frequently. Specifically, 35 out of 36 possible correlation pairs are positive and significant at the 5% (two-tailed) confidence level. Indeed, some of the correlations are extremely high. Especially dramatic are the residual correlations involving midcap

[18]For a given three-year period for a given APB group, we require at least five (no-load) mutual funds to each have at least 30 monthly returns during that period in order to have a reasonably diversified group return. Otherwise, we omit that three-year period from the 30-year record for that APB, and compute pairwise correlations involving that APB over the remaining residuals.

and/or smallcap fund groups as pairs. Of course, some of this comes from the overlap in the indexes, but some may also result from funds that do not neatly fit within one APB group.

In Panel B, we test whether these high correlations are due to the overlap in indexes (either through the same securities, or through different securities in similar industries), and/or to the potential inability of the four-factor model to price index returns precisely. Cremers, Petajisto, and Zitzewitz (CPZ; 2012) find evidence that common market indexes exhibit significant estimated four-factor model alphas, and interpret this evidence as the inability of the four-factor model of Fama and French (1993) and Carhart (1997) to properly price passive assets. To explain, the four-factor model uses equal-weighting of, for example, Small-High and Big-High portfolios for the value (high book-to-market) portion of their HML (value minus growth) portfolio. This weighting scheme underweights large capitalization stocks in favor of small stocks, while market indexes are generally capitalization-weighted.[19] Panel B shows correlations between the "best-fit" passive index return residuals, after regressing the index returns on the four-factor model.

The results show, in general, substantially different correlations between the index residuals (Panel B) and the fund APB residuals (Panel A). For example, funds in the Russell Midcap Growth and those in the Russell Midcap groups exhibit a correlation of 0.74 (panel A), while the residuals for the underlying indexes exhibit a much smaller correlation of 0.42 (panel B). The difference in correlations between panels A and B suggest that, while the indexes do indeed appear to exhibit unmodeled commonalities when using the four-factor model, as suggested by CPZ, there appears to be some unmodeled commonalities between APB groups as well, controlling for index commonalities.

These results suggest that we may need to include multiple APB "factors" as additions to the four-factor model for each mutual fund. Therefore, in our robustness tests in Section 4.6, we implement a multiple APB factor augmented model; as we shall see, this multiple APB model demonstrates some usefulness in picking active funds with superior out-of-sample performance. For our main results, however, we use more parsimonious single-APB augmented models, as this model performs somewhat better, out-of-sample, than the more complicated multiple-APB model (due to overfitting by the multiple model).

4.3. Correlation Between Individual Equity Fund Residuals

Next, we turn to evaluating the performance of the four-factor model at the individual fund level. If the four-factor model captures systematic variation in returns properly, then the individual fund residuals will exhibit commonalities with each other only due to their loading on similar idiosyncratic factors. For instance, during the 1990s, many growth funds overweighted technology and telecommunication stocks in common, whose residuals may not be fully captured by the four-factor model.

Table 3 presents the percentage of significantly positive and the percentage of significantly negative (at the 10% two-tailed confidence level) pairwise correlations between individual fund residuals from the

[19] CPZ find that large growth, large value, or small growth stock indexes are especially mispriced by the four-factor model.

four-factor model (Equation 7), out of all possible pairwise correlations in the group (see rows labeled "4 Factor"). For example, during 1980-1982, the Russell 1000 APB group contains 45 funds which yield 990 ($\frac{45\times44}{2}$) pairwise correlations of residuals, among which 45%, or 446, are significantly positively correlated, and 4%, or 40, are significantly negatively correlated.

First, note that the percentage of significant positive correlations, using the four-factor model, is always higher than the percentage of significant negative correlations–and, usually it is much higher. Specifically, on average across groups and subperiods, 37% of fund pairs have (significantly) positively correlated residuals, while 5% have negatively correlated residuals (see the values for the 4 Factor model in the final column and final four rows in Table 3). In fact, the percentage of negatively correlated residuals is what we would expect from randomly occurring correlations–5% with a two-tailed critical value of 10%. Further, this negative and significant percentage is reasonably constant across time-periods and fund groups, and rarely exceeds 10%.

Turning to the percentage of pairwise correlations that are positive and significant, we see that this percentage is rarely below 20%, and it is often above 30%. Other than a sharp rise in positively correlated residuals during the late stages of the internet boom and the period immediately afterward (1998-2000 and 2001-2003, respectively)–when funds likely commonly tilted heavily toward tech and telecom–there is no apparent time-trend to the correlations. Positive correlations of four-factor residuals are especially common in midcap funds and smallcap funds, indicating an especially high degree of cohesiveness in strategies in these groups. Overall, positive and significant correlations in all groups suggest significant commonalities in the investment strategies across funds that are not captured by the four-factor model.

To illustrate the impact of our approach, the table also shows similar correlation statistics, computed using individual fund residuals from the augmented model of Equation (8), where we add the APB residual to the four-factor model (see rows labeled "4 Factor + APB"). Note the large drop in the percentage of positive correlations that are significant with this model, relative to the four-factor model. Specifically, the average positive percentage drops from 37% to 13%, while the negative percentage increases from 5% to 16%. Interestingly, for almost all groups and time-periods, the fraction of significant correlations is reasonably balanced between positive and negative values. Especially noteworthy is that the spike in positive correlations noted above, during 1998-2003, are no longer present. Clearly, the addition of the APB successfully controls for a good deal of common idiosyncratic risk-taking by funds within groups.

To summarize, the results of Tables 2 and 3 present evidence that supports that (1) standard factors leave a significant degree of unexplained covariation among funds within a group and across groups, and (2) a significant part of this covariation within a group can be controlled by adding the APB to the four-factor model.[20] This provides strong support for the use of our augmented model of Equation (8).

[20]We also note that the above results support that the classification by "best-fit index" successfully (for the most part) groups funds by their strategies.

4.4. Alpha Estimation Diagnostics

In this section, we demonstrate the influence of active peer-group benchmarks on alpha estimation. First, we compare three models of equities: the traditional four-factor model (Equation (7)), the APB augmented models (Equations (8) and (9)), and (for comparison) the model with only the APB factor (Equation (10)). The use of the four-factor model and the baseline APB model will result in the same estimate of alpha, since the APB factor is mean-zero, by construction. However, the t-statistic of the alpha of funds may increase (in absolute value) with the APB augmented model, if the APB factor adequately captures commonality in idiosyncratic risk-taking. On the contrary, the alpha-adjusted version of the augmented model (Equation (9)) and the APB-only model (Equation (10)) will result in different alpha estimates, since they are based on a different set of (non-zero mean) factors than the first two models. If the APB factor adequately captures commonality in idiosyncratic risk-taking, away from the benchmark, then the alpha-adjusted model should tighten the distribution of estimated alphas around zero. Our goal in this section is the determine whether the addition of the APB results in a sharper separation of funds into those with positive and negative alphas, relative to the baseline four-factor model.

Columns four through seven of Table 4 show the percentage of funds (within each APB category) having statistically significant market (rmrf), small (smb), value (hml), and momentum (umd) exposures, respectively, while column eight shows similar statistics for the APB factor coefficient, λ, from the model of either Equation (8) or Equation (9). To compute these percentages, we count the number of significant p-values, which are those below 2.5% (to correspond to a two-tailed 95% confidence region), and divide by the total number of funds within a particular APB category. Further, within each group (e.g., "Russell 1000"), the first and fourth rows indicate the percentage of funds with significantly positive and negative alphas, respectively, while the second and third rows indicate the percentage of funds with insignificant alphas in each category.

Note that the results for rmrf, smb, hml, and umd are consistent with what we should expect from using a "best fit" index to categorize funds. For example, the majority of Russell 1000 Growth funds have a negative (and, in most cases, significant) exposure to hml, while the majority of Russell 1000 Value funds have a positive exposure. Meanwhile, "core funds" within the Russell 1000 or Russell Midcap categories have more balanced percentages of funds with statistically significant loadings on hml.[21] Further, midcap and smallcap funds are much more likely to have a positive loading on smb. In addition, the APB factor coefficient, λ, is significantly positive for over half of funds in each peer-group category, and much higher in midcap and smallcap categories (indicating that it is more helpful in capturing common idiosyncratic risk-taking in these groups).

[21] An anomaly is the Russell 2000 group. Here, funds tend to load significantly on hml, but this is chiefly due to the index having a significant loading on hml. In addition, the Russell 2000 value group has a slightly lower loading on hml than the Russell 2000 group, but this is likely due to the infrequency of Russell rebalancing the 2000 indices. Some value stocks, especially those chosen by skilled managers, become growth stocks prior to their elimination from the R2000V index.

Next, the first column of Table 4 shows the percentage of funds, within each group, having statistically significant four-factor alphas (see the column labeled "α"), while the second and third columns ("α_{aug}" and "a_{aug}", respectively) show the percentage of funds having significant alphas using the models of Equations (8) and (9). The reader should note that the level of alphas for the four-factor and the augmented model of Equation (8) are equal, but t-statistics will generally be different due to the addition of the zero-mean active-peer benchmark to create the augmented model.[22] However, the level of alphas with the "APB-adjusted alpha model" of Equation (9) will be different from the four-factor model due to the addition of both the peer-group alpha and the zero-mean APB factor. Our results for the APB factor coefficient, λ, cited above, indicate that the Equation (8) model should move alpha t-statistics further from zero, relative to the four-factor model, while the Equation (9) model will shrink alpha t-statistics back toward zero.

The results for all peer-groups can be illustrated by those for the Russell 1000 peer-group. First, the four-factor model indicates that there may be some pre-expense skilled fund managers, as the 6.9% of alphas having a p-value lower than 2.5% is much higher than expected by random chance. Next, the APB-augmented model alpha, α_{aug}, is more precisely separated into significantly positive and negative funds, relative to the four factor alpha, α, indicating that the APB is effective at capturing return variation that is common to many of the Russell 1000 funds. Specifically, the frequency of positive and significant alphas increase from 6.9 to 9.4%, while the frequency of negative and significant alphas increase from 3.9 to 5.1%. Clearly, the APB-augmented model indicates that there are more alpha outliers, relative to the four-factor model, especially in the positive alpha tail.

When we focus on the APB-adjusted alpha model, a_{aug}, we find that (as expected from the large frequency of positive APB factor coefficients, λ, noted above) t-statistics are pushed closer to zero. The result is 5.9 and 5.8% significant positive and negative values of a_{aug}, respectively. Thus, almost half of the significant positive alphas from the APB-augmented model, 9.4%, can be traced to strategies that are used in common by Russell 1000 funds (since the remaining significant positive alphas account for 5.9% of the group).

Results among other peer-groups are similar, except for the notable fact that the APB factor is more useful, in general, for explaining common variation in returns among midcap and smallcap funds, relative to largecap funds (easily seen from comparing the percentage of positive and significant values of λ, the coefficient on the APB factor). This result can be attributed to the large number of investable stocks within midcap and smallcap ranges, in addition to the apparent use of similar strategies by funds within these large choice sets.

Finally, it is instructive to consider the power of the APB factor alone to explain fund returns, using the

[22]Estimated alphas are the same because the first-stage APB residuals are estimated over the same three-year period as the second-stage fund regression, thus, the first-stage APB residuals are mean-zero in both the first and second stage regressions, and do not affect the level of estimated fund alpha.

model of Equation (10). In column nine, we see that this single-factor model performs quite well, achieving an adjusted R^2 above 75% for all peer-group categories. For comparison, the adjusted R^2 using the four-factor model is generally only a few percent higher. This result indicates that our categorization of funds is successful, as it reflects that exposures to risk-factors as well as idiosyncratic risk have strong commonalities within peer-groups.[23]

To summarize the results of this section, a significant percentage of funds appear to have both significantly positive and significantly negative alphas, using the APB-augmented model. However, a good deal of these funds lose their significant alphas when we control for the alphas earned by the common strategy (using the alpha-adjustment model). Indeed, among most peer-groups, the fraction of positive and significant alphas decrease, while the fraction of negative and significant alphas increase, indicating that common strategy alphas (controlled by the alpha-adjustment model) are generally positive. This result brings the possibility that we may capture superior alphas through a passive strategy of investing in an entire group of funds, rather than attempting to choose the best of the peer-group. Thus, a remaining important question is whether the above-noted alphas persist, and, if so, whether they are due to common strategies among a peer-group of funds or to idiosyncratic strategies of only a few funds in a peer-group.

4.5. Out-of-Sample Performance

4.5.1. Pre-Expense Alpha

Does our APB model improve the identification of skilled fund managers? And, if so, do these skilled managers use common strategies as a subgroup of a peer-group, or do they use strategies that are distinct from each other? Our out-of-sample tests are designed to determine the answers to these questions. First, in untabulated tests, we find a relatively high rank correlation between t-statistics of fund alphas estimated from models with and without the endogenous factor. Thus, we would expect that out-of-sample performance differences between these models will be small. However, it is possible that the small differences can be exploited to increase the persistence in alphas from a fund selection strategy if there exist a minority of funds with superior skills.

We first explore the persistence in alphas for funds ranked on the t-statistic for their trailing three-year APB-augmented four-factor model alpha (Equation (8)). If the addition of the APB factor sufficiently adjusts for common idiosyncratic risk-taking, then the t-statistic of alpha should be an improved indicator of manager skills.

First, we conduct a very simple test of performance persistence, using our APB-augmented model of Equation (8). At the end of each month, starting on December 31, 1982 and ending on December 31, 2009, we rank all U.S. equity mutual funds by the t-statistic of alpha from that model, measured over the prior

[23]It is also notable that the peer-group factor, by construction, represents a tradable group of no-load funds, while trading the four-factors is more difficult.

36 months (we require at least 30 months of returns to be non-missing during this period).[24] Then, quartile portfolios of funds are formed, and equal-weighted portfolio returns are computed over the following (out-of-sample) year. Next, we compute the alpha from Equation (8) over this year. Next, we move forward one month, and repeat this process. Finally, we compute time-series average alphas and time-series t-statistics of these alphas over all such (overlapping) out-of-sample years (with standard errors adjusted for the time-series overlapping nature of the windows over which the alphas are computed).

