**Portfolios of actively managed mutual funds**

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**Abstract**

Investors should focus on the performance of portfolios of active funds, not on the performance of individual active funds. Taking this portfolio approach with respect to active U.S. equity mutual funds, I build an optimized portfolio of funds that subsequently has low idiosyncratic volatility and a large, positive, statistically significant alpha. Consistent with a Berk and Green (2004) equilibrium, that outperformance is short lived if the optimized portfolio is not rebalanced often, as investors allocate substantial capital—in excess of that expected based on past performance—to the funds with a large weight in the optimized portfolio.

KEYWORDS
active management, alpha, mutual fund, portfolio

JEL CLASSIFICATION
G11, G14, G23

## 1 INTRODUCTION

The primary question for investors considering active management is whether choosing active management can be expected to result in better outcomes than equivalent passive investments. Analysis of this question tends to focus on the performance of individual actively managed funds. If, however, investors can use multiple funds at the same time, the analysis should not focus on actively managed funds as individuals. It should instead focus on portfolios of actively managed funds. Because of variation in strategies, ideas, and trading behavior, a portfolio of actively managed funds should offer a better risk-reward trade-off compared to an individual actively managed fund in the same way a portfolio of stocks offers a better trade-off compared to an individual stock.

I consider this portfolio approach with respect to actively managed U.S. equity mutual funds. I am not the first to form portfolios of mutual funds—forming equal-weight portfolios to facilitate the study of the average fund within a group is common practice, and Pastor and Stambaugh (2002) and Avramov and Wermers (2006) both develop methods to optimally weight fund portfolios; however, my portfolios are unique because they are constructed using a novel process derived from a fundamental concept. Treynor and Black's (1973) model of how active managers should build a portfolio of securities provides the goal of maximizing alpha relative to idiosyncratic volatility (i.e., maximizing the information ratio). The same idea should apply for an investor building a portfolio of funds. Therefore, I weight my portfolio of actively managed funds such that the expected information ratio is maximized.

Applying this approach to a group of funds with recent outperformance results in an optimally weighted portfolio that subsequently performs well by any metric. Compared to an equal-weight portfolio of the same funds, the optimal portfolio has a higher total return with less total risk and less idiosyncratic volatility. Although the conventional wisdom is that individual fund performance does not persist, the alpha of the optimal portfolio is positive, economically large, and statistically significant.[1] The Fama-French four-factor alpha of the optimal portfolio is 2.40% per year ($t$-stat = 2.24), compared to −0.45% per year ($t$-stat = −0.33) for the equal-weight portfolio. The performance of the optimal portfolio holds across many different models, including those with nontraditional factors (e.g., the profitability and investment factors of Fama & French, 2015) and those built using investible factors (e.g., the four- and seven-factor models of Cremers, Petajisto, & Zitzewitz, 2012). Although consistent with evidence of performance persistence shown in studies such as Bollen and Busse (2005), Busse and Irvine (2006), and Hunter, Kandel, Kandel, and Wermers (2014), these results differ from previous studies by demonstrating how a standard optimization technique can lead to a portfolio of mutual funds with persistent performance despite the performance of the average mutual fund in the portfolio not persisting.

The significantly greater alpha of the optimal portfolio relative to that of the equal-weight portfolio implies that the optimal portfolio weights contain information about future fund performance. After controlling for past performance and a set of activeness measures already known to have predictive power (e.g., active share from Cremers & Petajisto, 2009; selectivity from Amihud & Goyenko, 2013), I find that the optimal weights contain information about future fund performance that is unique. A 1% increase in a fund's optimal weight predicts an increase in Fama-French four-factor alpha of 0.18% per year ($t$-stat = 2.07).

This predictive power should not lead investors to abandon a portfolio approach to use the optimal weights to identify an individual fund to purchase. Even if an investor cannot purchase the full optimal portfolio, there is still significant value in the low residual correlations of funds with

[1] See Cremers, Fulkerson, and Riley (2019) for a full discussion of the literature on fund performance persistence.

large optimal weights. An equal-weight portfolio of the funds with the largest optimal weights has the same expected alpha as a randomly selected individual fund from that portfolio, but the equal-weight portfolio has an idiosyncratic volatility that is 40% less than the average idiosyncratic volatility of the individual funds.

All of the results discussed above use optimal weights recalculated every month. The resulting optimal portfolio has an average monthly turnover of 47%. Investors could encounter difficulties (e.g., short-term trading fees) in actually capturing that portfolio's performance, even though performance holds in a no-load sample. Those difficulties are important because although the idiosyncratic volatility of the optimal portfolio remains low without recalculating the optimal weights, the positive alpha persists for only about one quarter. Starting in the fourth month after portfolio formation, the alpha is, on a consistent basis, statistically indistinguishable from zero. Put another way, a given construction of the optimal portfolio generates a positive alpha in the short run and an alpha equivalent to a passive investment in the long run.

Despite the optimal portfolio not delivering a positive alpha indefinitely, I still find investors respond strongly to the total value implied by a large optimal weight. The average net flow in the month after portfolio formation is 0.71% greater ($t$-stat = 4.65) for funds with an optimal weight above 1% compared to funds with an optimal weight greater than zero but less than 1%. After controlling for past performance and other fund characteristics, that difference remains large at 0.65% ($t$-stat = 4.47) or about $9.5 million per month for an average-size fund. It is unclear if investors directly respond to the optimal weight or if the optimal weight proxies for investors' more general use of a synthesis of alpha, idiosyncratic volatility, and residual correlation. Either way, the results indicate a substantial flow of assets toward funds expected to have short-run outperformance.

The response of investors to the information in the optimal weights and the long-run performance of the optimal portfolio are consistent with the Berk and Green (2004) model of the mutual fund industry (henceforth, the BG model). A skilled manager cannot deliver a persistent positive alpha after fees in the BG model because investors will increase the assets of a skilled manager's fund until diseconomies of scale offset that manager's skill. In that context, a fund having a large optimal weight signals to investors that the manager of the fund has skill in excess of the fund's current assets. Because of that mismatch between skill and assets, the fund can be expected to outperform in the short run. In the long run, however, the fund's assets will increase to a level commensurate with the skill of the fund's manager and outperformance will cease. Then again, my results suggest a significant delay in some funds reaching their equilibrium, which is not posited by the BG model. Conjecturally, such a delay could exist in practice if fund investors collectively underreact to the information in the optimal weights or if, following a logic patterned after the resolution of the Grossman and Stiglitz (1980) paradox, sophisticated fund investors must be compensated for their research costs.[2]

There has been widespread debate about the validity of the BG model.[3] My results cannot prove that the model is correct, but they do provide an empirical situation in general alignment with the model's predictions. Of further importance, to the extent my results support the BG model, they also support the alternative measure of fund manager skill proposed in Berk and van Binsbergen (2015). The BG model suggests that analyses of fund manager skill should not consider whether net fund alphas persist because net fund alphas are not determined by fund manager skill.

[2] Collective underreaction requires that fund investors' deviations from rationality be correlated. Such irrationality has been documented in, for example, Cooper, Gulen, and Rau (2005), Sensoy (2009), and Del Guercio and Reuter (2014).
[3] Particularly, there has been wide testing of the BG model's assumption of diseconomies of scale. For example, Chen, Hong, Huang, and Kubik (2004) and Pastor, Stambaugh, and Taylor (2015) find evidence for diseconomies, whereas Adams, Hayunga, and Mansi (2018) and Phillips, Pukthuanthong, and Rau (2018) find evidence against diseconomies.