Panel A of Table 5 presents results from this exercise. The table shows that, in general, (pre-expense) alphas are monotonically decreasing from quartile 1 (top ranked funds from the prior three years) to quartile 4 (bottom ranked funds). For instance, in the Russell 1000 peer group, we find that top-quartile funds exhibit a *monthly* four-factor model alpha of 7 bps (84 bps/year), while the second-, third-, and fourth-quartiles exhibit alphas of 4, 4, and 0 bps, respectively. Among our nine peer-groups, we find that four exhibit significantly positive four-factor alphas for top-quartile funds, ranked by the APB-augmented model, while, in eight of nine groups, top-quartile funds significantly outperform bottom-quartile funds during the following year. And, no peer-groups exhibit negative alphas for top-quartile funds during the year following the ranking date.

It is also instructive to note the differences in the persistence of performance across different peer groups. Positive performance persistence (statistically significant 1st-quartile performance during the following year) is especially strong among midcap funds, but is also present among largecap funds. Among smallcap funds, the difference in alphas between 1st and 4th quartiles are especially pronounced, since persistence in underperformance is present in these groups of funds. Since these alphas are gross of fees, but net of trading costs, the absence of stock-selection skills among smallcap funds is especially costly–since trading costs are a significant drag on smallcap fund performance.

In Panel B, we conduct the same ranking and portfolio formation procedures, but we measure the following-year performance with the redefined alpha from the alpha-adjustment model of Equation (9). If our 1st quartile funds manage to outperform simply due to the (leveraged) use of strategies common to the peer group, then the inclusion of the peer group alpha (leveraged by the fund's exposure to the peer group factor) will result in an insignificant residual alpha (a_i from Equation (9)). However, the results indicate that top-quartile funds exhibit significant persistence in 6 of 9 peer groups. Among largecap and midcap peer groups, the alpha is reduced from its value in Panel A, but, among smallcap groups, the alpha actually increases. This observation reflects that the common strategies of largecap and midcap funds produce persistent and positive alphas, but those of smallcap funds produce somewhat negative alphas. The overall results indicate evidence of skills among several fund groups–large, mid, and small–but indicate that skilled smallcap fund managers perform better when they deviate from the group. Largecap and midcap managers

[24]Note that we rank by alpha t-statistic, since the advantage of our APB-augmented model is reflected in this parameter. In addition, Kosowski, et al. (2006) show that ranking by the alpha t-statistic is especially effective in locating skilled managers.

with skills produce performance both with their group-like strategies and through their deviations from the group.

Although we have found evidence of persistent (pre-expense) alphas using our APB-augmented four-factor model, it is unclear whether this model produces significantly different results from the standard four-factor model. Recall that several papers find evidence of significant pre-expense fund manager skills (e.g., Barras, Scaillet, and Wermers, 2010) using the four-factor model. Thus, we next construct a simple test of the differential performance of the APB-augmented model, relative to the standard four-factor model.

To accomplish this differential test, we implement a very simple modification to the portfolio formation exercise described above. Instead of ranking funds by their APB-augmented model alpha t-statistic, we rank funds by the *difference* between this t-statistic and the alpha t-statistic from the standard four-factor model.[25] Thus, top-quartile funds are those where the t-statistic increases the most (becomes more positive), while bottom-quartile funds are those where the t-statistic decreases the most (becomes more negative).[26] Second and third quartile funds are those which experience relatively modest shifts in t-statistics. If the APB factor helps to decrease the common unpriced noise in fund returns, relative to the four-factor model, then we should observe higher following year four-factor alphas for 1st quartile relative to 4th quartile funds using this differential ranking approach.

Equal-weighted following-year alphas for each ranked quartile, within each peer group, and their overlapping-observation adjusted time-series t-statistics are reflected in Table 6. The results are qualitatively similar to those shown in Table 5: the same four peer groups exhibit significantly persistent first-quartile performance. It is not surprising that the superior alphas of Table 6 (using incremental rankings, relative to the simple four-factor model) are similar to those in Table 5 (using absolute rankings): most prior research (e.g., Carhart, 1997) that indicates that simple four-factor alphas, which might exist, do not appear to strongly persist. Thus, the APB-augmented model substantially improves the identification of persistent (positive) performers, relative to the standard four-factor model. And, in five peer groups, the model improves the relative ranking of funds, as the 1st minus 4th quartile results in Panel A show.

Panel B shows reduced persistence in positive performance when controlling for the (leveraged) peer-group alpha, indicating that the improvement experienced by the APB-augmented model is partially due to capturing leveraged exposures to a group strategy that produces alpha. However, eight of nine top quartile portfolios exhibit positive alphas (two of these are statistically significant), while all nine peer groups exhibit

[25]This difference is normalized so that positive differences sum to 1, and negative differences sum to -1, to make results comparable to the prior table.

[26]Note that this differencing method implies that any fund with an increasing t-statistic will be held long, and any fund with a decreasing t-statistic will be held short. Among funds with a large increase in t-statistics, some will change from a negative and significant to an insignificant t-statistic, while others will change from an insignificant to a positive and significant t-statistic. In either case, the APB-augmented model indicates that the fund is better than the standard four-factor model, and we wish to test whether the APB-augmented model is correct in indicating this. An investor would likely not use such a differenced t-statistic strategy, as it discards any performance persistence attributable to the baseline four-factor model. We use it to show the value-added of the APB factor, and note that it likely understates the usefulness of the APB factor.

a positive difference between alphas of the equal-weighted 1st and equal-weighted 4th quartiles (six of these are statistically significant).

We may further magnify the differences between the APB-augmented and standard four-factor models by weighting the following-year portfolios, at the beginning of the year, by the difference in t-statistics (rather than equal-weighting). This approach corresponds to an investor who places complete trust in the difference between the two models as being an indicator of true skill (this is motivated by the information-ratio assessment approach promulgated by Treynor and Black, 1973).

The Internet Appendix presents results for this exercise. Similar to the Table 6 results, we again find positive (and statistically significant) persistent alphas for 1st quartile funds among four of nine peer groups when judging with the APB-augmented model, and three of nine groups when judging with the APB-adjusted alpha model (Panel B). Especially noteworthy is that 1st quartile funds within the Russell 1000 category exhibit persistence with either approach–that is, largecap fund managers with skills may be better identified with the APB-augmented model, relative to the four-factor model. The superior identification of skilled managers using the APB model is not limited to smallcap or midcap managers.

4.5.2. Net Return Alpha

While our above results indicate that our APB-augmented model identifies skilled managers better than the standard four-factor model, it is useful to consider whether retail investors can exploit our approach to select funds with superior net-of-expense alphas. While large investors may be able to negotiate lower expenses with skilled managers through institutional shareclasses, retail investors have little power to do so.

Accordingly, we measure out-of-sample net-of-expense four-factor alphas for the baseline ranking and portfolio weighting strategy used in Table 5. That is, funds are ranked, each month, by their pre-expense alpha t-statistic from the APB-augmented four-factor model (computed over the prior 36 months), then equal-weighted quartile portfolios are formed. While this ranking procedure retains the use of pre-expense returns, out-of-sample four-factor alphas are computed for these portfolios using their equal-weighted *net* returns.

Panel A of Table 7 presents these results. As expected, the alphas of all quartile portfolios drop from their pre-expense values in Table 5. As a result, two top-quartile portfolios exhibit statistically significant net-of-expense four-factor alphas, compared to four top-quartile portfolios that exhibit statistically significant gross-of-expense four-factor alphas in Table 5. However, no top-quartile portfolios exhibit negative and significant alphas, and eight of nine groups exhibit positive and significant alpha differences between top- and bottom-quartile equal-weighted portfolios. In fact, these differenced portfolio alphas, net of fees, are quite similar to their gross-of-fee counterparts in Panel A of Table 5. Since expenses have little impact on these differenced portfolio alphas, expense ratios appear to be largely constant across quintiles (thus, having little relation with gross-of-fee performance).

Panel B presents results, using the alpha-adjustment model to measure out-of-sample performance of the equal-weighted portfolios. Here, we use a net-of-expense ratio APB factor (orthogonalized to the standard four factors) rather than the gross-of-expenses version used in Panel B of Table 5, since the retail investor would like to know whether some funds outperform, net of expenses, a leveraged position in the group (again, net of expenses). Panel B of Table 8 shows very similar results to those in Panel B of Table 5. Several groups show positive and significant top-quartile performance, although at a reduced level from Panel A. Results for the 1st minus 4th quartile are very similar to those in Table 5, Panel B.

To summarize our main empirical results in this section and the last section, the APB-augmented four-factor model outperforms the standard four-factor model in locating managers with persistently good (and bad) performance, both pre- and net-of-expenses. A portion of the alphas of top-quartile funds, ranked by lagged 36-month APB-augmented four-factor alphas, can be explained by a commonality in strategies among the peer-group (but, leveraged differently by different funds). However, a significantly positive alpha remains after controlling for these "common alphas" in the top quintile funds of several groups.

4.5.3. Relation to Pastor and Stambaugh (2002)

Pastor and Stambaugh (PS; 2002) suggest augmenting the risk model with a nonbenchmark passive asset to measure active fund performance, even if this passive asset is fully priced by the risk model. Similar to our approach, the key is that the nonbenchmark asset adds information about idiosyncratic returns contained in the active fund returns, so the addition of the passive asset to the risk model reduces the estimation error in alpha that is measured with a short time-series of active fund returns.

In the case where the investor assumes that the risk factors fully price the passive asset (i.e., the passive asset has a true alpha of zero), PS show that adding the (fully priced) asset to the short-run (e.g., three-year) regression improves the precision of the alpha estimate. In this case, our APB-adjusted alpha model of Equation (6) is the same as the short-run model that is prescribed by PS, except that we replace their passive (fully priced) asset with our (potentially fully priced) active APB factor. In our model, only fund alphas that are uncorrelated with that of the average fund are considered an indication of manager skill.

In untabulated tests, we ranked funds, during each three-year in-sample period, by the difference in alpha t-statistics between the APB-adjusted alpha of Equation (9) and the four-factor model–which more closely follows the spirit of the above PS model–rather than the difference between the simple augmented model of Equation (8) and the four-factor model.[27] We found that this modified ranking scheme produced modestly lower out-of-sample alphas than ranking by the simple residual-augmented model–while top-quartile funds

[27]The reader should recall that the results shown in Tables 5-8 use the alpha t-statistic from Equation (8)–or its difference from that of the four-factor model–to rank funds, then measure following-year out-of-sample performance in two different ways: with Equation (8)–in each Panel A–and Equation (9)–in each Panel B. There, we applied the alpha-adjustment model of Equation (9) in order to determine whether persistence in alpha within an APB group is due to common or idiosyncratic fund manager skills. We found a role for both in explaining persistence in alphas.

outperformed bottom-quartile funds for most APB groups, top-quartile fund alphas were lower, out-of-sample, compared to our baseline ranking (using either the model of Equation (8) or Equation (9) to measure out-of-sample performance). This result is to be expected, however, since our results of the prior sections show that much of the persistence in superior alphas of top-quartile funds is due to their use of common strategies. Since the in-sample three-year APB alpha reflects, in large part, these superior (common strategy) top-quartile fund alphas, ranking on the Equation (9) alphas reduced the power of the model to find skilled fund managers.

PS also suggest another approach. If we assume that active fund management might produce a non-zero true alpha, on average (i.e., the risk factors do not fully price active funds), PS prescribe running a long-run regression of the APB factor on the risk factors to obtain a more precise estimate of APB alpha.[28] Then, PS suggest to adjust the second-stage alpha (obtained from the short-run regression of the fund excess returns on the returns of the risk factors and the APB factor) by adding the long-run APB alpha (from the first stage) multiplied by the second-stage short-run loading of the fund on the APB factor (see their Equation (13) and the related discussion in PS).

In our mutual fund setting, using a long-run APB alpha presents some challenges. First, our APB factors are not very long-lived, since we have returns data on our APB groups only since 1980 (and, over a much shorter period for several APB groups). Thus, the "long-run returns" of the APB benchmarks are not really very long-run, especially when we control for look-ahead bias (as described below), limiting their usefulness. Second, recent research suggests that the APB alpha is not stationary over time, while stationarity is assumed by the use of the long-run returns prescribed by PS. For example, Barras, Scaillet, and Wermers (2010) find that four-factor alphas have decreased substantially from 1975 to 2006. Thus, a long-run alpha is likely a severely upward-biased estimate of the true alpha of the average fund within an APB group during later time-periods. Both of these issues limit the usefulness of a long-run APB alpha as a proxy for true fund skills in the short-term.

Nevertheless, in further (untabulated) tests, we apply our analog of the long-run model of PS. Specifically, to avoid look-ahead bias, at the end of a particular three-year period, we run a first-stage regression of the entire (available) history–up to the end of that three-year period–of each APB (equal-weighted) factor on the four equity risk factors. In addition, we run a (short-run) regression of the APB factor on the four equity risk factors over the particular three-year period, as we did in the first stage when we applied our (second-stage) APB-adjusted alpha model of Equation (9). Now, in the second stage, we apply a modified

[28] PS discuss the case where nonbenchmark assets may not be fully priced by the risk model. In this discussion, we treat the APB as the nonbenchmark asset, which may not be fully-priced.

version of our model of Equation (9):

$$r_{i,t} = a_i^{PS} + \beta_{i,rmrf} r_{rmrf,t} + \beta_{i,smb} r_{smb,t} + \beta_{i,hml} r_{hml,t} + \beta_{i,umd} r_{umd,t} + \lambda_i(\alpha_{APB} - \alpha_{APB}^{Long-Run} + \epsilon_{APB_i,t}) + \epsilon_{i,t} \ , \tag{11}$$

where $\alpha_{APB}^{Long-Run}$ equals the first-stage long-run alpha described above, and α_{APB} is the three-year APB alpha. The resulting intercept from this regression, a_i^{PS}, equals $a_i + \lambda_i \alpha_{APB}^{Long-Run}$ (where a_i = the intercept from Equation (9)), our analog to the improved fund performance measure of PS (their Equation (13)).