They are determined by competition between investors. Berk and van Binsbergen (2015) consequently contend that such analyses should instead consider whether the value a fund extracts from capital markets persists.

Related to that point, my results contribute more commonly to the ongoing debate on fund manager skill. Studies including Carhart (1997) and Fama and French (2010) claim that there is little evidence of skill, whereas studies including Kosowski, Timmermann, Wermers, and White (2006) and Barras, Scaillet, and Wermers (2010) claim that there is meaningful evidence of skill. Recent work has shown that the methods used in notable prior work often lack power and are sensitive to sample and time period, which suggests a need for additional analysis.[4] My results support the claim for skilled fund managers. Within the BG model framework, my results require skilled fund managers. If that framework is rejected, the ability of the optimal weights to predict future performance still implies that some fund managers have skill in the same way that previously identified predictive measures imply skill.[5]

Pastor and Stambaugh (2002) and Avramov and Wermers (2006) both develop methods to optimally weight mutual fund portfolios. Beyond differences in weighting methods, my study differs from theirs in several important ways. We all find the optimal weights have substantial value, but I consider a number of novel analyses with respect to the performance of the optimal portfolio.[6] I show that using the capital asset pricing model (CAPM) to form the optimal portfolio produces the best outcomes, regardless of the model an investor uses to evaluate subsequent

[4] Examples among that recent work include Andrikogiannopoulou and Papakonstantinou (2019), Harvey and Liu (2018, 2020), and Riley (2019).

[5] Many predictive measures have been identified. Beyond those previously mentioned, see, for example, the measures in Kacperczyk, Sialm, and Zheng (2008) and Cremers and Pareek (2016).

[6] The large, positive alpha of my optimal portfolio is particularly notable because Kosowski, Timmermann, Wermers, and White (2006) and Riley (2019), among others, show a downward trend over time in the percentage of mutual funds with a true (i.e., not due to luck) positive net alpha. My sample period (2000–2016) is almost entirely after the end of Pastor and Stambaugh's (2002) and Avramov and Wermers's (2006) sample periods (1998 and 2002).

performance. My set of potential evaluation models includes the standard models (e.g., the CAPM and the Fama-French four-factor), models that add nontraditional factors (e.g., Frazzini & Pedersen, 2014; Asness, Frazzini, & Pedersen, 2019) to the standard models, and models with significant separation from the standard models (e.g., Cremers, Petajisto, & Zitzewitz, 2012; Hou, Xue, & Zhang, 2015). My study also covers many broader topics that have not been previously addressed. I assess whether the information in the optimal weights is unique relative to other predictive measures, how the optimal portfolio performs in the long run, and the relation between the optimal weights and fund flows.

The explanation for the optimal weights' predictive power with respect to alpha remains uncertain and is left for future research; however, the inputs used to calculate the optimal weights suggest a possibility. Funds with large optimal weights tend to have a combination of a high alpha, a low idiosyncratic volatility, and a low residual correlation with other active funds. Hoberg, Kumar, and Prabhala (2018) show that funds with past outperformance tend to perform better in the future when they face less competition, and the combination of strong performance and strategy distinctiveness that leads to a nontrivial optimal weight is consistent with that result. Most notably, residual correlation can serve as a proxy for the level of competition by measuring the extent to which a given fund employs a strategy similar to other funds. Capturing a predictive relation is not the nominal goal of the optimization, but the value of the optimal weights is increased by the fact that it does, regardless of the explanation.

Although constraints could limit the ability of investors to hold the exact optimal portfolio I first described, the general concept remains valid. Comparisons between individual actively managed funds and equivalent passive investments are flawed from an investor's perspective. For an investor, the correct comparison is between a portfolio of actively managed funds and equivalent passive investments. Even if constrained to annual rebalancing of the optimal portfolio, an investor can expect short-run outperformance with no long-run underperformance. Ignoring the benefits of a portfolio approach understates the value of active management.

## 2 DATA AND METHODS

### 2.1 Selecting the mutual fund sample

My sample of actively managed U.S. equity mutual funds is built using the Center for Research in Security Prices (CRSP) Survivor-Bias-Free U.S. Mutual Fund database. I exclude any fund that CRSP identifies as an index fund, exchange-traded fund, or variable annuity; use funds whose Lipper codes identify them as following a traditional long-only U.S. equity strategy; and require that funds invest at least 70% of their assets in common equities. I search fund names for key terms to further remove any index funds and any funds not following a traditional long-only U.S. equity strategy. To address the Evans (2010) incubation bias, I exclude a fund from the sample until it is at least two years old and until it first reaches at least $20 million in assets.

All my analysis is conducted at the fund level. I collapse multiple share classes of a fund into a single fund using the Wharton Financial Institution Center Numbers (WFICNs) available in the MFLINKS database. Fund assets are the sum of the assets across all share classes of a fund. All other fund values, including return, are asset weighted averages of the share class values. I show in the Internet Appendix that dropping all share classes with a front- or back-end load or creating separate samples based on distribution channel (identified following Sun, 2014, and Del Guercio & Reuter, 2014) produces results consistent with those presented in the paper.

### 2.2 Measuring risk-adjusted returns

I measure the risk-adjusted returns of funds using several different factor models with the same basic design:

$$r_t - rf_t = \alpha + \sum_{i=1}^{N} \beta_i * f_{i,t} + \varepsilon_t \quad (1)$$

where $r_t$ is the return for a given fund in period *t*, $rf_t$ is the risk-free rate in period *t*, α is the risk-adjusted return (or alpha) of the fund, and $\varepsilon_t$ is the residual of the fund in period *t*. I use net fund returns to capture alpha from the prospective of investors. Throughout the paper, I estimate the model using daily returns but report annualized values to ease interpretation.

$f_{i,t}$ is the return on pricing factor *i* in period *t*. I consider many different sets of pricing factors to help protect my analysis from the potential biases of any individual model. Sets include the following:

(1) Sharpe (1964) and Lintner (1965) CAPM
(2) Fama and French (1993) three-factor model (FF3)
(3) FF3 model augmented with the Carhart (1997) momentum factor (FF4)
(4) FF4 model augmented with the Fama and French (2015) profitability and investment factors (FF6)
(5) FF4 model augmented with the Stambaugh and Yuan (2017) mispricing factors (FFSY)
(6) FF4 model augmented with the Frazzini and Pedersen (2014) "betting against beta" factor and the Asness, Frazzini, and Pedersen (2019) "quality minus junk" factor (FFAQR)
(7) Hou, Xue, and Zhang (2015) four-factor q-model (Q4)
(8) Cremers, Petajisto, and Zitzewitz (2012) four-factor model (CPZ4)
(9) Cremers, Petajisto, and Zitzewitz (2012) seven-factor model (CPZ7)[7]

**2.3 Determining the optimal portfolio**

I determine the optimal portfolio of mutual funds at the beginning of each month. For a given month and factor model, I first use daily returns over the previous 12 months to estimate an alpha and a set of residuals for every fund. Using a 12-month window allows me to capture a fund's recent performance while still generating a large set of residuals. As shown in the Internet

[7] The sources of the daily factor data are as follows: the Fama-French factors are from WRDS and Kenneth French's data library (https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html); the mispricing factors are from Robert Stambaugh's website (http://finance.wharton.upenn.edu/~stambaug/); the "betting against beta" and "quality minus junk" factors are from AQR's website (https://www.aqr.com/Insights/Datasets); and the q-model factors and CPZ model factors are self-calculated using CRSP, Compustat, and Morningstar.

Appendix, alternative windows such as six or 24 months produce similar, albeit somewhat weaker, results.

Using those alpha and residuals, I form the optimal portfolio of funds by calculating the portfolio weights that maximize the expected information ratio (alpha divided by idiosyncratic volatility). This process is equivalent to the textbook example of using the total returns on individual securities to calculate the portfolio weights that maximize the expected Sharpe ratio. I do not assume that the correlations between funds' residuals are zero, as ignoring those correlations has a substantial negative impact on optimal portfolio performance (see Section 4).

At the start of this calculation, I set to zero the weight on any fund not in the top 5% of alpha. The calculation, which is performed using the Stata "ovport" command, is impracticably slow when considering large numbers of funds with commercial hardware and software.[8] Creating a tractable subsample of top-performing funds is a natural choice for an investor trying to build an outperforming portfolio. It is possible that funds with relatively poor performance could improve the optimal portfolio's expected information ratio, but I do not study that possibility in this paper. Using the top 5% is an arbitrary choice, but I show in the Internet Appendix that results for the optimal portfolio are robust to changes in the subsample of top-performing funds (e.g., top 2.5% and top 10%). I also show in the Internet Appendix that filtering on the information ratio, rather than alpha, does not improve the optimal portfolio's performance.

I require that all weights in the optimal portfolio be greater than or equal to zero, and I set the maximum weight on any fund at 10%. Mutual funds cannot be sold short, so allowing negative weights generates a portfolio that cannot be held by an investor. Setting an upper limit on the

[8] The command performs the calculation using a deterministic algorithm that iteratively solves for the constrained optimal weights—a process that proves empirically useful but is not guaranteed to converge to the true solution. Both the code for the command (http://fmwww.bc.edu/RePEc/bocode/o/ovport.ado) and a discussion of the code (https://www.stata.com/meeting/mexico13/abstracts/materials/mex13_dorantes.pdf) are available.

weights forces diversification across funds. The Internet Appendix shows that results for the optimal portfolio are similar using 5% and 15% maximum weights.

I form separate optimal portfolios using the alphas and residuals from each of the factor models discussed previously. However, I focus my attention on the optimal portfolio formed using the CAPM. Relative to the other models, the CAPM makes few assumptions about the factor structure of equity returns, and Section 4.2 shows that those limited assumptions result in better optimal portfolio performance. Furthermore, I show in the Internet Appendix that imposing no factor structure (i.e., using total returns) results in inferior outcomes compared to the CAPM. Unless otherwise indicated, all generic references to the optimal portfolio throughout the paper refer to the CAPM optimal portfolio.

Daily returns for mutual funds are not available in CRSP for a full calendar year until 1999, so I begin calculating optimal weights at the beginning of January 2000. My sample ends in December 2016. All else equal, a longer sample would be preferable. As shown in the Internet Appendix, though, switching to monthly returns to calculate alphas and residuals has a severe negative impact on optimal portfolio performance. That outcome is consistent with Busse and Irvine (2006, 2285) who "find that daily fund returns dominate the more common monthly returns in the context of forecasting future performance" and Busse (1999, 1015) who notes that "monthly data cannot fully capture the higher frequency dynamics that characterize the day-to-day activities of actively managed mutual funds." Empirically, it appears that considering those higher frequency dynamics is essential when constructing the optimal portfolio.

There are 2,298 unique funds during this time period with the average month having 1,244 funds. The CAPM optimal weights have a large month-over-month serial correlation ($\rho = 61.1\%$), but the year-over-year serial correlation is low ($\rho = 3.7\%$). Depending on the factor model used, the average fund has an alpha of between 0.02% ($t$-stat = 0.03) and −0.96% per year ($t$-stat = −3.22).

## 3 OPTIMAL WEIGHTS AND FUND CHARACTERISTICS

Before considering the performance of the CAPM optimal portfolio, I first consider the optimal weights themselves. Figure 1 shows the distribution of the weights in the optimal portfolio for funds in the top 5% of alpha. For context, note that the number of funds in the top 5% of alpha in a given month varies between 51 and 70. Hence, an equal-weight portfolio of those funds has weights of between 1.4% and 2.0% on each fund.

[[Please insert Figure 1 here]]

About 73% of funds have an optimal weight less than 1%. Among those funds, about 87% have an optimal weight less than 0.1%. Put another way, about 64% of funds have an inconsequential weight in the optimal portfolio and another 9% have a near-inconsequential weight. Funds in the top 5% of alpha never have a weight exactly equal to zero, but the weights are effectively zero in many cases.

About 21% of funds have an optimal weight between 1% and 10%, and about 6% have the maximum optimal weight of 10%. The 27% of funds with an optimal weight greater than 1% have an average of 97.3% of the total weight in the optimal portfolio. The optimal portfolio is diversified across funds, although it is significantly more concentrated than an equal-weight portfolio of the funds in the top 5% of alpha. I find in untabulated results that the average Herfindahl-Hirschman Index of the percentage portfolio weights of the equal-weight portfolio is 163, whereas that of the optimal portfolio is 738.

Table 1 compares the funds with an economically meaningful weight in the optimal portfolio to the other funds in the top 5% of alpha. To facilitate that comparison, I sort the funds in the top 5% of alpha into groups depending on whether their weight in the optimal portfolio is above or below 1%. In my discussion of the table, I refer to the funds with a weight above 1% as having a nontrivial weight and those with a weight below 1% as having a trivial weight.

[[Please insert Table 1 here]]

Starting with Panel A, funds with a nontrivial weight have an average CAPM alpha over the prior year that is economically and statistically indistinguishable from that of funds with a trivial weight. Given the nature of the optimization, it is not mathematically required but still reasonable to expect that the funds with a nontrivial weight will have a greater CAPM alpha. Nevertheless, that expectation is not met in this univariate sort. Other results are aligned with expectations. The average CAPM idiosyncratic volatility during the prior year is lower for funds with a nontrivial weight. Also lower for funds with a nontrivial weight is the average CAPM residual correlation during the prior year, which I define for a given fund as the average of the correlations between that fund's CAPM residuals and the CAPM residuals of all other funds in the top 5% of alpha. The optimization should favor funds with low idiosyncratic volatility and low residual correlation, and the univariate sort shows that outcome.

Turning to Panel B, funds with a nontrivial weight and those with a trivial weight have about the same average assets and average age. That is, the optimal portfolio does not appear to be tilted toward small, young funds of limited economic importance. Funds with a nontrivial weight have statistically lower average expense ratios and average turnover ratios, but the economic differences are small. The average expense ratios in particular differ by only about four basis points per year.

I use three measures to consider the activeness of the funds. Cremers and Petajisto's (2009) active share is the sum of the absolute differences between a fund's portfolio weights and its benchmark's portfolio weights;[9] Doshi, Elkamhi, and Simutin's (2015) active weight is the sum of the absolute differences between a fund's portfolio weights and the weights of a market cap weighted portfolio of the same securities; and Amihud and Goyenko's (2013) selectivity is one minus the $r^2$ from regressing the previous two years of monthly fund returns against the FF4 model. Fund activeness increases with each measure. The results for the two groups of funds are mixed with respect to activeness: active share is greater for funds with a trivial weight, but active weight and selectivity are greater for funds with a nontrivial weight.

Panel C shows that the two groups have significant differences in style. Regarding market cap, there is greater diversification across categories among funds with a nontrivial weight. Across Lipper's four market cap categories (large, mid, small, and multi cap), the funds with a nontrivial weight have no category with more than 34.0% or less than 19.2% of funds (multi cap and mid cap, respectively). In comparison, the funds with a trivial weight are 46.1% small cap and only 12.2% large cap. Regarding Lipper's valuation categories (value, growth, and blend), the diversification across categories is similar for the two groups, although the funds with a nontrivial weight tend toward blend and those with a trivial weight tend toward growth.