Again, the results from this approach are qualitatively similar, but weaker, than the out-of-sample results shown in Tables 5 and 6. For example, Panel B of Table 6 shows that six out of nine APB groups exhibit positive and significant alpha differences between (equal-weighted) 1st and 4th quartiles, when funds are ranked by the difference in alpha t-statistics between Equation (8) and the four-factor model. When we rank by the difference in alpha t-statistics between Equation (11) and the four-factor model, only two out of nine are positive and significant (for comparability, in both cases, we use the model of Equation (9) to measure out-of-sample performance). Using a long-run alpha–(Equation (11)–appears to only add noise to the identification of superior active managers.

To summarize, our empirical results indicate that the baseline APB-augmented model of Equation (8) performs best in identifying skilled fund managers, partly due to these skilled fund managers using common successful strategies. However, in the next section, we will revisit this issue by using a four-factor model augmented by a (assumed fully-priced) passive index–the PS approach–to more closely determine whether our "active factor" approach adds value over this "passive factor" PS approach.

4.6. Robustness Tests

4.6.1. Adding a Passive Index to the Four-Factor Model

As mentioned above, Pastor and Stambaugh (PS; 2002) find that the addition of a carefully chosen passive benchmark serves to improve the identification of skilled fund managers. Our approach is somewhat similar, but we suggest that an active factor that captures strategies of competitor funds may perform even better, as it will capture dynamic loadings on risk factors as well as dynamically changing loadings on potentially multiple unknown passive benchmarks. To test whether our approach adds to the power of the PS approach, we implement the PS approach and compare results with our approach.

Specifically, we augment the four-factor model with the "best fit" passive market index. Then, we implement tests of performance persistence that are exactly the same as those discussed in Tables 6 and Internet Appendix Table IA.1, except that we rank funds using this passive market index augmented four-factor model. The results are shown in Panel C of Table 8. For ease of comparison, Panel A includes the results from Table 6 and Table IA.1.

We first confirm the usefulness of the PS passive factor, relative to the standard four-factor model. Panel

C shows the difference in following-year alpha between 1st and 4th quartile funds, when funds are ranked using the four-factor model augmented with the peer-group passive index (e.g., the Russell 1000 index monthly returns for funds within the Russell 1000 peer group). Ranking is conducted using the difference in alpha t-statistics between that model and the four-factor model. Following-year out-of-sample performance is measured with the four-factor model, either augmented with (1) the passive index minus its four-factor alpha (labeled "Passive Index Regression") or (2) the passive index (without deducting its alpha; labeled "α Adj Passive Idx Regr") during the same 12 months–i.e., both ranking and out-of-sample performance are conducted from the point-of-view of an investor who strongly believes in the pricing ability of the passive-augmented four-factor model. The difference in alpha is positive and statistically significant for only one of nine fund peer groups when we weight portfolios by the difference in alpha t-statistics between the passive-augmented model and the four-factor model (see the first two rows of Panel C). However, Panel A shows that our active APB factor exhibits positive and statistically significant alpha differences (between top and bottom quartile funds, ranked and evaluated using the APB-augmented four-factor model) for seven of nine peer groups. Other weighting schemes also show better results when using the APB benchmark, relative to the passive index.

Next, in Table 9, we form ranked portfolios based on the difference in alpha t-statistics, for each fund, between our APB-augmented four-factor model and the passive index-augmented four-factor model described above. We measure out-of-sample performance with the APB-augmented four-factor model, but (untabulated) results are similar when we measure out-of-sample performance with the passive index-augmented four-factor model. Using alpha t-statistic differenced ranking and following-year portfolio weighting, we find the following results (see rows 1-4 of Panel A). In two of nine peer-groups, the APB-augmented four-factor model selects funds with greater levels of persistent four-factor alphas than those chosen by the passive-index augmented four-factor model (rows 1 and 2); these funds persist after controlling for any group-commonality in their alphas, as shown when we measure out-of-sample performance with the APB-corrected alpha model (rows 3 and 4). When we equal-weight following-year portfolios (but maintain our ranking by the difference in t-statistics), we continue to find superior ranking performance for our APB-augmented model, compared to the passive index augmented four-factor model.

Since our APB factor exhibits incremental power to identify skilled managers, relative to passive indexes, this also addresses any concerns that our manager may achieve "alpha" through their mere exposure to market indexes. That is, since we assign actively managed funds to market indexes (e.g., the Russell 1000 index), there is some possibility that our funds may exhibit spurious four-factor alphas due to biases introduced by the weightings of the four factors, as discussed in Cremers, Petajisto, and Zitzewitz (2012). Our results cited above indicate that our skilled managers are not merely loading on the mispricing of the market indexes by the four-factor model.

4.6.2. Adding a Liquidity Factor to the Four-Factor Model

It is also possible that our APB factor is highly correlated with an "illiquidity factor," since a number of papers have shown that liquidity is a priced factor (e.g., Pastor and Stambaugh, 2003, and Sadka, 2006). That is, perhaps funds within a group commonly overweight less liquid securities or sectors to achieve the associated risk-premium, and some fund managers simply use this strategy more aggressively than others to achieve higher "alphas" against the four-factor model. To address this possibility, we consider yet another form of augmented four-factor model–the model augmented with the Pastor and Stambaugh (2003) monthly liquidity factor, and we compare the success of this factor in locating skilled managers with our APB-augmented model.[29]

Panel D of Table 8 shows the results from a strategy that adds the liquidity factor to the four-factor model to rank funds during 36-month periods (from the difference in this alpha t-statistic and that of the standard four-factor model), then measures the following-year performance using the same augmented model (both with and without a control for the four-factor alpha of the liquidity factor). The results show some limited success of the liquidity-augmented model in ranking funds. Top quartile funds outperform bottom quartile funds, significantly, in one of nine peer-group categories using differential t-statistic weightings for following year portfolios, but in no peer-groups for equal-weighted portfolios. And, the group exhibiting outperformance with t-statistic rankings is different from the group exhibiting differential skills when using the passive index augmented model (Pastor and Stambaugh, 2002) of Panel C, indicating that these different augmenting factors capture different idiosyncratic factors that are common to each peer group. Some groups exhibit more commonality in loading on illiquidity, while other groups exhibit more commonality in loading on the passive index. In general, both added factors (liquidity and passive) assist in finding skilled fund managers to a greater degree among midcap and smallcap funds, where there is both more noise in returns and less liquidity. Most importantly, both added factors do not eliminate alphas of managers, indicating that skilled managers are not achieving illusory alphas through mispricing of passive market indexes or through loading on illiquid securities or sectors.

As further evidence of the relative power of our baseline APB model, Panel B of Table 9 presents results when we form portfolios based on the difference in t-statistics between the alpha estimated by our APB-augmented four-factor model (Equation (8)) and the liquidity factor-augmented four-factor model. Using t-statistic differenced ranking and following-year portfolio weighting, we find the following results. In five of nine peer-groups, our APB-augmented four-factor model selects funds with greater levels of persistent four-factor alphas than those chosen by the liquidity-factor augmented four-factor model. When we equal-weight following year portfolios (but maintain our ranking by the difference in t-statistics), we continue to find superior ranking performance for our APB-augmented model, compared to the liquidity-factor augmented

[29] We obtained the Pastor and Stambaugh *traded* monthly liquidity factor (value weighted) from Wharton Research Data Services (WRDS).

model.

4.6.3. Value-Weighted Active Peer-Group Benchmarks

Our paper, thus far, has formed equal-weighted APB benchmarks to augment the four-factor model. This approach has several advantages, as it aggregates the strategies of all fund managers equally. Indeed, it is likely that larger funds cannot implement common strategies to a greater (proportionate) degree than smaller funds, due to the difficulty in implementing large scale trades. Thus, we believe that equal-weighting captures common strategies effectively, with the least amount of noise. However, a drawback of this approach is that an equal-weighted benchmark has the opportunity cost interpretation of an equal investment in each fund as an alternative to selecting funds based on some criteria. For a retail investor, this may not be an issue, but it could present greater difficulties for a larger institution that attempts to implement our procedure, and decides to forego investment in the top-rated active funds, and, instead, invest in the group as a whole.

For robustness, we repeat our baseline analysis, using an APB benchmark that value weights fund returns within a peer group. Each month, we rebalance fund weights to value-weighted, which represents a minor amount of trading that is necessary–due to fund distributions of capital gains or dividends, to fund flows from investors, or to liquidations of funds. Thus, a value-weighted APB may better represent an investable alternative, especially for large investors.

Panel B of Table 8 shows results when we rank by the VW-APB-augmented four-factor model, and measure out-of-sample performance with the same model. Note that the results are qualitatively very similar to those using the equal-weighted APB factor, which is shown in Panel A. That is, these panels exhibit similar results when using the VW-APB benchmark under the various portfolio weighting schemes shown in those panels, whether out-of-sample performance is measured using the standard APB model of Equation (8) or the alpha-adjustment model of Equation (9). These results indicate that a more simplified and expedient peer group might be formed by aggregating the returns of the largest several mutual funds within a given peer group.[30] In addition, investing in a smaller set of larger funds would be a much more palatable alternative investment strategy if one cannot find differentially skilled managers within a particular group using our methodology.

4.6.4. Self-Designated Benchmarks

As mentioned earlier in this paper, we prefer categorizing funds by their portfolio holdings, since funds may "game" their self-designated benchmarks (as documented by Sensoy, 2009). However, in a prior version of this paper, we used self-designated fund categories as our peer-grouping approach. Specifically, we form

[30]A caveat to this approach: if a few funds are much larger than the remainder, the VW-APB benchmark will almost solely reflect these ultra-large funds. Thus, we would expect that their idiosyncratic strategies would worsen the effectiveness of adding an APB factor to standard regressions.

peer groups using self-designated investment objective categories, as identified in the Thomson CDA mutual fund database. Each fund is assigned to a category at the end of a three-year period according to its objective at that date. Persistence tests are then performed, similar to those we conduct using the "best fit" categorization approach of this paper. In general, our results using self-designated groups are similar to those used in this version of the paper–based on "best fit" benchmark grouping.

4.6.5. Multiple Active Peer Benchmarks

In Section 4.2, we found evidence of significant across-group correlations of four-factor residuals. This finding suggests that there may be strategy commonalities across APB groups, as well as within groups. For instance, funds with the Russell 1000 Growth index as their best-fit may implement some strategies common to funds having the Russell Midcap Growth index as their best-fit, especially since there are overlapping holdings between these two indexes (the Russell Midcap index is a subset of the Russell 1000 index). Indeed, we find a very high correlation (56%) between the four-factor residuals of the APB factors (Panel A), as well as the best-fit indexes (Panel B) for these two groups in Table 2.

Recall that, in Table 3, we performed correlation tests between APB-augmented model residuals of pairs of funds, to determine whether a single "factor" removes the correlations. We found that 29% of pairs, on average across peer-groups (see the final two rows/final column of that table), exhibited significant correlations (either positive or negative) at the 10% significance level (two-tailed). While this is an improvement over 42% of pairs under the standard four-factor model, it remains greater than we would expect to find by random chance if the augmented model completely removed correlations (i.e., 10%).

Since we find that some significant residual correlations remain, we run our baseline persistence tests using a multiple-APB model to see whether controlling a mutual fund for using a strategy common to funds across *different* peer groups improves the ability to identify truly skilled funds. Here, we augment the standard four-factor model with all nine equal-weighted APB factors (each orthogonalized by the four-factors in a first-stage regression, then demeaned), then use this model to rank funds within each group by this 13-factor model alpha t-statistic, as we did in Table 5 for the single APB-augmented models. Out-of-sample performance is measured by our baseline APB model of Equation (8), since we have limited degrees-of-freedom.

For brevity, we describe the results without tabulating. Here, although we find similar results for the differenced out-of-sample alphas of equal-weighted 1st- minus 4th-quartile portfolios when we use this 13-factor multiple-APB model, compared to the results of Table 5, we find that 1st-quartile portfolios in only two peer-groups–Midcap and Midcap Value–remain positive and statistically significant. This compares to four peer-groups in Panel A of Table 5. Apparently, the loss in degrees-of-freedom (the regression overfit) from using multiple factors penalizes this model, and eliminates any advantage that it may have over the single-APB models.

4.7. Results for U.S.-Domiciled Domestic Bond Funds

In results shown in the Internet Appendix, we apply our active peer-group benchmarking technique to U.S. bond mutual funds. Since reliable holdings data are generally unavailable for bond funds or for bond indexes over long time-periods, we use asset allocation data from the CRSP Mutual Fund Database to assign funds to categories. We require that a fund invests 70% or more of its assets in that asset category (on average over time) to belong to a given category.

We examine six categories of bond funds:

- Government: Intermediate and Long-Term
- Corporate: Intermediate and Long-Term
- Municipal: Intermediate and Long-Term

A fund must have a weighted-average maturity of 1 to 7 years to be classified as intermediate term; otherwise, we classify it as long-term.

Our APB-augmented specification for bond funds uses the residual of the APB (equal-weighted) excess return (plus 1/12 the annual expense ratio) regressed on the excess return of the (1) Intermediate Sub-Index of the Barclays Capital U.S. Government Bond Index (formerly Lehman Brothers U.S. Government Bond Index) (ig), (2) Long Sub-Index of the Barclays Capital U.S. Government Bond Index (lg), (3) Intermediate Sub-Index of the Barclays Capital U.S. Corporate Bond Index (formerly Lehman Brothers U.S. Corporate Bond Index) (ic), (4) Long Sub-Index of the Barclays Capital U.S. Corporate Bond Index (lc), (5) Barclays Capital U.S. Mortgage Backed Security (MBS) Index (mbs) (formerly Lehman Brothers U.S. Mortgage Backed Security Index), (6) Barclays Capital U.S. Corporate High-Yield Bond Index (hy) (formerly Lehman Brothers U.S. Corporate High-Yield Bond Index), and (7) the CRSP value-weighted NYSE/AMEX/Nasdaq portfolio ($rmrf$). We add $rmrf$, since some papers suggest that a stock market factor is important for explaining bond returns in some sectors (e.g., Fama and French, 1993, and Cornell and Green, 1991). As with equity funds, we run this regression on overlapping three year periods, including only funds with at least 30 months of NAV returns and expense ratios during each three-year period. Funds are reassigned to groups, based on our above sector-based classification of funds, at the beginning of each three-year period.