These univariate sorts, while informative, are limited in their ability to capture the relation between a fund's weight in the optimal portfolio and other dimensions of the fund. To better understand the relation, I model the optimal weight as

$$\mathrm{Weight}_{i,t+1} = \gamma + \beta * \mathrm{Performance}_{i,t} + \delta * \mathrm{Characteristics}_{i,t} + \mathrm{Fixed\ Effects} + \varepsilon_{i,t} \qquad (2)$$

where $\mathrm{Weight}_{i,t+1}$ is either the percentage optimal weight of fund *i* in month *t* + 1 or a dummy variable equal to one if that weight is greater than 1%. $\mathrm{Performance}_{i,t}$ is a vector of variables related to the performance of fund *i* over the 12 months ending in month *t*. It includes a fund's

[9] I use minimum active share rather than prospectus active share throughout the paper, but my conclusions hold regardless. I thank Martijn Cremers for providing his active share data (http://activeshare.nd.edu/data/).

alpha, idiosyncratic volatility, and residual correlation (all calculated using the CAPM). $\text{Characteristics}_{i,t}$ is a vector of variables related to the characteristics of fund *i* at the end of month *t*. Assets, age, expense ratio, turnover ratio, and selectivity are included in the vector.[10] Lipper class fixed effects are included in the model to account for style. When using the continuous measure of weight, I estimate the coefficients through a tobit regression with a lower limit of 0% and an upper limit of 10%. When using the binary measure of weight, I estimate the coefficients through a logit regression (with odds ratios reported).[11]

I place two constraints on the estimation sample. First, only the funds in the top 5% of alpha during the prior year are included. The model is designed to identify the dimensions of a fund associated with the optimal weights, not to identify the dimensions associated with being a top-performing fund. Second, only the weights calculated for January of each year are included. The weights are serially correlated, so consistently using the weights from a single month of the year provides a cleaner test (because those weights are calculated from nonoverlapping data). Nonetheless, if a month other than January is used or if all months are used, the key takeaways from the model are the same.

Table 2 shows results for this model. Consistent with the nature of the optimization, a fund's weight in the optimal portfolio increases as alpha increases, idiosyncratic volatility decreases, and residual correlation decreases. Because of differences in their distributions, the relative importance of those variables can be difficult to ascertain from the raw coefficients—a one standard deviation increase in alpha in the full tobit model increases the optimal weight by

[10] Conclusions about fund activeness are the same if active share or active weight is placed in the vector instead of selectivity. Using selectivity allows for a larger sample size because it does not require fund holdings.

[11] When using the tobit model, I cluster the standard errors of the coefficients by year. I do not cluster the standard errors when using the logit model because the fixed effects prevent it. If I drop the fixed effects from the model and cluster by year, the key takeaways are unchanged.

1.75%, whereas one standard deviation decreases in idiosyncratic volatility and residual correlation increase the optimal weight by 1.33% and 1.16%, respectively. Changes in age, expense ratio, and turnover ratio have statistically and economically insignificant impacts on the optimal weight. Selectivity's impact is economically small before accounting for past performance and becomes statistically insignificant after accounting for past performance. The logit model indicates that funds with fewer assets are more likely to have a nontrivial optimal weight, but the tobit model shows no relation between assets and optimal weight. As a whole, the optimal weights primarily appear to be a function of the inputs used to calculate them: alpha, idiosyncratic volatility, and residual correlation.

[[Please insert Table 2 here]]

## 4 THE PERFORMANCE OF THE OPTIMAL PORTFOLIO

### 4.1 The CAPM optimal portfolio

The intention of the CAPM optimal portfolio is to maximize the expected information ratio, not total return. Despite that intention, Table 3 shows that the annualized total return of the optimal portfolio is still larger than that of an equal-weight portfolio of all funds with nonzero weight in the optimal portfolio (i.e., all funds in the top 5% of alpha during the prior year)—10.2% versus 8.8%. The comparison of these portfolios is of particular importance because it speaks to the value added by applying the optimal weights to a given set of funds. The value of the optimal weights cannot be evaluated based on total return alone, though, so Table 3 also shows several other annualized performance measures for those two portfolios. Starting with Panel A, the optimal portfolio has lower total risk accompanying its higher total return. The Sharpe ratio of the optimal portfolio is 36% greater than that of the equal-weight portfolio. The optimal portfolio is less diversified across funds, but the optimal portfolio's CAPM idiosyncratic volatility is still lower than the equal-weight portfolio's (5.5% vs. 8.2%).[12]

[[Please insert Table 3 here]]

Panel B shows the alphas for the optimal portfolio and equal-weight portfolio using the same nine factor models.[13] The results presented in the panel are estimated using the full time series of daily portfolio returns, but I find similar results using monthly portfolio returns (see the Internet Appendix). The *t*-statistics associated with the alphas are also shown and, in this instance, have a unique purpose beyond statistical testing. Rather than estimate the information ratio directly, I use the alpha *t*-statistic as the information ratio. Although the actual information ratio will differ in value from the alpha *t*-statistic, the two measures have the same interpretation when making comparisons between portfolios.[14]

Regardless of the evaluation model, the optimal portfolio performs well in isolation and relative to the equal-weight portfolio. The alpha of the optimal portfolio across all models is economically large, positive, and statistically significant. The average alpha across all models is 3.32% per year—a result that the Internet Appendix shows is almost unchanged after including in each model the Jordan and Riley (2015) LVH (Low Volatility versus High Volatility) factor. Addressing the concern that the factor models are not investible benchmarks (see, e.g., Berk & van Binsbergen, 2015), the index-based models of Cremers, Petajisto, and Zitzewitz (2012) show alphas of 2.46% and 3.05% per year. Compared to the equal-weight portfolio, the optimal portfolio

[12] I find a large difference in idiosyncratic volatility regardless of the measurement model. Averaged across all nine previously discussed factor models, the idiosyncratic volatility of the optimal portfolio is about 22% less than the idiosyncratic volatility of the equal-weight portfolio.
[13] In untabulated results, I find that the optimal portfolio has a positive small cap exposure and a positive momentum exposure that is consistent across all models. The optimal portfolio also has negative exposures to each of the nontraditional factors in the FF6, FFSY, and FFAQR models.
[14] Assuming homoscedasticity, the standard errors for a set of portfolios can be linked to the idiosyncratic volatilities of those portfolios with a single constant if the factor model and time period used for all the portfolios are identical. I use standard errors robust to heteroskedasticity in this paper, but those standard errors are economically indistinguishable from the standard errors calculated assuming homoscedasticity.

has an across-model average alpha that is greater by 2.10% per year (with all individual differences statistically significant). The alpha *t*-statistics of the optimal portfolio are also consistently greater than those of equal-weight portfolio. That difference is due in part to the optimal portfolio's greater alpha, but it is also due in part to the optimal portfolio's lower idiosyncratic volatility. To see this effect, consider the seven models with a positive alpha for both the optimal portfolio and the equal-weight portfolio. In those cases, alpha is greater for the optimal portfolio by an average of 2.7x, while the alpha *t*-statistic is greater by an average of 3.5x.

As mentioned earlier, when calculating the optimal weights, accounting for the correlations between funds' residuals is critical. To demonstrate this point, Panel C repeats Panel B but forms the CAPM optimal portfolio under the assumption that the correlations between funds' residuals are zero. As shown, this alternative CAPM optimal portfolio performs significantly worse, regardless of whether it is considered in isolation or relative to the equal-weight portfolio. Moreover, in untabulated tests, I find that across all evaluation models the alphas for this alternative CAPM optimal portfolio are statistically less than those of the original CAPM optimal portfolio.[15] Consequently, the remainder of my results do not assume zero residual correlations.

Thinking broadly, the results in this section suggest that taking a portfolio approach with respect to actively managed mutual funds produces significant economic benefits. Evaluated using several different measures, the optimal weights lead to a portfolio with strong absolute performance and add substantial value relative to equal weighting.

[15] The original CAPM optimal portfolio is substantially more concentrated than the alternative portfolio. The Herfindahl-Hirschman Index of the portfolio weights of the original portfolio, averaged across all months, is 738, whereas the equivalent for the alternative is only 212. Despite that difference and despite the fact that the funds in the two portfolios have similar optimal-weighted-average idiosyncratic volatilities (averaged across all months and evaluation models, 4.6% for original vs. 4.5% for alternative), the original portfolio still has a lower idiosyncratic volatility (again averaged across all months and evaluation models, 2.3% vs. 2.6%). Hence, the greater diversification that arises from not assuming zero residual correlations more than offsets the greater concentration that also arises from not making that assumption.

## 4.2 Alternative optimal portfolios

There are many factor models available that could be employed to calculate the alphas and residuals used to determine the optimal portfolio. In this section, I consider the performance of optimal portfolios formed using each of the nine previously discussed factor models. I compare the optimal portfolios to each other, and I compare each optimal portfolio to its equivalent equal-weight portfolio.

Table 4 shows multiple measures of alpha for each of the alternative optimal portfolios. As a group, the optimal portfolios perform well, with only 12% of the reported alphas not positive and statistically significant. The insignificant alphas primarily occur when an optimal portfolio formed using a model that includes nontraditional factors (FF6, FFSY, and FFAQR) is evaluated using one of the standard Fama-French models (FF3 and FF4). Compared to the optimal portfolios formed using other models, the CAPM optimal portfolio has strong performance regardless of the evaluation model. The CAPM optimal portfolio has the largest alpha using each evaluation model, and its alpha *t*-statistic is among the top two using six out of nine evaluation models.

[[Please insert Table 4 here]]

Table 5 shows the alphas for equivalent equal-weight portfolios. These portfolios set a baseline so that I can consider the extent to which the optimal weights for a given formation model add value. There is limited evidence that these equal-weight portfolios perform well. Only 40% of the alphas are positive and statistically significant, with most of those alphas occurring when the models with nontraditional factors are used to evaluate performance.

[[Please insert Table 5 here]]

In terms of alpha *t*-statistics, a comparison of Table 4 and Table 5 shows that the optimal weights consistently add value relative to equal weighting. In terms of alpha, however, the optimal weights do not consistently add value, with the exception of the CAPM optimal weights. Table 6 shows the differences in alpha between each optimal portfolio and its equivalent equal-weight portfolio. The CAPM optimal portfolio has an economically and statistically greater alpha compared to the CAPM equal-weight portfolio regardless of the evaluation model. Across the other formation models, the average number of statistically significant differences in alpha is only 3.5 out of nine. Relative to other formation models' optimal portfolios, the CAPM optimal portfolio is particularly effective when the evaluation models include nontraditional factors.

[[Please insert Table 6 here]]

Overall, there does not appear to be an obvious benefit to expanding the optimal portfolio formation model beyond a single market risk factor, even if an investor uses a more complex performance evaluation model.

## 5 OPTIMAL WEIGHTS AND SUBSEQUENT FUND PERFORMANCE

The alpha of the CAPM optimal portfolio indicates that the optimal weights contain information about the future performance of individual funds. In this section, I consider the extent to which that information is unique. One goal is to determine whether the predictive power of the optimal weights is driven by the relation between the optimal weights and past performance. A fund must be in the top 5% of CAPM alpha during the prior year to have a nonzero optimal weight, and Section 3 shows a positive relation between CAPM alpha and optimal weight within the top 5%. A further goal is to determine whether the predictive power of the optimal weights is subsumed by a set of activeness measures already known to predict performance. I use the following model to make these determinations:

$$\mathrm{Perf}_{i,t+1} = \gamma + \beta * \mathrm{Alpha}_{i,t} + \delta * \mathrm{Top\ 5\%}_{i,t} + \pi * \mathrm{Alpha}_{i,t} * \mathrm{Top\ 5\%}_{i,t} + \varphi * \mathrm{Weight}_{i,t} + \mu * \mathrm{Active}_{i,t} + \mathrm{Fixed\ Effects} + \varepsilon_{i,t} \quad (3)$$

where $\mathrm{Perf}_{i,t+1}$ is the annualized percentage alpha of fund *i* in month *t* + 1. It is measured using daily returns and each of the nine previously discussed factor models. $\mathrm{Alpha}_{i,t}$ is the annualized percentage alpha of fund *i* measured using daily returns and the CAPM over the 12 months ending in month *t*. Top $5\%_{i,t}$ is a dummy variable equal to one if $\mathrm{Alpha}_{i,t}$ for fund *i* at the end of month *t* is among the top 5%. $\mathrm{Weight}_{i,t}$ is the percentage CAPM optimal weight of fund *i* calculated using daily returns over the 12 months ending in month *t*. $\mathrm{Active}_{i,t}$ is a vector of variables measured at the end of month *t* that are related to the activeness of fund *i*. It includes active share, active weight, and selectivity. Lipper class fixed effects and year-month fixed effects are also included in the model. I estimate the model using the full sample of funds with available data, not just those funds in the top 5% of CAPM alpha.[16]

Table 7 shows the results from this model and indicates that across all evaluation models there is a positive relation between optimal weight and subsequent alpha. The relation is statistically significant in seven out of nine models, and the economic effect is large. A 1% increase in the optimal weight predicts an annualized increase in alpha in the range of 0.11% to 0.34%. Put another way, a fund with the maximum weight in the optimal portfolio (10%) could be expected to outperform a fund with the same style and past alpha but a near-zero optimal weight by 0.09% to 0.28% in the next month. There is some evidence of short-run persistence in alpha, but that persistence does not eliminate the impact of the optimal weights. Likewise, the activeness measures do not subsume the predictive power of the optimal weights.[17]

[[Please insert Table 7 here]]

[16] If the model uses a dummy variable equal to one when $\mathrm{Weight}_{i,t}$ is greater than 1% instead of $\mathrm{Weight}_{i,t}$, if the model is estimated without fixed effects, if the model is estimated using a Fama and Macbeth (1973) regression, if the model is reconfigured to use only funds in the top 5% of CAPM alpha, or if the model includes fund-level controls (e.g., size), my conclusions about the predictive power of the optimal weights are unchanged.

[17] My conclusions are the same if the model is estimated separately using each individual measure of activeness, if the activeness measures are interacted with the dummy variable Top $5\%_{i,t}$, or if the activeness measures are excluded.

Of great importance, this predictive relation should not be taken as an encouragement to abandon a portfolio approach. After seeing the results above, an investor might decide to simply buy a single fund with a large optimal weight. That choice would be a mistake. To demonstrate, consider two options: buying a random fund with the maximum optimal weight (10%) or buying an equal-weight portfolio of all funds with the maximum optimal weight. Both options have the same expected alpha, but as shown below, the portfolio option has substantially less idiosyncratic volatility because it takes advantage of the fact that funds with large optimal weights have relatively low residual correlations.