In the second stage, we regress $r_{i,t}$, the monthly fund i NAV excess return plus 1/12 of its annual expense ratio, on the above seven factors plus $\epsilon_{APB_i,t}$, the first-stage residual from the regression above for the APB group that includes fund i. The second-stage model is

$$\begin{aligned} r_{i,t} = \alpha_i + \beta_{i,ig} r_{ig,t} + \beta_{i,lg} r_{lg,t} + \beta_{i,ic} r_{ic,t} + \beta_{i,lc} r_{lc,t} + \beta_{i,mbs} r_{mbs,t} \\ + \beta_{i,hy} r_{hy,t} + \beta_{i,rmrf} r_{rmrf,t} + \lambda_i \epsilon_{APB_i,t} + \epsilon_{i,t} \ . \end{aligned} \tag{12}$$

A full analysis of bond funds, analogous to this paper's tests on equity funds, can be found in the Internet

Appendix. We briefly describe only the persistence tests here. Analogous to the Table 6 stock fund results, we test for persistence in bond fund performance by ranking funds on the difference between alpha t-statistics from the APB-augmented 7-factor model (Equation (12)) and their corresponding values using the non-augmented 7-factor model. We estimate 12-month out-of-sample performance using either the APB-augmented 7-factor model or the APB-adjusted alpha version of the APB-augmented 7-factor model (computed analogously to Equation (9)). The ranking and out-of-sample performance evaluation is repeated at the end of each calendar month, and overlapping-observation adjusted time-series average alpha t-statistics are computed.

Similar to the results we found in Section 4.5 of the paper for stock funds, we find stronger evidence of persistence when we use the APB-augmented model to rank funds (vs. the baseline 7-factor model), although levels of improvement in performance are more muted than they were for equity funds. Specifically, Long-Term Corporate bond funds exhibit the highest following-year alpha difference between (prior 36 month) 1st- and 4th-ranked quartiles, at 22 bps/month (consistent with manager skills being most apparent in the bond sector with the most heterogeneity). And, Intermediate Government funds exhibit a following-year alpha of 6 bps/month. The other four bond fund categories exhibit insignificant differences between 1st- and 4th-quartiles. Further, we find that significant alphas remain in these two categories, although smaller, when we measure out-of-sample performance with the alpha-adjusted version of the APB-augmented 7-factor model. Thus, as with equity funds, a portion (but not all) of skills of bond fund managers are common among top-quartile managers.

5. Conclusion

The contribution of this paper is to propose a conceptually simple and easily implementable way to control for common, unpriced idiosyncratic risks taken by mutual funds. We propose adding the active peer-group benchmark (APB) return, which is based on the endogenous selection of each fund in a group, in addition to the exogenously determined factors in the standard regressions estimating the fund loadings and Jensen's α. This approach has intuitive support, since it represents the investment strategy that is always feasible for investors.

We show that the APB substantially decreases the between-fund residual correlations within a group, when the APB is added to standard factor models. This result indicates that the APB successfully captures common idiosyncratic risk-taking within peer-groups. In addition, we find that a single APB performs about as well as a multiple APB, when added to standard models, which indicates that funds within one peer-group tend not to use strategies that are common to other peer-groups, at least not to the degree needed to compensate for the loss in degrees-of-freedom of adding more APB factors to a fund's model. Finally, we demonstrate that the added APB benchmark significantly improves the identification of skilled (and unskilled) fund managers within several of the equity and bond fund peer-groups.

Appendix A. Active Peer Group Designation

Mutual funds in this study are grouped according to their closest matching passive index, as measured by each fund's "active share." The "active share" of a fund, as defined by Cremers and Petajisto (2009) quantifies the active management of a portfolio, where active management is defined as that portfolio's degree of deviation from a passive index portfolio. It is directly measured by aggregating the absolute differences between the weight of a portfolio's actual holdings and the weight of its closest matching index,

$$\text{Active Share } = \frac{1}{2}\Sigma_{i=1}^{N}\left|w_{fund,i} - w_{index,i}\right|, \tag{A.1}$$

where $w_{fund,i}$ and $w_{index,i}$ are the portfolio weights of asset i in the fund and in the index, summed over the universe of all N assets. The total number of funds in each best fitted active share group is presented in table A.1.

After identifying each fund's closest matching index, (the "best-fit index"with the lowest Active Share for that fund), we further group funds together that have very similar best-fit indexes. This is done to make each group of funds large enough to meaningfully represent a group for a reasonable number of years within our sample period. Similarity of indexes was identified by index correlations. Table A.2 presents these correlations. Each set of indexes between a pair of dashed lines represents similar indexes that were grouped together. Panel A presents total index return correlations, and shows that all indexes share high raw return correlations. This is not surprising, because of the market exposure that all stocks share, but it also shows that each of the grouped indexes share particularly high correlations with each other, relative to the other index groups. Panel B presents residual correlations after regressing index returns upon 36 month, non-overlapping 4 risk factor model regressions. Panel B shows that grouped indexes share high residual correlations while residual correlations with other indexes are quite low, which is even stronger evidence that we have performed a reasonable grouping of funds into best-fit index "clusters." Table A.3 presents the the total number of funds in each group after merging correlated best-fit index groups.

Table A.1: Original Active Share Groups

This table presents the number of no-load U.S. equity mutual funds, by their best fitting active share benchmark. Funds with multiple shareclasses of the same fund are represented by only a single shareclass in our sample. If a fund has more than one no-load shareclass, then only one shareclass is arbitrarily selected. In situations where that shareclass no longer exists, it is replaced with the other shareclass if it continues to exist. To be counted within a particular three-year period, a fund must have at least 30 monthly return observations.

	Russell 1000	S&P 500	Russell 3000	S&P 100	Russell Top 200	Russell 1000 Growth	S&P 500 Growth	Russell 3000 Growth	Russell 1000 Value	S&P 500 Value	Russell 3000 Value	Russell Midcap	S&P Midcap 400
80 82	5	6	0	0	33	59	0	0	21	0	0	0	0
81 83	7	7	0	0	40	60	0	3	18	0	0	0	0
82 84	2	13	0	0	69	43	0	2	17	0	0	0	0
83 85	2	5	1	0	67	48	0	1	29	0	0	0	0
84 86	0	8	1	0	75	55	0	2	28	0	0	0	0
85 87	0	6	2	0	87	68	0	0	23	0	0	0	0
86 88	0	12	0	0	94	69	0	0	27	0	0	0	0
87 89	0	8	0	0	82	73	0	2	17	0	0	0	0
88 90	1	12	0	0	97	100	0	0	39	0	0	3	0
89 91	1	14	0	36	94	121	0	0	43	0	0	3	0
90 92	4	12	0	15	73	10	0	0	6	0	0	2	0
91 93	5	18	0	34	99	19	0	0	1	0	0	2	11
92 94	2	25	1	32	106	15	171	0	19	98	0	3	4
93 95	4	33	1	51	147	91	74	0	49	62	0	1	4
94 96	6	31	1	46	169	131	71	3	64	58	0	1	4
95 97	10	34	1	57	171	118	84	2	88	53	5	3	9
96 98	13	41	3	50	192	137	106	2	115	46	4	2	8
97 99	12	63	2	77	239	152	62	1	175	43	4	2	8
98 00	17	65	5	107	243	154	111	3	207	22	5	9	12
99 01	18	74	6	149	218	171	99	2	196	31	5	3	14
00 02	13	88	10	167	208	228	105	0	205	28	4	3	22
01 03	20	76	10	175	197	126	148	3	206	9	1	10	24
02 04	14	78	14	203	189	146	77	1	186	14	4	7	18
03 05	16	73	12	252	156	192	48	1	178	6	1	6	19
04 06	6	83	13	373	124	119	94	1	95	42	2	7	21
05 07	5	85	11	353	97	91	138	3	98	34	1	12	28
06 08	9	81	10	349	99	109	109	2	99	40	1	13	27
07 09	6	75	9	380	113	108	53	3	91	35	1	6	44
08 10	4	79	8	242	257	52	79	0	97	36	1	6	50

Original Active Share Groups (cont'd)

	Russell Midcap Growth	S&P Midcap 400 Growth	Russell Midcap Value	S&P Midcap 400 Value	Russell 2000	S&P Smallcap 600	Russell 2000 Growth	S&P Smallcap 600 Growth	Russell 2000 Value	S&P Smallcap 600 Value
80 82	4	0	0	0	0	0	16	0	0	0
81 83	2	0	0	0	0	0	15	0	2	0
82 84	17	0	0	0	0	0	11	0	2	0
83 85	21	0	2	0	0	0	17	0	7	0
84 86	22	0	9	0	0	0	15	0	10	0
85 87	13	0	7	0	0	0	15	0	12	0
86 88	18	0	3	0	0	0	16	0	24	0
87 89	17	0	5	0	0	0	21	0	23	0
88 90	27	0	7	0	0	0	33	0	35	0
89 91	38	0	13	0	2	0	31	0	30	0
90 92	30	0	13	0	4	0	36	0	35	0
91 93	53	0	10	0	1	0	42	0	44	0
92 94	49	0	5	0	4	0	42	0	80	0
93 95	47	0	7	0	5	0	27	0	142	0
94 96	40	0	15	0	7	0	34	0	194	0
95 97	42	34	15	0	9	0	30	0	251	0
96 98	51	52	22	2	10	0	37	16	258	0
97 99	107	49	36	4	14	7	42	45	226	1
98 00	137	38	48	2	14	13	70	39	223	3
99 01	130	46	61	7	15	11	48	62	256	2
00 02	127	42	89	8	16	14	54	86	226	3
01 03	113	37	113	4	22	12	70	54	251	3
02 04	101	33	134	7	21	14	47	39	321	3
03 05	96	49	157	1	27	14	75	44	258	5
04 06	119	84	63	36	20	26	105	122	43	64
05 07	115	82	56	48	22	29	112	105	40	63
06 08	137	99	65	47	21	29	106	79	36	54
07 09	115	120	56	49	15	59	73	44	32	25
08 10	95	97	44	47	13	54	54	60	24	33

Table A.2: Index Total Return and Residual Return Correlations
This table presents the correlation between market indexes that were used in the estimation of mutual fund active share. Panel A presents the correlation of total index monthly returns throughout the entire time series from 1980 through 2010 using pairwise complete index return data. Panel B presents the residual correlations after regressing monthly index returns upon 36 month non-overlapping 4 risk factor model regressions. The 36 month windows are appended together to form a single time series for each index, then the index correlations are calculated using pairwise complete observations. The 4 factor model included the standard factors of RMRF, SMB, HML, and UMD.

Panel A: Total Return Index Correlations
Calculated From Raw Index Returns

	R1	S5	R3	S1	RT	**R1G**	S5G	R3G	**R1V**	S5V	R3V	S4	**RM**	**RMG**	S4G	**RMV**	S4V	**R2**	S6	**R2G**	S6G	**R2V**
S5	1.00																					
R3	1.00	0.99																				
S1	0.98	0.99	0.97																			
RT	0.99	0.99	0.98	0.99																		
R1G	0.97	0.96	0.97	0.95	0.96																	
S5G	0.96	0.96	0.96	0.97	0.97	0.98																
R3G	0.97	0.95	0.97	0.94	0.96	1.00	0.98															
R1V	0.95	0.94	0.95	0.91	0.94	0.84	0.82	0.84														
S5V	0.95	0.96	0.95	0.93	0.94	0.84	0.85	0.84	0.99													
R3V	0.95	0.94	0.95	0.91	0.93	0.85	0.82	0.85	1.00	0.99												
S4	0.92	0.90	0.94	0.84	0.87	0.87	0.84	0.89	0.87	0.89	0.89											
RM	0.96	0.93	0.97	0.88	0.91	0.92	0.87	0.93	0.92	0.91	0.93	0.98										
RMG	0.90	0.86	0.92	0.83	0.86	0.94	0.87	0.95	0.77	0.77	0.78	0.91	0.94									
S4G	0.90	0.88	0.92	0.83	0.85	0.89	0.85	0.91	0.80	0.83	0.81	0.98	0.95	0.95								
RMV	0.91	0.89	0.92	0.83	0.87	0.80	0.76	0.81	0.96	0.94	0.97	0.92	0.95	0.79	0.83							
S4V	0.83	0.81	0.84	0.75	0.77	0.71	0.69	0.72	0.88	0.87	0.89	0.91	0.89	0.73	0.83	0.94						
R2	0.86	0.80	0.89	0.76	0.80	0.84	0.76	0.86	0.81	0.79	0.83	0.92	0.94	0.91	0.91	0.85	0.82					
S6	0.84	0.81	0.86	0.75	0.77	0.79	0.75	0.82	0.78	0.81	0.81	0.93	0.93	0.88	0.91	0.85	0.84	0.98				
R2G	0.84	0.78	0.87	0.74	0.79	0.86	0.78	0.89	0.74	0.72	0.76	0.88	0.91	0.95	0.91	0.77	0.73	0.98	0.94			
S6G	0.83	0.80	0.86	0.75	0.77	0.81	0.76	0.84	0.75	0.78	0.77	0.92	0.93	0.91	0.93	0.81	0.80	0.97	0.99	0.96		
R2V	0.84	0.78	0.86	0.73	0.77	0.76	0.68	0.78	0.85	0.84	0.88	0.89	0.92	0.80	0.82	0.92	0.88	0.96	0.95	0.88	0.90	
S6V	0.83	0.81	0.85	0.75	0.77	0.73	0.71	0.76	0.84	0.85	0.86	0.92	0.91	0.79	0.85	0.91	0.90	0.94	0.97	0.85	0.92	0.98

Panel B: Residual Return Correlations after (36 month rolling) 4 Factor Regressions
Calculated from non-overlapping 36 month 4-factor model regressions