Table 8 compares the idiosyncratic volatility of an equal-weight portfolio of all funds with the maximum optimal weight to the idiosyncratic volatilities of the individual funds with the maximum optimal weight. Because the group of funds with the maximum optimal weight can change each month, the average of month-by-month estimates of idiosyncratic volatility are reported for the portfolio, and the average of month-by-month averages of idiosyncratic volatility are reported for the individual funds. All reported values are annualized. Using the FF4 model, average idiosyncratic volatility is 4.11% for the individual funds compared to an average of 2.43% for the portfolio. Across all models, the portfolio has an average idiosyncratic volatility that is 40% less than the average for the individual funds. This risk reduction is not difficult to obtain as there are only about four funds with the maximum optimal weight in the average month.

[[Please insert Table 8 here]]

For an investor, buying an equal-weight portfolio of funds with the maximum optimal weight could be a reasonable alternative to the full optimal portfolio. In untabulated analysis, I find that the maximum-weight portfolio has a large, positive, statistically significant alpha across all models. Moreover, those alphas are not meaningfully different from the alphas of the optimal portfolio. Switching from the optimal portfolio to the maximum-weight portfolio does increase idiosyncratic volatility, though. Averaged across all models, the full-period idiosyncratic volatility of the maximum-weight portfolio is about 16% more than that of the optimal portfolio. An investor would have to trade off the benefit of the increased risk reduction of the optimal portfolio against that portfolio's increased formation difficulties. There could be an ideal point somewhere between the optimal portfolio and the maximum-weight portfolio, but regardless of where that point is, a portfolio approach remains superior to buying an individual fund.

## 6 THE LONG-RUN PERFORMANCE OF THE OPTIMAL PORTFOLIO

The results presented to this point have used optimal weights recalculated at the beginning of each month. As a result, all the statements made about the performance of the optimal portfolio so far apply only to the month after formation. Real-world constraints (e.g., short-term trading fees) could prevent investors from recalculating optimal weights and reforming the optimal portfolio every month, especially given the optimal portfolio's high turnover (47% in the average month). I now consider the long-run performance of the optimal portfolio.[18]

Table 9 shows the alpha of the CAPM optimal portfolio in the first month after formation ($t + 1$) and in each of the subsequent 12 months ($t + 2$ through $t + 13$). To keep the time period constant across all months after formation, the year 2000 is dropped from the sample. Without recalculating the optimal weights, the positive and statistically significant alpha of the optimal portfolio persists for about three months. As in Section 4, the alphas are positive and statistically significant across all evaluation models in the first month after formation. In the second and third months after formation, the alphas are still positive across all models, but they are not statistically significant in all instances (five out of nine in the second month and eight out of nine in the third

[18] The turnover for the maximum-weight portfolio described in the previous section is similarly high. The maximum-weight portfolio also has long-run performance like that of the optimal portfolio.

month). After three months, the alphas are statistically indistinguishable from zero regardless of the model. That is, the optimal portfolio cannot be expected to deliver a statistically significant positive alpha every month unless the optimal weights are recalculated at least quarterly.[19]

[[Please insert Table 9 here]]

In untabulated tests, I find that after one quarter the optimal portfolio still outperforms its equivalent equal-weight portfolio. Averaged across all models, the alpha of the optimal portfolio in month $t$ + 13 is 1.89% per year greater than that of the equal-weight portfolio (average $t$-stat = 2.86). Although, over longer periods of time, the alphas of the two portfolios do become statistically indistinguishable from each other. The across-model average idiosyncratic volatility of the optimal portfolio in month $t$ + 13 is 19% less than that of the equal-weight portfolio.[20]

While those results are notable, the value of the optimal weights after one quarter is less certain than before because of the lack of positive alpha for the optimal portfolio after month $t$ + 3. Passive investments should have alphas and idiosyncratic volatilities of near zero. Granting that fact, the model of Glode (2011) does provide a potential reason investors could still prefer the optimal portfolio over passive investments after one quarter. In his model, if the alpha for both options is the same, the costs of idiosyncratic volatility must be considered against the benefits of active managers focusing their "work toward realizing good performance in bad states of the economy, when investors' marginal utility of consumption is high" (Glode, 2011, 557).

## 7 INVESTOR RESPONSE TO THE OPTIMAL WEIGHTS

The alpha of the optimal portfolio does not persist indefinitely without optimal weight recalculation. Investors, however, should still have a strong motivation to buy the funds with large

[19] Using alternative formation models does not meaningfully improve optimal portfolio performance persistence.
[20] Compared to the month $t$ + 1 optimal portfolio, the month $t$ + 13 optimal portfolio has, across the models, an average alpha that is 2.58% per year less (average $t$-stat = −2.34) and an average idiosyncratic volatility that is 11% greater.

optimal weights—whether individually or, ideally, as part of the optimal portfolio. Those funds have alphas that tend to be initially positive and afterward equivalent to passive investments, and those funds offer substantial diversification value.

I use net flows estimated as in Sirri and Tufano (1998) to test whether there is a relation between the optimal weights and investor's capital allocations. Untabulated univariate sorts suggest that there is a positive relation between the optimal weights and subsequent net flows. Among the funds in the top 5% of CAPM alpha during the prior year (i.e., funds with nonzero weight in the optimal portfolio), those with an optimal weight greater than 1% have a net flow of 2.36% in the next month, whereas those with an optimal weight less than 1% have a net flow of only 1.65%. The difference between those values, 0.71% (*t*-stat = 4.65), is equivalent to $11.1 million per month for the average fund in the top 5% of CAPM alpha.

The above results indicate that investors do tend to allocate more capital to funds with large optimal weights, but univariate sorts cannot control for other known determinants of net flows. Therefore, as a proper test, I model the relation between the optimal weights and net flows as

$$\text{Net Flow}_{i,t+1} = \gamma + \beta * \text{Weight}_{i,t} + \delta * \text{Perf}_{i,t} + \pi * \text{Control}_{i,t} + \text{Fixed Effects} + \varepsilon_{i,t} \quad (4)$$

where $\text{Net Flow}_{i,t+1}$ is the percentage net flow of fund *i* in month *t* + 1. $\text{Weight}_{i,t}$ is either the percentage optimal weight of fund *i* calculated using daily returns over the 12 months ending in month *t* or a dummy variable equal to one if that optimal weight is greater than 1%. $\text{Perf}_{i,t}$ is a vector containing piecewise performance variables (Low, Mid, and High) created following Sirri and Tufano (1998) and a dummy variable equal to one if a fund is in the top 5% of performance. Performance is based on funds' CAPM alphas over the 12 months ending in month *t*.[21] $\text{Control}_{i,t}$

[21] I use the CAPM to estimate performance because Barber, Huang, and Odean (2016) and Berk and van Binsbergen (2016) show that the CAPM has the most explanatory power with respect to funds' net flows.

is a vector of control variables for fund *i* measured as of the end of month *t*. It includes assets, age, turnover ratio, expense ratio, selectivity, CAPM beta, and CAPM idiosyncratic volatility. Lipper class fixed effects and year-month fixed effects are also included in the model. I estimate the model using the full sample of funds, including those not in the top 5% of CAPM alpha.[22]

Table 10 shows results from this model. Before accounting for past performance, the optimal weight is a strong proxy for past performance, which makes the true effect difficult to identify. After accounting for past performance, a 1% increase in optimal weight increases net flow by 0.11% in the next month (*t*-stat = 5.09). Analyzed another way, the net flow of a fund with an optimal weight greater than 1% is 0.65% larger in the next month (*t*-stat = 4.47) compared to an otherwise identical fund with an optimal weight less than 1%. That difference is equivalent to about $9.5 million for the average fund in the sample. Although investors could be responding to a more general synthesis of alpha, idiosyncratic volatility, and residual correlation rather than the exact optimal weights I calculate, both interpretations indicate a significant net asset flow toward funds expected to have short-run outperformance.

[[Please insert Table 10 here]]

The positive relation between the optimal weights and net flows points to an explanation for the passive-equivalent long-run performance of the optimal portfolio. In the Berk and Green (2004) model of the mutual fund industry, a skilled manager will be unable to generate a persistent positive net alpha because a skilled manager generating positive net alpha will continue to attract new capital to his/her fund until an equilibrium is reached in which diseconomies of scale offset

[22] I come to the same conclusions about the relation between the optimal weights and net flows if I interact the High performance variable with the top 5% dummy, if I use the raw fund alpha instead of the piecewise measures, if I use the other previously discussed factor models to estimate past performance, or if I reconfigure the model to use only funds in the top 5% of CAPM alpha (or if I include residual correlation in the $\mathrm{Control}_{i,t}$ vector of that model). Likewise, the addition to the model of optimal weights calculated under the assumption that funds' residual correlations are zero does not meaningfully change the relation between the original optimal weights and net flows. The zero-correlation weights themselves have either a weaker relation or no relation with net flows.

the manager's skill. Using that context, a large optimal weight for a fund serves as a signal to investors that the fund's manager has skill in excess of the fund's current assets. Consequently, the fund can be expected to outperform at that moment for its current investors, but as new investors allocate capital to the fund in an attempt to capture that outperformance, diseconomies of scale will begin to offset the fund manager's skill and the fund's outperformance will begin to disappear. I conjecture that full offsetting may not occur instantaneously either because investors collectively underreact to the optimal weight signal or because, following a Grossman and Stiglitz (1980)–style logic, sophisticated investors must be compensated for their research costs. Regardless, a long-run persistent positive net alpha from the optimal portfolio can only be expected if that portfolio is consistently refreshed with funds whose managers have yet to reach their equilibrium.

## 8 CONCLUSION

It is well known that investors should not evaluate individual assets in isolation. They should consider an asset's role in a portfolio. In the same way, investors should not evaluate individual actively managed funds in isolation but instead consider a fund's role in a portfolio. I take this approach with respect to actively managed U.S. equity mutual funds and build an optimal portfolio of those funds that subsequently has low idiosyncratic volatility and a large, positive, statistically significant alpha. Consistent with Berk and Green's (2004) model, funds with a large weight in the optimal portfolio attract substantial capital, and unless the weights of the optimal portfolio are recalculated often, the initial outperformance of the optimal portfolio is short lived. Why the optimal portfolio's weights are able to successfully predict alpha remains uncertain, which suggests a need for further research.

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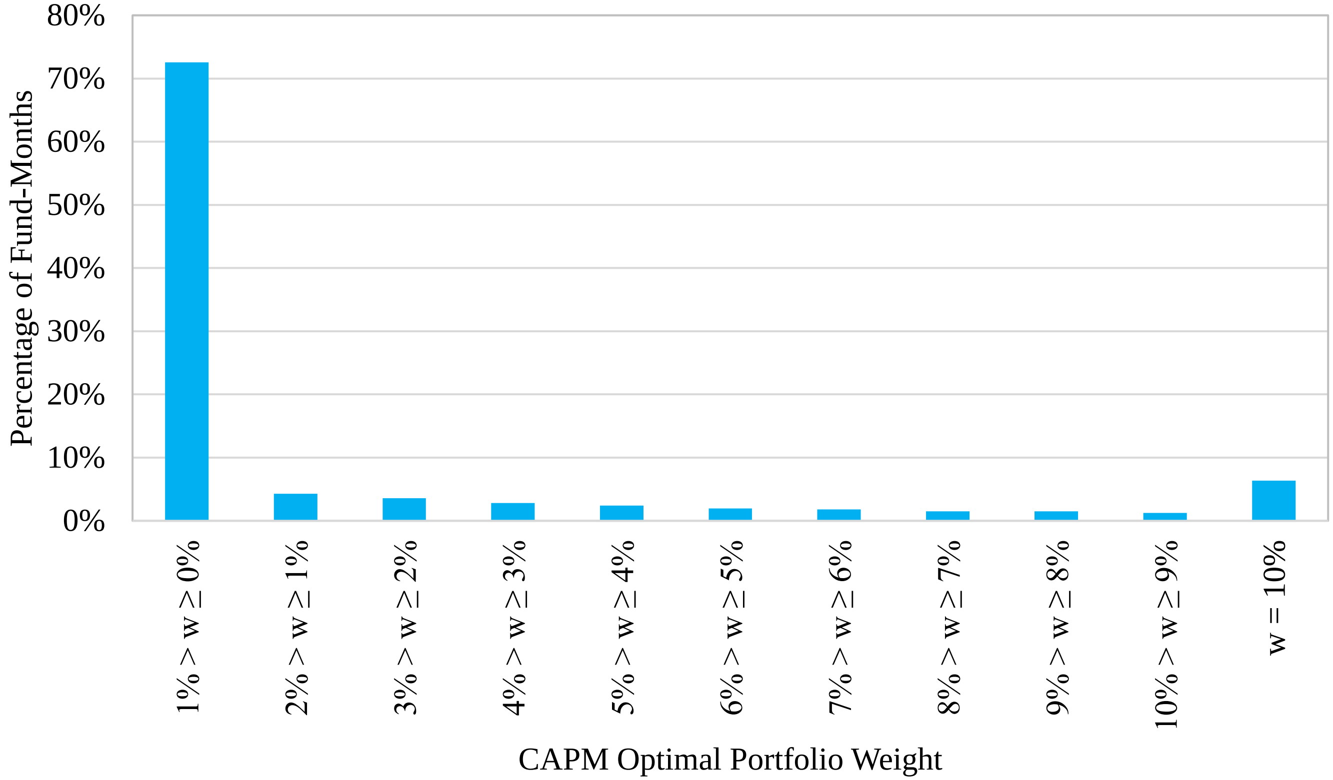
**FIGURE 1** Distribution of the CAPM optimal weights




*Note.* This figure shows the distribution of the portfolio weights for the CAPM optimal portfolio. Only the weights for the funds in the top 5% of CAPM alpha during the prior year are included. The weights are calculated at the beginning of each month for the period January 2000 through December 2016.