	R1	S5	R3	S1	RT	**R1G**	S5G	R3G	**R1V**	S5V	R3V	S4	**RM**	**RMG**	S4G	**RMV**	S4V	**R2**	S6	**R2G**	S6G	**R2V**
S5	0.82																					
R3	0.98	0.84																				
S1	0.51	0.78	0.57																			
RT	0.52	0.81	0.75	0.72																		
R1G	0.40	0.28	0.24	0.21	0.23																	
S5G	0.37	0.57	0.26	0.50	0.48	0.62																
R3G	0.81	0.56	0.92	0.19	0.49	0.99	0.42															
R1V	0.36	0.33	0.52	0.16	0.20	-0.70	-0.34	-0.69														
S5V	0.44	0.39	0.58	0.26	0.30	-0.43	-0.53	0.18	0.76													
R3V	0.16	0.01	0.26	-0.25	-0.11	-0.75	-0.50	-0.96	1.00	0.74												
S4	0.15	-0.27	0.20	-0.46	-0.41	0.10	-0.28	0.32	0.11	0.05	0.37											
RM	0.12	-0.29	0.18	-0.55	-0.53	0.03	-0.36	-0.08	0.13	0.08	0.55	0.86										
RMG	-0.10	-0.47	-0.03	-0.49	-0.52	0.22	-0.30	0.57	-0.21	-0.13	-0.01	0.66	0.80									
S4G	0.13	-0.23	0.18	-0.43	-0.39	0.15	-0.22	0.75	0.02	0.02	0.32	0.93	0.78	0.65								
RMV	0.20	-0.12	0.33	-0.32	-0.35	-0.25	-0.27	-0.06	0.42	0.25	0.69	0.58	0.79	0.29	0.42							
S4V	0.26	0.07	0.31	-0.11	-0.13	0.05	-0.11	-0.80	0.26	0.18	0.34	0.79	0.68	0.30	0.59	0.73						
R2	0.18	-0.05	0.46	-0.24	-0.16	-0.18	-0.39	0.80	0.34	0.40	0.43	0.42	0.41	0.28	0.38	0.45	0.21					
S6	0.26	0.11	0.37	-0.16	0.00	0.02	-0.20	0.85	0.25	0.33	0.32	0.45	0.45	0.31	0.40	0.38	0.28	0.71				
R2G	-0.02	-0.27	0.21	-0.34	-0.31	-0.31	-0.45	0.82	0.28	0.20	0.28	0.45	0.51	0.53	0.47	0.26	0.16	0.81	0.53			
S6G	0.16	-0.03	0.27	-0.29	-0.16	0.03	-0.21	0.84	0.15	0.21	0.32	0.52	0.50	0.42	0.52	0.36	0.25	0.62	0.93	0.56		
R2V	0.26	0.27	0.53	0.06	0.03	-0.06	-0.10	0.68	0.20	0.43	0.43	0.28	0.18	-0.08	0.18	0.40	0.25	0.75	0.63	0.12	0.46	
S6V	0.47	0.37	0.54	0.23	0.37	-0.14	-0.16	NA	0.55	0.55	0.65	0.08	0.08	-0.04	-0.08	0.29	0.22	0.64	0.82	0.17	0.46	0.76

Table A.3: Number of Funds in Major Benchmark APB Groups

This table presents the number of no-load U.S. equity mutual funds in each "Major Benchmark APB Group", as derived from the primary best fitting indexes of table A.1, using the correlations of table A.2. Funds with multiple shareclasses of the same fund are represented by only a single shareclass in our sample. If a fund has more than one no-load shareclass, then only one shareclass is arbitrarily selected. In situations where that shareclass no longer exists, it is replaced with the other shareclass if it continues to exist. To be counted within a particular three-year period, a fund must have at least 30 monthly return observations. To be included as a group of funds within any 3 year period, that group must include at least 5 qualifying funds during that period.

	Russell 1000	Russell 1000 Growth	Russell 1000 Value	Russell Midcap	Russell Midcap Growth	Russell Midcap Value	Russell 2000	Russell 2000 Growth	Russell 2000 Value
80 82	45	61	21	-	-	-	-	16	-
81 83	55	63	18	-	-	-	-	15	-
82 84	84	45	17	-	17	-	-	11	-
83 85	75	49	29	-	21	-	-	17	7
84 86	84	57	28	-	22	9	-	15	10
85 87	96	69	25	-	13	7	-	15	12
86 88	107	72	27	-	18	-	-	16	24
87 89	133	75	19	-	17	5	-	21	23
88 90	149	101	41	-	27	7	-	33	35
89 91	145	128	43	17	38	13	-	31	30
90 92	104	161	108	20	30	13	-	36	35
91 93	156	153	117	13	53	10	-	42	44
92 94	166	187	117	7	49	5	5	42	80
93 95	236	167	113	5	75	10	5	44	142
94 96	253	205	123	5	69	17	7	48	194
95 97	273	204	146	12	76	19	10	41	253
96 98	299	245	165	10	103	24	11	53	258
97 99	393	215	222	10	156	40	21	87	227
98 00	437	268	234	21	175	50	27	109	226
99 01	465	272	232	17	176	68	26	110	258
00 02	486	333	237	25	169	97	30	140	229
01 03	478	277	216	34	150	117	34	124	254
02 04	498	224	204	25	134	141	35	86	324
03 05	509	241	185	25	145	158	41	119	263
04 06	599	213	139	28	203	99	46	227	107
05 07	551	232	133	40	197	104	51	217	103
06 08	548	220	140	40	236	112	50	185	90
07 09	583	164	127	50	235	105	74	117	57
08 10	590	131	134	56	192	91	67	114	57

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Table 1: In-Sample Alpha Estimates of Gross Excess Returns

This table presents mutual fund α estimates from equal weighted average gross excess returns when funds are grouped by their active share peer group from 1980 through 2009. Group values are not reported if less than 5 funds in a group have 30 or more return observations during the respective three-year period. Estimates are for U.S. equity styles regressed on the 4-factor risk model ($r_{APB,t} = \alpha_{APB} + \beta_{APB,rmrf} r_{rmrf,t} + \beta_{APB,hml} r_{hml,t} + \beta_{APB,smb} r_{smb,t} + \beta_{APB,umd} r_{umd,t} + \epsilon_{APB,t}$). Alpha estimates are presented on the first row of each style with the corresponding t-statistics immediately below in parenthesis. Alpha estimates that are significant at the 90% confidence level are presented in bold, those significant at the 95% level are presented in bold with one asterisk (*), and those significant at the 99% level are presented in bold with two asterisks (**). The final column presents alpha estimates throughout the full sample from 1980 through 2010.

(first row: alpha, second row: t-statistic)

	Period										
	80 - 82	83 - 85	86 - 88	89 - 91	92 - 94	95 - 97	98 - 00	01 - 03	04 - 06	07 - 09	80 - 10
Russell 1000	**0.26%***	0.13%	**0.14%**	0.03%	**0.07%**	-0.01%	**0.22%***	-0.07%	-0.01%	-0.01%	**0.08%****
	(2.133)	*(1.648)*	***(1.956)***	*(0.428)*	***(1.683)***	*(-0.154)*	***(2.262)***	*(-1.179)*	*(-0.317)*	*(-0.196)*	***(2.836)***
Russell 1000 Growth	**0.29%**	0.14%	**0.33%****	**0.17%**	0.11%	0.00%	**0.55%****	**-0.25%**	0.10%	**0.21%**	**0.16%****
	(1.707)	*(1.182)*	***(4.316)***	***(1.893)***	*(1.508)*	*(0.020)*	***(2.752)***	***(-1.909)***	*(1.163)*	***(1.950)***	***(3.154)***
Russell 1000 Value	**0.29%***	-0.10%	0.02%	0.05%	0.02%	-0.01%	**0.34%**	-0.01%	0.03%	**-0.20%**	0.07%
	(2.485)	*(-1.159)*	*(0.265)*	*(0.726)*	*(0.362)*	*(-0.181)*	***(1.711)***	*(-0.084)*	*(0.343)*	***(-1.791)***	*(1.595)*
Russell Midcap	-	-	-	**0.48%***	-0.11%	-0.03%	0.25%	-0.20%	0.13%	0.12%	0.10%
				(2.041)	*(-0.880)*	*(-0.167)*	*(0.706)*	*(-1.073)*	*(1.193)*	*(0.825)*	*(1.335)*
Russell Midcap Growth	-	-0.02%	**0.69%****	0.25%	0.14%	-0.10%	**0.65%**	**-0.57%***	**0.30%***	0.15%	**0.17%****
		(-0.145)	***(3.611)***	*(1.559)*	*(1.009)*	*(-0.451)*	***(1.659)***	***(-2.193)***	***(2.509)***	*(0.946)*	***(2.955)***
Russell Midcap Value	-	-	-	**0.31%**	-0.08%	-0.02%	**0.45%**	-0.06%	0.17%	0.01%	**0.12%**
				(1.919)	*(-0.709)*	*(-0.144)*	***(1.922)***	*(-0.385)*	*(1.352)*	*(0.104)*	***(1.669)***
Russell 2000	-	-	-	-	-	-0.17%	-0.19%	**-0.33%***	0.12%	-0.15%	0.07%
						(-1.184)	*(-0.676)*	***(-2.445)***	*(1.241)*	*(-1.322)*	*(1.595)*
Russell 2000 Growth	0.11%	-0.06%	**0.47%***	0.29%	**0.34%**	0.13%	0.21%	**-0.64%****	0.09%	-0.03%	0.10%
	(0.559)	*(-0.460)*	***(2.340)***	*(1.344)*	***(1.847)***	*(0.420)*	*(0.580)*	***(-2.753)***	*(0.906)*	*(-0.271)*	*(1.567)*
Russell 2000 Value		0.10%	**0.21%***	0.06%	**0.26%****	0.06%	0.38%	-0.10%	0.05%	-0.18%	0.01%
		(0.884)	***(2.171)***	*(0.734)*	***(3.555)***	*(0.598)*	*(1.633)*	*(-0.815)*	*(0.578)*	*(-1.609)*	*(0.097)*

Table 2: Correlations Across Group Residuals

This table shows the correlation between pairs of active peer benchmarks (Panel A) and market indexes (Panel B) from 1980 through 2010. APB categories are identified by mutual fund's best fitting Active Share benchmark, including the Russell 1000, Russell 1000 Growth, Russell 1000 Value, Russell Midcap, Russell Midcap Growth, Russell Midcap Value, Russell 2000, Russell 2000 Growth, and Russell 2000 Value. Panel B presents similar correlations when a market index is used instead of the Active Peer Benchmark. The correlations represent pairwise correlations between APB residuals (Panel A) and market index residuals (Panel B) after regressing the return of each upon the four-factor risk model. ($r_{APB,t} = \alpha_{APB} + \beta_{APB,rmrf} r_{rmrf,t} + \beta_{APB,hml} r_{hml,t} + \beta_{APB,smb} r_{smb,t} + \beta_{APB,umd} r_{umd,t} + \epsilon_{APB,t}$). Numbers in bold are statistically significant at a 90% confidence level, those bold with one asterisk (*) are significant at the 5% level and those bold with two asterisks (**) are significant at the 99% level. T-statistics are shown in parenthesis.

Panel A: Correlation Coefficients Across Group Return Residuals
Includes all Pairwise Complete Observations (1980-2010)

	Russell 1000	Russell 1000 Growth	Russell 1000 Value	Russell Midcap	Russell Midcap Growth	Russell Midcap Value	Russell 2000	Russell 2000 Growth
Russell 1000 Growth	**0.46****							
	(9.921)							
Russell 1000 Value	**0.44****	0.02						
	(9.333)	*(0.354)*						
Russell Midcap	**0.22****	**0.46****	**0.30****					
	(3.589)	***(8.097)***	***(5.044)***					
Russell Midcap Growth	**0.13***	**0.64****	**0.15****	**0.74****				
	(2.305)	***(14.943)***	***(2.772)***	***(17.266)***				
Russell Midcap Value	**0.27****	**0.16***	**0.61****	**0.58****	**0.43****			
	(4.378)	***(2.550)***	***(12.149)***	***(11.141)***	***(7.473)***			
Russell 2000	**0.13**	**0.16***	**0.37****	**0.67****	**0.57****	**0.56****		
	(1.706)	***(2.190)***	***(5.305)***	***(11.961)***	***(9.299)***	***(9.041)***		
Russell 2000 Growth	**0.18****	**0.44****	**0.27****	**0.64****	**0.73****	**0.40****	**0.73****	
	(3.491)	***(9.366)***	***(5.252)***	***(113.240)***	***(9.207)***	***(6.799)***	***(14.297)***	
Russell 2000 Value	**0.38****	**0.22****	**0.48****	**0.53****	**0.45****	**0.58****	**0.72****	**0.61****
	(7.279)	***(4.015)***	***(9.739)***	***(9.861)***	***(8.939)***	***(11.356)***	***(13.800)***	***(13.834)***

Panel B: Correlation Coefficients Across Best-Fit Index Return Residuals
Includes all Pairwise Complete Return Observations (1980-2010)

	Russell 1000	Russell 1000 Growth	Russell 1000 Value	Russell Midcap	Russell Midcap Growth	Russell Midcap Value	Russell 2000	Russell 2000 Growth
Russell 1000 Growth	**0.50****							
	(11.001)							
Russell 1000 Value	**0.46****	**0.36****						
	(9.681)	***(7.239)***						
Russell Midcap	**0.29****	**0.37****	**0.13***					
	(4.711)	***(6.342)***	***(2.010)***					
Russell Midcap Growth	**0.33****	**0.56****	**0.19****	**0.42****				
	(5.900)	***(11.363)***	***(3.331)***	***(7.414)***				
Russell Midcap Value	**0.28****	**0.28****	**0.51****	**0.33****	**0.27****			
	(4.550)	***(4.693)***	***(9.267)***	***(5.461)***	***(4.468)***			
Russell 2000	0.07	0.06	**0.25****	**0.49****	**0.16***	**0.34****		
	(0.913)	*(0.785)*	***(3.474)***	***(7.448)***	***(2.225)***	***(4.843)***		
Russell 2000 Growth	**0.26****	**0.42****	**0.28****	**0.41****	**0.45****	**0.20****	**0.63****	
	(5.132)	***(8.656)***	***(5.605)***	***(7.090)***	***(8.635)***	***(3.163)***	***(10.889)***	
Russell 2000 Value	**0.34****	**0.31****	**0.37****	**0.27****	**0.23****	**0.39****	**0.54****	**0.49****
	(6.411)	***(5.918)***	***(7.190)***	***(4.345)***	***(4.061)***	***(6.748)***	***(8.647)***	***(9.975)***

Table 3: Percentage of U.S. Equity Funds with Statistically Significant Residual Correlations

This table presents the percentage of statistically significant positive and negative pairwise residual correlations (with 90% confidence using a 2-tailed test) within each group of mutual funds from 1980 through 2010. Values are not included if less than 5 funds in a group have 30 or more return observations during the respective three-year period. The table presents results for funds in U.S. equity groups after regressing each individual fund's monthly gross excess return on (1) the 4-factor model ($r_{i,t} = \alpha_i + \beta_{i,rmrf} r_{rmrf,t} + \beta_{i,hml} r_{hml,t} + \beta_{i,smb} r_{smb,t} + \beta_{i,umd} r_{umd,t} + \epsilon_{i,t}$) and (2) the 4 factor model plus the active peer benchmark. The APB model includes an additional regressor that is created using the average return of the group of funds, and orthogonalized against the other risk factors in the model. The final column reports the average of each row's percentages in the table.

Correlation Pairs	**Model**		**Period**										
		Significance	80-82	83-85	86-88	89-91	92-94	95-97	98-00	01-03	04-06	07-09	Average
Russell 1000	4 Factor	Positive	45%	22%	24%	18%	15%	19%	32%	31%	24%	28%	26%
		Negative	4%	4%	7%	5%	5%	7%	5%	7%	5%	12%	6%
	4 factor + APB	Positive	11%	10%	13%	10%	9%	14%	15%	14%	13%	17%	13%
		Negative	13%	12%	15%	10%	10%	13%	13%	12%	11%	15%	12%
Russell 1000 Growth	4 Factor	Positive	52%	32%	20%	21%	19%	21%	34%	33%	26%	37%	29%
		Negative	3%	3%	8%	5%	4%	9%	5%	5%	5%	7%	5%
	4 factor + APB	Positive	14%	8%	14%	11%	10%	11%	16%	17%	19%	19%	14%
		Negative	11%	11%	15%	10%	9%	11%	15%	16%	17%	14%	13%
Russell 1000 Value	4 Factor	Positive	28%	19%	23%	21%	17%	24%	47%	47%	26%	35%	29%
		Negative	20%	7%	16%	12%	9%	10%	1%	3%	8%	11%	10%
	4 factor + APB	Positive	11%	12%	17%	19%	13%	17%	13%	16%	18%	23%	16%
		Negative	18%	17%	23%	25%	13%	18%	12%	14%	15%	21%	17%
Russell Midcap	4 Factor	Positive	-	-	-	58%	86%	50%	94%	83%	61%	59%	70%
		Negative	-	-	-	1%	0%	0%	0%	0%	0%	2%	0%
	4 factor + APB	Positive	-	-	-	6%	19%	8%	16%	21%	19%	17%	15%
		Negative	-	-	-	13%	52%	26%	24%	21%	19%	18%	25%
Russell Midcap Growth	4 Factor	Positive	-	32%	31%	35%	42%	54%	62%	71%	38%	47%	46%
		Negative	-	2%	3%	5%	2%	1%	1%	0%	1%	3%	2%
	4 factor + APB	Positive	-	10%	12%	8%	10%	13%	15%	12%	10%	14%	11%
		Negative	-	19%	23%	12%	12%	15%	14%	13%	10%	14%	15%
Russell Midcap Value	4 Factor	Positive	-	-	-	12%	10%	35%	45%	29%	39%	40%	30%
		Negative	-	-	-	4%	0%	11%	3%	4%	3%	3%	4%
	4 factor + APB	Positive	-	-	-	4%	10%	21%	12%	15%	14%	12%	13%
		Negative	-	-	-	19%	30%	32%	16%	16%	16%	13%	20%
Russell 2000	4 Factor	Positive	-	-	-	-	-	51%	84%	64%	59%	56%	63%
		Negative	-	-	-	-	-	0%	2%	2%	1%	1%	1%
	4 factor + APB	Positive	-	-	-	-	-	16%	18%	23%	13%	14%	17%
		Negative	-	-	-	-	-	27%	22%	22%	18%	17%	21%
Russell 2000 Growth	4 Factor	Positive	32%	24%	46%	39%	48%	77%	66%	63%	23%	35%	45%
		Negative	0%	5%	3%	4%	1%	0%	0%	0%	4%	2%	2%
	4 factor + APB	Positive	6%	8%	14%	8%	7%	10%	13%	12%	10%	11%	10%
		Negative	14%	15%	24%	13%	10%	15%	14%	13%	11%	12%	14%
Russell 2000 Value	4 Factor	Positive	-	19%	16%	14%	16%	15%	32%	23%	36%	41%	24%
		Negative	-	5%	6%	9%	5%	6%	2%	5%	4%	6%	5%
	4 factor + APB	Positive	-	10%	8%	12%	9%	10%	10%	13%	11%	15%	11%
		Negative	-	24%	12%	12%	10%	9%	10%	11%	11%	15%	13%
Average	4 Factor	Positive	39%	25%	27%	27%	32%	38%	55%	49%	37%	42%	37%
		Negative	7%	4%	7%	5%	3%	5%	2%	3%	4%	5%	5%
	4 factor + APB	Positive	10%	9%	13%	10%	11%	13%	14%	16%	14%	16%	13%
		Negative	14%	16%	19%	14%	18%	18%	16%	15%	14%	15%	16%

Table 4: Percent of Funds with Significant or Insignificant Coefficient Estimates

This table presents the percentage of funds with significant (95% confidence, based upon a two-tailed test) and insignificant coefficient estimates when gross excess fund returns are regressed on risk factor models both with and without the APB benchmark included. Regressions are run over non-overlapping 36 month periods from 1980 through 2010. The table presents the percentage of U.S. equity mutual funds with significant and insignificant estimates of each α and coefficient under 4 different models: (1) the 4-factor model ($r_{i,t} = \alpha_i + \beta_{i,rmrf} r_{rmrf,t} + \beta_{i,hml} r_{hml,t} + \beta_{i,smb} r_{smb,t} + \beta_{i,umd} r_{umd,t} + \epsilon_{i,t}$); (2) the 4 factor model, augmented with the Active Peer Benchmark; (3) the 4 factor model augmented with the Active Peer Benchmark which includes the average alpha of the group; and (4) a single Active Peer Benchmark model which excludes the commonly used 4 factors. In the first column, the percentage of funds with statistically significant and insignificant α estimates under the 4 factor model are shown (labeled α). The second column shows the same for α estimates under the 4 factor plus Active Peer Benchmark model (labeled α_{aug}), and the third column shows the same for α estimates under the 4 factor model with an Active Peer Benchmark that includes the group alpha (labeled a_{aug}). The percentage of funds with statistically significant and insignificant coefficient estimates under these models are then presented in columns four through eight where the statistical significance of the Active Peer Benchmark is reported in column 8 (labeled λ). Column 9 reports the percent of mutual funds with statistically significant and insignificant α estimates under the APB-only model (labeled α_i^{APB}). The bottom row in each style group reports the average adjusted R^2 that corresponds to the model used to estimate the results shown in that column.

	α	α_{aug}	a_{aug}	rmrf	smb	hml	umd	λ	α_i^{APB}
Russell 1000									
Positive Significant	6.9%	9.4%	5.9%	99.7%	7.4%	25.9%	14.9%	50.8%	6.6%
Positive	46.1%	43.6%	44.5%	0.2%	20.1%	29.2%	33.4%	36.0%	40.2%
Negative	43.1%	41.9%	43.9%	0.1%	31.1%	30.2%	32.1%	11.7%	46.6%
Negative Significant	3.9%	5.1%	5.8%	0.0%	41.4%	14.7%	19.6%	1.4%	6.7%
Adj. R^2	91.0%	92.0%	92.0%						88.3%
Russell 1000 Growth									
Positive Significant	8.9%	10.9%	4.6%	99.1%	23.5%	3.3%	32.4%	54.6%	5.6%
Positive	52.1%	49.9%	43.2%	0.8%	32.3%	12.6%	40.2%	34.5%	41.4%
Negative	34.1%	32.4%	44.8%	0.1%	26.9%	24.9%	22.3%	9.8%	44.3%
Negative Significant	5.0%	6.8%	7.4%	0.0%	17.3%	59.2%	5.1%	1.2%	8.8%
Adj. R^2	85.4%	87.7%	87.7%						82.1%
Russell 1000 Value									
Positive Significant	6.8%	8.8%	5.5%	99.4%	13.5%	67.9%	12.4%	59.5%	5.6%
Positive	49.1%	47.0%	45.6%	0.6%	32.0%	21.8%	25.0%	33.3%	42.0%
Negative	40.5%	38.9%	44.7%	0.0%	34.3%	7.8%	33.2%	6.7%	46.2%
Negative Significant	3.6%	5.4%	4.2%	0.0%	20.2%	2.5%	29.4%	0.5%	6.3%
Adj. R^2	81.6%	84.1%	84.1%						77.8%
Russell Midcap									
Positive Significant	5.3%	16.4%	11.7%	99.4%	93.0%	34.5%	41.5%	87.1%	8.8%
Positive	54.4%	43.3%	43.9%	0.6%	5.3%	21.1%	25.7%	11.7%	45.0%
Negative	38.0%	32.8%	38.0%	0.0%	1.8%	26.9%	23.4%	1.2%	37.4%
Negative Significant	2.3%	7.6%	6.4%	0.0%	0.0%	17.5%	9.4%	0.0%	8.8%
Adj. R^2	90.9%	94.7%	94.7%						88.3%
Russell Midcap Growth									
Positive Significant	11.0%	17.3%	5.6%	99.1%	82.9%	6.8%	46.0%	78.7%	8.5%
Positive	51.4%	45.0%	43.0%	0.9%	15.5%	13.5%	32.7%	18.6%	40.0%
Negative	31.7%	28.4%	45.3%	0.0%	1.5%	25.3%	17.8%	2.8%	43.1%
Negative Significant	5.9%	9.3%	6.1%	0.0%	0.1%	54.4%	3.5%	0.0%	8.5%
Adj. R^2	87.1%	90.3%	90.3%						82.1%
Russell Midcap Value									
Positive Significant	8.0%	11.6%	5.8%	99.5%	64.5%	57.5%	10.6%	68.4%	8.0%
Positive	54.1%	50.2%	47.3%	0.5%	25.4%	25.4%	32.1%	26.3%	41.3%
Negative	35.8%	35.5%	43.2%	0.0%	9.7%	13.3%	35.0%	5.3%	42.3%
Negative Significant	2.2%	2.7%	3.6%	0.0%	0.5%	3.9%	22.2%	0.0%	8.5%
Adj. R^2	81.3%	84.7%	84.7%						77.8%
Russell 2000									
Positive Significant	2.6%	9.3%	6.7%	100.0%	98.5%	54.9%	34.2%	90.2%	8.3%
Positive	33.2%	26.4%	42.0%	0.0%	1.6%	30.1%	31.6%	8.3%	46.1%
Negative	46.1%	37.8%	40.9%	0.0%	0.0%	12.4%	28.0%	1.6%	37.8%
Negative Significant	18.1%	26.4%	10.4%	0.0%	0.0%	2.6%	6.2%	0.0%	7.8%
Adj. R^2	94.9%	96.9%	96.9%						95.6%
Russell 2000 Growth									
Positive Significant	7.2%	11.4%	6.6%	100.0%	97.1%	10.9%	45.0%	72.9%	11.1%
Positive	46.0%	41.5%	43.5%	0.0%	2.8%	14.9%	37.5%	24.0%	37.0%
Negative	36.9%	32.9%	41.3%	0.0%	0.1%	32.0%	13.9%	3.1%	41.4%
Negative Significant	10.0%	14.2%	8.6%	0.0%	0.0%	42.3%	3.6%	0.0%	10.5%
Adj. R^2	89.3%	91.9%	91.9%						89.7%
Russell 2000 Value									
Positive Significant	9.1%	11.0%	6.8%	99.2%	90.1%	51.4%	12.4%	50.4%	13.3%
Positive	47.4%	45.4%	43.5%	0.8%	7.7%	25.6%	32.7%	39.8%	42.8%
Negative	39.6%	38.5%	43.3%	0.0%	1.7%	14.8%	41.4%	9.3%	34.3%
Negative Significant	3.9%	5.1%	6.4%	0.0%	0.5%	8.3%	13.5%	0.5%	9.6%
Adj. R^2	81.6%	83.4%	83.4%						76.4%

Table 5: Out of Sample Investment Performance as a Function of In Sample Alpha T-Statistic Magnitudes

The table presents average out-of-sample monthly α estimates from portfolios of mutual funds, ranked into quartiles by the statistical significance of in-sample α t-statistic estimates of the Active Peer Benchmark Model. The Active Peer Benchmark is equally weighted across the mutual funds it contains. The quartile portfolios of funds were equally weighted. The α's were estimated monthly from 1980 through 2010 using 36 month regression windows. Every month, funds were then sorted into quartiles by their α t-statistic estimate. The table presents average out-of-sample performance over the subsequent 12 months as well as time-series t-statistics of alphas over all (overlapping) 12-month periods. T-statistics were adjusted to allow for overlapping data. Panel A presents 12 month performance results when regressed on the Active Peer Benchmark model. Panel B presents results for the same portfolios, but out-of-sample performance is regressed using the APB-adjusted alpha model. Numbers in bold are statistically significant at a 90% confidence level, those bold with one asterisk (*) are significant at the 95% level and those bold with two asterisks (**) are significant at the 99% level. T-statistics are shown in parenthesis.

Panel A: Quartile Portfolios are Equal Weighted, and Regressed On the APB Model

	Russell 1000	Russell 1000 Growth	Russell 1000 Value	Russell Midcap	Russell Midcap Growth	Russell Midcap Value	Russell 2000 2000	Russell 2000 Growth	Russell 2000 Value
1st − 4th Quartile	**0.07%****	**0.10%****	0.07%	**0.13%****	**0.16%****	**0.13%***	**0.16%****	**0.16%****	**0.15%****
	(3.004)	***(2.625)***	*(1.405)*	***(2.620)***	***(3.158)***	***(2.140)***	***(2.966)***	***(2.607)***	***(2.660)***
1st Quartile	**0.07%***	**0.14%****	0.05%	**0.19%****	0.14%	**0.31%****	0.06%	0.09%	0.14%
	(2.165)	***(2.952)***	*(0.973)*	***(11.284)***	*(1.107)*	***(3.429)***	*(1.107)*	*(0.593)*	*(1.596)*
2nd Quartile	0.04%	**0.11%***	0.07%	**0.23%****	0.08%	**0.18%****	-0.04%	0.04%	0.09%
	(1.078)	***(2.426)***	*(1.138)*	***(7.629)***	*(0.584)*	***(3.816)***	*(-0.646)*	*(0.272)*	*(1.080)*
3rd Quartile	0.04%	**0.08%**	0.03%	**0.17%****	-0.01%	**0.14%**	-0.05%	-0.05%	0.05%
	(1.228)	***(1.889)***	*(0.546)*	***(4.480)***	*(-0.057)*	***(1.788)***	*(-0.763)*	*(-0.404)*	*(0.583)*
4th Quartile	0.00%	0.04%	-0.02%	0.05%	-0.02%	**0.19%***	-0.10%	-0.07%	-0.01%
	(0.147)	*(0.865)*	*(-0.251)*	*(0.990)*	*(-0.173)*	***(2.155)***	*(-1.177)*	*(-0.532)*	*(-0.118)*

Panel B: Quartile Portfolios are Equal Weighted, and Regressed On the Alpha Adjustment APB Factor Model

	Russell 1000	Russell 1000 Growth	Russell 1000 Value	Russell Midcap	Russell Midcap Growth	Russell Midcap Value	Russell 2000 2000	Russell 2000 Growth	Russell 2000 Value
1st − 4th Quartile	**0.07%****	0.06%	0.07%	**0.20%***	**0.17%****	**0.11%***	**0.19%****	**0.18%****	**0.13%***
	(3.623)	*(1.467)*	*(1.316)*	***(2.607)***	***(3.002)***	***(2.113)***	***(3.045)***	***(2.976)***	***(2.114)***
1st Quartile	**0.03%***	0.00%	0.01%	0.05%	**0.08%****	**0.11%****	**0.11%****	**0.09%***	**0.06%**
	(2.114)	*(0.153)*	*(0.276)*	*(1.516)*	***(2.905)***	***(3.020)***	***(4.923)***	***(2.523)***	***(1.868)***
2nd Quartile	0.00%	0.00%	**0.04%****	**0.09%****	0.02%	-0.04%	0.00%	**0.03%**	0.01%
	(-0.391)	*(0.227)*	***(3.425)***	***(3.737)***	*(0.909)*	*(-1.306)*	*(-0.809)*	***(1.803)***	*(0.710)*
3rd Quartile	0.00%	0.00%	-0.01%	0.00%	**-0.06%****	**-0.08%***	**-0.04%****	-0.06%	**-0.04%**
	(0.128)	*(-0.015)*	*(-0.591)*	*(0.170)*	***(-3.923)***	***(-2.226)***	***(-3.240)***	*(-1.659)*	***(-1.678)***
4th Quartile	**-0.05%****	**-0.05%****	**-0.07%***	**-0.15%****	**-0.08%***	-0.01%	**-0.07%**	**-0.09%****	**-0.08%***
	(-4.248)	***(-2.789)***	***(-2.225)***	***(-3.579)***	***(-2.421)***	*(-0.238)*	***(-1.786)***	***(-2.980)***	***(-2.136)***

Table 6: Out of Sample Investment Performance as a Function of In Sample Alpha T-Stat Differences: Equal Weighted Portfolios

This table presents the out-of-sample average monthly α estimates from portfolios of mutual funds, ranked into quartiles by the difference in statistical significance between in-sample α estimates of the Active Peer Benchmark Model and the common 4 factor model. The quartile portfolios of funds were equally weighted. The Active Peer Benchmark is equally weighted across the mutual funds it contains. The differenced t-statistics were estimated monthly from 1980 through 2010 using 36 month regression windows. Every month, funds were then sorted into quartiles by their α t-statistic difference. The table presents average out-of-sample performance over the subsequent 12 months as well as time-series t-statistics of alphas over all (overlapping) 12-month periods. T-statistics were adjusted to allow for overlapping data. Panel A presents 12 month performance results when regressed on the Active Peer Benchmark model. Panel B presents results for the same portfolios, but out-of-sample performance is regressed using the APB-adjusted alpha model. Numbers in bold are statistically significant at a 90% confidence level, those bold with one asterisk (*) are significant at the 95% level and those bold with two asterisks (**) are significant at the 99% level. T-statistics are shown in parenthesis.

Panel A: Quartile Portfolios are Equal Weighted, and Regressed On the APB Model

	Russell 1000	Russell 1000 Growth	Russell 1000 Value	Russell Midcap	Russell Midcap Growth	Russell Midcap Value	Russell 2000 2000	Russell 2000 Growth	Russell 2000 Value
1st − 4th Quartile	**0.04%**	**0.08%***	0.06%	0.20%	**0.12%***	0.06%	**0.13%****	0.10%	**0.08%**
	(1.939)	***(2.166)***	*(1.477)*	*(1.612)*	***(2.183)***	*(0.778)*	***(3.224)***	*(1.588)*	***(1.877)***
1st Quartile	**0.07%**	**0.13%***	0.06%	**0.28%****	0.10%	**0.28%***	0.03%	0.05%	0.10%
	(1.734)	***(2.297)***	*(1.007)*	***(3.630)***	*(0.738)*	***(2.604)***	*(0.515)*	*(0.299)*	*(1.097)*
2nd Quartile	0.04%	**0.09%***	0.05%	**0.16%****	0.05%	**0.19%****	-0.02%	0.00%	0.08%
	(1.188)	***(2.079)***	*(0.839)*	***(4.636)***	*(0.395)*	***(3.542)***	*(-0.348)*	*(-0.020)*	*(0.949)*
3rd Quartile	0.03%	**0.09%***	0.02%	**0.11%***	0.06%	0.13%	-0.04%	0.02%	0.07%
	(0.915)	***(2.396)***	*(0.434)*	***(2.414)***	*(0.488)*	*(1.634)*	*(-0.752)*	*(0.139)*	*(0.786)*
4th Quartile	0.02%	0.06%	0.00%	0.08%	-0.02%	**0.22%***	-0.09%	-0.05%	0.02%
	(0.716)	*(1.224)*	*(-0.071)*	*(1.473)*	*(-0.151)*	***(2.461)***	*(-1.156)*	*(-0.385)*	*(0.301)*

Panel B: Quartile Portfolios are Equal Weighted, and Regressed On the Alpha Adjustment APB Factor Model

	Russell 1000	Russell 1000 Growth	Russell 1000 Value	Russell Midcap	Russell Midcap Growth	Russell Midcap Value	Russell 2000 2000	Russell 2000 Growth	Russell 2000 Value
1st − 4th Quartile	**0.04%***	0.02%	0.03%	**0.24%**	**0.13%***	0.03%	**0.16%****	**0.14%***	**0.07%***
	(2.246)	*(0.402)*	*(0.616)*	***(1.855)***	***(2.529)***	*(0.397)*	***(3.984)***	***(2.465)***	***(2.002)***
1st Quartile	0.01%	-0.02%	0.01%	0.12%	0.04%	0.05%	**0.09%****	**0.07%***	0.02%
	(1.002)	*(-0.662)*	*(0.441)*	*(1.427)*	*(1.098)*	*(1.006)*	***(3.793)***	***(2.152)***	*(0.706)*
2nd Quartile	0.00%	-0.01%	0.01%	**0.02%***	0.00%	0.00%	0.00%	-0.01%	0.00%
	(-0.487)	*(-0.676)*	*(0.439)*	***(2.340)***	*(0.024)*	*(-0.062)*	*(-0.136)*	*(-0.271)*	*(0.244)*
3rd Quartile	0.00%	0.02%	**-0.03%***	-0.03%	0.00%	**-0.10%**	**-0.03%***	0.00%	-0.01%
	(0.062)	*(1.105)*	***(-2.184)***	*(-1.103)*	*(0.080)*	***(-1.717)***	***(-2.320)***	*(-0.020)*	*(-0.679)*
4th Quartile	**-0.03%****	**-0.04%**	-0.02%	**-0.12%****	**-0.09%****	0.02%	**-0.06%****	**-0.08%***	**-0.06%***
	(-2.745)	***(-1.918)***	*(-0.541)*	***(-2.683)***	***(-2.979)***	*(0.400)*	***(-3.236)***	***(-2.474)***	***(-2.476)***

Table 7: Out of Sample Net-of-Expense Investment Performance as a Function of In Sample Alpha T-Statistic Magnitudes: Equal Weighted Portfolios

This table presents the out-of-sample average monthly α estimates of returns net-of-fees from portfolios of mutual funds, ranked into quartiles by the α t-statistic estimates of the Active Peer Benchmark Model, then equally weighted within those quartiles. The α t-statistics were estimated monthly from 1980 through 2010 using 36 month regression windows. The Active Peer Benchmark is equally weighted across the mutual funds it contains. Every month, funds were then sorted into quartiles by their α t-statistic difference. The table presents average out-of-sample performance over the subsequent 12 months. T-statistics were adjusted to allow for overlapping data. Panel A presents 12 month performance results when regressed on the Active Peer Benchmark model. Panel B presents results for the same portfolios, but out-of-sample performance is regressed using the APB-adjusted alpha model. Numbers in bold are statistically significant at a 90% confidence level, those bold with one asterisk (*) are significant at the 95% level and those bold with two asterisks (**) are significant at the 99% level. T-statistics are shown in parenthesis.

Panel A: Quartile Portfolios are Equal Weighted, and Regressed On the APB Factor Model

	Russell 1000	Russell 1000 Growth	Russell 1000 Value	Russell Midcap	Russell Midcap Growth	Russell Midcap Value	Russell 2000 2000	Russell 2000 Growth	Russell 2000 Value
1st − 4th Quartile	**0.07%****	**0.10%***	0.07%	**0.16%****	**0.17%****	**0.13%***	**0.16%****	**0.16%***	**0.16%****
	(2.995)	***(2.551)***	*(1.344)*	***(3.293)***	***(3.249)***	***(2.374)***	***(2.638)***	***(2.552)***	***(2.611)***
1st Quartile	-0.01%	0.05%	-0.04%	**0.12%****	0.04%	**0.21%***	-0.01%	-0.03%	0.02%
	(-0.193)	*(0.929)*	*(-0.794)*	***(7.038)***	*(0.312)*	***(2.300)***	*(-0.191)*	*(-0.173)*	*(0.232)*
2nd Quartile	-0.05%	0.02%	-0.03%	**0.16%****	-0.03%	0.08%	**-0.11%**	-0.07%	-0.04%
	(-1.302)	*(0.352)*	*(-0.522)*	***(4.661)***	*(-0.216)*	*(1.595)*	***(-1.893)***	*(-0.524)*	*(-0.522)*
3rd Quartile	-0.04%	-0.02%	-0.07%	**0.08%**	-0.11%	0.04%	**-0.11%**	-0.16%	-0.08%
	(-1.249)	*(-0.351)*	*(-1.230)*	***(1.978)***	*(-0.865)*	*(0.485)*	***(-1.805)***	*(-1.354)*	*(-1.069)*
4th Quartile	**-0.08%***	-0.05%	-0.11%	-0.04%	-0.13%	0.08%	**-0.17%**	-0.19%	**-0.14%**
	(-2.323)	*(-1.043)*	*(-1.653)*	*(-0.756)*	*(-1.085)*	*(0.933)*	***(-1.853)***	*(-1.313)*	***(-1.890)***

Panel B: Quartile Portfolios are Equal Weighted, and Regressed On the Alpha Adjustment APB Factor Model

	Russell 1000	Russell 1000 Growth	Russell 1000 Value	Russell Midcap	Russell Midcap Growth	Russell Midcap Value	Russell 2000 2000	Russell 2000 Growth	Russell 2000 Value
1st − 4th Quartile	**0.07%****	**0.08%***	0.02%	**0.21%****	**0.18%****	**0.12%***	**0.19%****	**0.18%****	**0.14%***
	(2.748)	***(2.003)***	*(0.424)*	***(2.969)***	***(3.175)***	***(2.411)***	***(2.651)***	***(2.970)***	***(2.133)***
1st Quartile	**0.03%**	0.02%	-0.01%	**0.06%***	**0.09%****	**0.10%****	**0.11%****	**0.09%***	**0.06%**
	(1.779)	*(0.737)*	*(-0.418)*	***(2.535)***	***(3.121)***	***(3.090)***	***(3.988)***	***(2.433)***	***(1.673)***
2nd Quartile	0.00%	0.00%	**0.03%***	**0.09%****	0.02%	-0.03%	0.00%	**0.03%**	0.01%
	(-0.498)	*(0.227)*	***(2.414)***	***(2.712)***	*(0.997)*	*(-1.197)*	*(-0.045)*	***(1.959)***	*(1.205)*
3rd Quartile	0.00%	-0.01%	0.00%	-0.01%	**-0.06%****	**-0.08%***	**-0.04%****	-0.06%	-0.03%
	(-0.288)	*(-0.520)*	*(-0.300)*	*(-0.311)*	***(-3.820)***	***(-2.069)***	***(-4.316)***	*(-1.579)*	*(-1.312)*
4th Quartile	**-0.04%****	**-0.06%****	-0.04%	**-0.15%****	**-0.09%***	-0.02%	**-0.08%**	**-0.09%****	**-0.08%***
	(-3.144)	***(-3.045)***	*(-1.330)*	***(-3.319)***	***(-2.575)***	*(-0.509)*	***(-1.721)***	***(-3.015)***	***(-2.360)***

Table 8: Out of Sample Investment Performance as a Function of In Sample Alpha T-Stat Differences: Augmented Model Comparisons

This table summarizes the outer quartile differential (top minus bottom quartile) out-of-sample average monthly α estimates, representing a long position in a portfolio of top quartile ranked mutual funds and a short position in bottom ranked quartile mutual funds. Mutual funds were ranked into quartiles by the difference in statistical significance between in-sample α estimates of the indicated Augmented Benchmark Model and the common 4 factor model. The differenced t-statistics were estimated monthly from 1980 through 2010 using 36 month regression windows. The Active Peer Benchmark may be either equally weighted or cap weighted across its contained mutual funds as indicated. The augmented benchmark models shown include the equally weighted active peer benchmark (Panel A), the cap weighted active peer benchmark (Panel B), the passive index model where a group's corresponding 'best-fit' index according to the group's active share is used in place of the active peer benchmark (Panel C), and the liquidity index model where the Pastor Stambaugh traded liquidity measure is used in place of the active peer benchmark (Panel D). Every month, funds were then sorted into quartiles by their α t-statistic difference. The table presents average out-of-sample performance over the subsequent 12 months as well as time-series t-statistics of alphas over all (overlapping) 12-month periods. T-statistics were adjusted to allow for overlapping data. Results show 12 month performance when regressed on either the Active Peer Benchmark Model or the APB-adjusted alpha model as indicated. Numbers in bold are statistically significant at a 90% confidence level, those bold with one asterisk (*) are significant at the 95% level and those bold with two asterisks (**) are significant at the 99% level. T-statistics are shown in parenthesis.

Panel A: Equal Weighted Active Peer Benchmark Results

	Russell 1000	Russell 1000 Growth	Russell 1000 Value	Russell Midcap	Russell Midcap Growth	Russell Midcap Value	Russell 2000 2000	Russell 2000 Growth	Russell 2000 Value
T-Stat Difference Weighted Portfolio	**0.07%****	**0.13%****	**0.07%**	**0.22%***	**0.13%***	0.05%	**0.14%***	0.11%	**0.12%****
APB model	***(2.681)***	***(2.692)***	***(1.722)***	***(2.384)***	***(2.155)***	*(0.786)*	***(2.225)***	*(1.584)*	***(2.927)***
T-Stat Difference Weighted Portfolio	**0.08%****	0.06%	0.03%	**0.28%***	**0.14%***	0.00%	**0.16%***	**0.16%****	**0.11%****
APB-adjusted alpha model	***(3.076)***	*(1.070)*	*(0.626)*	***(2.565)***	***(2.174)***	*(0.057)*	***(2.593)***	***(2.764)***	***(2.808)***
Equal Weighted Portfolio	**0.04%**	**0.08%***	0.06%	0.20%	**0.12%***	0.06%	**0.13%****	0.10%	**0.08%**
APB model	***(1.939)***	***(2.166)***	*(1.477)*	*(1.612)*	***(2.183)***	*(0.778)*	***(3.224)***	*(1.588)*	***(1.877)***
Equal Weighted Portfolio	**0.04%***	0.02%	0.03%	**0.24%**	**0.13%***	0.03%	**0.16%****	**0.14%***	**0.07%***
APB-adjusted alpha model	***(2.246)***	*(0.402)*	*(0.616)*	***(1.855)***	***(2.529)***	*(0.397)*	***(3.984)***	***(2.465)***	***(2.002)***

Panel B: Cap Weighted Active Peer Benchmark Results

	Russell 1000	Russell 1000 Growth	Russell 1000 Value	Russell Midcap	Russell Midcap Growth	Russell Midcap Value	Russell 2000 2000	Russell 2000 Growth	Russell 2000 Value
T-Stat Difference Weighted Portfolio	**0.09%****	**0.13%****	**0.04%**	**0.20%****	**0.15%**	0.04%	**0.16%***	0.10%	**0.10%**
APB model	***(3.081)***	***(2.942)***	***(1.729)***	***(3.196)***	***(1.841)***	*(0.522)*	***(2.510)***	*(1.466)*	***(1.952)***
T-Stat Difference Weighted Portfolio	**0.07%****	**0.07%**	0.03%	**0.26%****	**0.19%***	-0.03%	**0.15%***	**0.12%**	**0.11%***
APB-adjusted alpha model	***(2.752)***	***(1.833)***	*(1.379)*	***(2.897)***	***(2.371)***	*(-0.299)*	***(2.006)***	***(1.897)***	***(2.411)***
Equal Weighted Portfolio	**0.04%**	**0.06%**	**0.04%**	**0.17%**	**0.11%**	0.05%	**0.15%****	0.08%	**0.08%***
APB model	***(1.890)***	***(1.746)***	***(1.845)***	***(1.917)***	***(1.802)***	*(0.635)*	***(3.417)***	*(1.403)*	***(2.072)***
Equal Weighted Portfolio	0.03%	0.01%	**0.05%***	**0.20%***	**0.15%***	0.00%	**0.13%****	0.10%	0.06%
APB-adjusted alpha model	*(1.567)*	*(0.205)*	***(2.012)***	***(2.049)***	***(2.578)***	*(-0.012)*	***(2.708)***	*(1.590)*	*(1.558)*

Panel C: Passive Index Benchmark Results

	Russell 1000	Russell 1000 Growth	Russell 1000 Value	Russell Midcap	Russell Midcap Growth	Russell Midcap Value	Russell 2000 2000	Russell 2000 Growth	Russell 2000 Value
T-Stat Difference Weighted Portfolio	-0.05%	-0.01%	0.02%	-0.05%	0.04%	-0.04%	0.07%	**0.12%***	0.04%
Passive Index Regression	*(-1.517)*	*(-0.095)*	*(0.277)*	*(-0.902)*	*(0.629)*	*(-0.684)*	*(0.997)*	***(2.282)***	*(0.376)*
T-Stat Difference Weighted Portfolio	**0.37%****	**0.34%**	0.08%	0.06%	0.10%	0.04%	**0.14%***	**0.11%***	0.10%
α Adj Passive Idx Regr	***(4.036)***	***(1.933)***	*(1.048)*	*(1.055)*	*(1.336)*	*(0.538)*	***(2.477)***	***(2.012)***	*(1.167)*
Equal Weighted Portfolio	-0.05%	-0.01%	0.02%	-0.06%	0.02%	-0.06%	0.00%	**0.11%***	0.04%
Passive Index Regression	*(-1.503)*	*(-0.201)*	*(0.290)*	*(-0.803)*	*(0.389)*	*(-1.034)*	*(-0.043)*	***(2.285)***	*(0.558)*
Equal Weighted Portfolio	**0.31%****	**0.29%***	0.06%	0.05%	0.08%	0.00%	0.05%	**0.10%***	0.08%
α Adj Passive Idx Regr	***(3.984)***	***(2.134)***	*(0.860)*	*(0.783)*	*(1.118)*	*(-0.047)*	*(0.683)*	***(1.985)***	*(1.001)*

Panel D: Pastor Stambaugh Liquidity Index Benchmark Results

	Russell 1000	Russell 1000 Growth	Russell 1000 Value	Russell Midcap	Russell Midcap Growth	Russell Midcap Value	Russell 2000 2000	Russell 2000 Growth	Russell 2000 Value
T-Stat Difference Weighted Portfolio	0.01%	0.04%	0.03%	-0.01%	**0.16%**	0.10%	0.00%	-0.03%	-0.01%
Liquidity Index Regression	*(0.193)*	*(0.532)*	*(0.312)*	*(-0.214)*	***(1.861)***	*(1.091)*	*(-0.047)*	*(-0.500)*	*(-0.165)*
T-Stat Difference Weighted Portfolio	0.01%	0.05%	0.03%	0.00%	**0.16%**	0.11%	-0.02%	-0.03%	-0.01%
α Adj Liquidity Idx Regr	*(0.468)*	*(0.798)*	*(0.239)*	*(0.031)*	***(1.895)***	*(1.463)*	*(-0.270)*	*(-0.388)*	*(-0.181)*
Equal Weighted Portfolio	0.01%	0.05%	0.00%	0.01%	0.10%	0.10%	0.02%	-0.01%	-0.02%
Liquidity Index Regression	*(0.581)*	*(0.774)*	*(0.046)*	*(0.229)*	*(1.533)*	*(1.192)*	*(0.245)*	*(-0.202)*	*(-0.497)*
Equal Weighted Portfolio	0.02%	0.05%	0.00%	0.03%	0.09%	0.11%	0.02%	0.00%	-0.02%
α Adj Liquidity Idx Regr	*(0.896)*	*(0.985)*	*(-0.042)*	*(0.512)*	*(1.485)*	*(1.515)*	*(0.188)*	*(-0.064)*	*(-0.444)*

Table 9: Out of Sample Investment Performance as a Function of In Sample Alpha T-Stat Differences: Augmented Passive Index or Liquidity Index Differences

This table presents the out-of-sample average monthly α estimates from portfolios of mutual funds, ranked into quartiles by the difference in statistical significance between in-sample α estimates of the Active Peer Benchmark Model and the Augmented Passive Benchmark Model in Panel A, and the Augmented Liquidity Benchmark Model in Panel B. The quartile portfolios of funds were weighted as indicated in each respective row heading across all contained funds. The Active Peer Benchmark is equally weighted across the mutual funds it contains. The Augmented Passive Benchmark is simply each group's corresponding market index, used in place of the Active Peer Benchmark. The differenced t-statistics were estimated monthly from 1980 through 2010 using 36 month regression windows. Every month, funds were then sorted into quartiles by their α t-statistic difference. The table presents average out-of-sample performance over the subsequent 12 months as well as time-series t-statistics of alphas over all (overlapping) 12-month periods. T-statistics were adjusted to allow for overlapping data. Numbers in bold are statistically significant at a 90% confidence level, those bold with one asterisk (*) are significant at the 95% level and those bold with two asterisks (**) are significant at the 99% level. T-statistics are shown in parenthesis.

Panel A: Active Peer Benchmark Model (Equal Weighted Benchmark) minus the Passive Benchmark Model)

	Russell 1000	Russell 1000 Growth	Russell 1000 Value	Russell Midcap	Russell Midcap Growth	Russell Midcap Value	Russell 2000 2000	Russell 2000 Growth	Russell 2000 Value
Panel A: Active Peer Benchmark Model Minus the Augmented Passive Benchmark Model									
T-Stat Difference Weighted Portfolio	**0.06%**	0.02%	-0.07%	**0.10%***	0.06%	0.05%	-0.19%	-0.02%	0.01%
APB Model	***(1.852)***	*(0.263)*	*(-1.023)*	***(2.457)***	*(0.973)*	*(0.609)*	*(-1.654)*	*(-0.151)*	*(0.175)*
T-Stat Difference Weighted Portfolio	**0.07%***	0.06%	-0.03%	**0.09%***	0.08%	0.00%	-0.15%	0.03%	0.03%
APB-adjusted alpha model	***(2.263)***	*(0.704)*	*(-0.437)*	***(1.991)***	*(1.470)*	*(-0.041)*	*(-1.372)*	*(0.265)*	*(0.299)*
Equal Weighted Portfolio	0.05%	0.03%	-0.03%	**0.15%****	0.06%	0.06%	-0.08%	0.01%	0.01%
APB Model	*(1.587)*	*(0.434)*	*(-0.476)*	***(2.923)***	*(1.198)*	*(1.021)*	*(-0.797)*	*(0.121)*	*(0.173)*
Equal Weighted Portfolio	**0.05%**	0.05%	-0.01%	**0.12%***	0.06%	0.06%	-0.05%	0.05%	0.01%
APB-adjusted alpha model	***(1.778)***	*(0.706)*	*(-0.143)*	***(2.175)***	*(1.390)*	*(1.035)*	*(-0.496)*	*(0.628)*	*(0.154)*

Panel B: Active Peer Benchmark Model Minus the Augmented Liquidity Benchmark Model

	Russell 1000	Russell 1000 Growth	Russell 1000 Value	Russell Midcap	Russell Midcap Growth	Russell Midcap Value	Russell 2000 2000	Russell 2000 Growth	Russell 2000 Value
T-Stat Difference Weighted Portfolio	**0.07%***	**0.14%****	0.07%	**0.18%****	**0.10%**	-0.01%	**0.16%****	0.05%	0.07%
APB Model	***(2.325)***	***(2.811)***	*(1.323)*	***(3.678)***	***(1.919)***	*(-0.146)*	***(2.733)***	*(0.582)*	*(1.255)*
T-Stat Difference Weighted Portfolio	**0.07%***	0.06%	0.06%	**0.22%****	0.09%	-0.04%	**0.18%****	**0.11%**	0.05%
APB-adjusted alpha model	***(2.232)***	*(1.286)*	*(1.031)*	***(3.599)***	*(1.648)*	*(-0.493)*	***(3.526)***	***(1.980)***	*(0.881)*
Equal Weighted Portfolio	0.03%	**0.07%***	0.06%	**0.15%***	**0.08%**	-0.01%	**0.15%****	0.09%	0.06%
APB Model	*(1.214)*	***(2.046)***	*(1.500)*	***(2.492)***	***(1.968)***	*(-0.210)*	***(6.608)***	*(1.439)*	*(1.097)*
Equal Weighted Portfolio	0.03%	0.02%	0.07%	**0.15%***	**0.08%**	0.00%	**0.20%****	**0.12%***	0.05%
APB-adjusted alpha model	*(1.414)*	*(0.732)*	*(1.554)*	***(2.451)***	***(1.760)***	*(-0.038)*	***(8.682)***	***(2.409)***	*(0.960)*

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