**TABLE 1** Past performance, characteristics, and style of top-performing funds

*Panel A. Past performance*

| | All | w ≥ 1% | w < 1% | Difference | *t*-stat |
|---|---|---|---|---|---|
| Total Return | 26.1% | 26.1% | 26.1% | 0.0% | 0.03 |
| Total Volatility | 20.2% | 18.0% | 21.0% | –3.0% | –7.86 |
| CAPM Alpha | 15.2% | 15.6% | 15.1% | 0.5% | 0.84 |
| CAPM Beta | 0.99 | 0.89 | 1.02 | –0.13 | –9.60 |
| CAPM Idio Volatility | 8.3% | 7.0% | 8.7% | –1.7% | –8.96 |
| CAPM Residual Correlation | 33.6% | 21.8% | 38.0% | –16.2% | –20.4 |

*Panel B. Characteristics*

| | All | w ≥ 1% | w < 1% | Difference | *t*-stat |
|---|---|---|---|---|---|
| Size (billions of $) | 1.44 | 1.50 | 1.41 | 0.09 | 0.56 |
| Age (years) | 14.6 | 14.8 | 14.5 | 0.3 | 0.54 |
| Expense Ratio | 1.28% | 1.25% | 1.29% | –0.04% | –1.89 |
| Turnover Ratio | 84.4% | 76.8% | 87.3% | –10.5% | –2.82 |
| Active Share | 85.4% | 83.3% | 86.1% | –2.8% | –4.57 |
| Active Weight | 38.0% | 41.2% | 36.8% | 4.4% | 7.02 |
| Selectivity | 11.9% | 13.2% | 11.4% | 1.8% | 3.89 |

*Panel C. Style*

| | All | w ≥ 1% | w < 1% | Difference | *t*-stat |
|---|---|---|---|---|---|
| FF4 SMB | 0.37 | 0.19 | 0.43 | –0.24 | –13.3 |
| FF4 HML | 0.09 | 0.08 | 0.09 | –0.01 | –0.80 |
| Large Cap | 15.3% | 23.7% | 12.2% | 11.5% | 6.08 |
| Mid Cap | 22.8% | 19.2% | 24.2% | –5.0% | –2.42 |
| Small Cap | 40.0% | 23.1% | 46.1% | –23.0% | –8.49 |
| Multi Cap | 21.9% | 34.0% | 17.5% | 16.5% | 7.03 |
| Value | 30.6% | 30.9% | 30.4% | 0.5% | 0.21 |
| Growth | 38.9% | 29.6% | 42.3% | –12.7% | –4.79 |
| Blend | 30.5% | 39.4% | 27.3% | 12.1% | 5.11 |

*Note.* This table shows summary statistics for funds that were the top 5% of CAPM alpha during the prior year. Means are reported for the full sample of those funds and for subsamples sorted by whether a fund's weight in the optimal portfolio is above or below 1%. The differences between the values for the subsamples are also reported along with *t*-statistics associated with tests of whether the differences are statistically distinguishable from zero. The *t*-statistics are calculated using standard errors clustered by fund and year-month. Panel A reports annualized performance measures calculated during the prior year. Panel B reports fund characteristics. Panel C reports fund style, including factor exposures during the prior year and style classifications (from Lipper class codes).

**TABLE 2** CAPM optimal weight as a function of past performance, characteristics, and style

| Estimation method | Tobit | | | Logit | | |
|---|---|---|---|---|---|---|
| Dependent variable | CAPM optimal weight | | | Weight ≥ 1% dummy | | |
| Alpha | 0.13 | | 0.14 | 1.14 | | 1.14 |
| | [5.36] | | [6.24] | [9.72] | | [9.65] |
| Idio Vol | –0.27 | | –0.27 | 0.75 | | 0.73 |
| | [–3.40] | | [–3.49] | [–7.13] | | [–7.56] |
| Residual Correlation | –0.05 | | –0.06 | 0.93 | | 0.93 |
| | [–5.67] | | [–5.96] | [–11.10] | | [–10.69] |
| Assets | | 0.07 | –0.03 | | 0.90 | 0.83 |
| | | [0.94] | [–0.42] | | [–2.28] | [–3.41] |
| Age | | –0.16 | 0.05 | | 0.94 | 1.04 |
| | | [–0.92] | [0.44] | | [–0.48] | [0.32] |
| Expense Ratio | | 0.38 | 0.19 | | 1.04 | 1.02 |
| | | [1.04] | [0.62] | | [0.18] | [0.08] |
| Turnover Ratio | | 0.00 | 0.00 | | 1.00 | 1.00 |
| | | [–0.57] | [–1.02] | | [–0.48] | [–0.09] |
| Selectivity | | 0.02 | –0.02 | | 1.03 | 1.01 |
| | | [1.48] | [–0.89] | | [3.21] | [0.66] |
| Style Fixed Effects | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 1,070 | 1,070 | 1,070 | 1,070 | 1,070 | 1,070 |

*Note.* This table reports results from the following model:

$$\text{Weight}_{i,t+1} = \gamma + \beta * \text{Performance}_{i,t} + \delta * \text{Characteristics}_{i,t} + \text{Fixed Effects} + \varepsilon_{i,t}$$

where $\text{Weight}_{i,t+1}$ is either the percentage CAPM optimal weight of fund *i* in month *t* + 1 or a dummy variable equal to one if that weight is greater than 1%. A tobit regression with a lower limit of 0% and an upper limit of 10% is used to estimate the model when using the continuous measure of weight. A logit regression is used to estimate the model when using the binary measure of weight. The coefficients reported for the logit regression are odds ratios. $\text{Performance}_{i,t}$ is a vector of variables related to the performance of fund *i* over the 12 months ending in month *t* and includes alpha, idiosyncratic volatility, and residual correlation (all calculated using the CAPM). $\text{Characteristics}_{i,t}$ is a vector of variables related to characteristics of fund *i* as of the end of month *t* and includes assets, age, expense ratio, turnover, and selectivity. Lipper class fixed effects are included in the model. Only the funds in the top 5% of CAPM alpha over the prior year and only the weights calculated for use in January of each year are included in the sample. *t*-statistics are in square brackets below each reported coefficient.

**TABLE 3** The performance of the CAPM optimal portfolio

*Panel A. Standard performance evaluation measures*

| | CAPM equal-weight portfolio | CAPM optimal portfolio |
|---|---|---|
| Average Return | 8.8% | 10.2% |
| Geometric Return | 6.6% | 8.7% |
| Standard Deviation | 21.9% | 18.9% |
| Beta | 1.02 | 0.91 |
| CAPM Idio Volatility | 8.2% | 5.5% |
| Sharpe Ratio | 0.33 | 0.45 |
| Treynor Ratio | 7.0% | 9.4% |

*Panel B. Factor model alphas*

| | Evaluation model | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | CAPM | FF3 | FF4 | FF6 | FFSY | FFAQR | Q4 | CPZ4 | CPZ7 |
| Optimal | 3.90 | 3.14 | 2.40 | 3.76 | 3.42 | 4.27 | 3.47 | 3.05 | 2.46 |
| | [2.94] | [2.71] | [2.24] | [3.71] | [3.32] | [4.27] | [3.04] | [2.62] | [2.55] |
| Equal Weight | 1.97 | 0.66 | –0.45 | 2.20 | 1.52 | 2.89 | 1.52 | 0.66 | –0.07 |
| | [1.00] | [0.43] | [–0.33] | [1.82] | [1.18] | [2.36] | [1.00] | [0.47] | [–0.06] |
| Difference | 1.93 | 2.47 | 2.85 | 1.56 | 1.90 | 1.38 | 1.95 | 2.39 | 2.53 |
| | [1.90] | [2.96] | [3.53] | [2.10] | [2.40] | [1.78] | [2.31] | [3.22] | [3.55] |

*Panel C. Factor model alphas—zero residual correlations*

| | Evaluation model | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | CAPM | FF3 | FF4 | FF6 | FFSY | FFAQR | Q4 | CPZ4 | CPZ7 |
| Optimal | 2.48 | 1.33 | 0.24 | 2.41 | 1.79 | 3.04 | 1.90 | 1.19 | 0.46 |
| | [1.39] | [0.93] | [0.18] | [2.09] | [1.47] | [2.63] | [1.32] | [0.89] | [0.43] |
| Equal Weight | 1.97 | 0.66 | –0.45 | 2.20 | 1.52 | 2.89 | 1.52 | 0.66 | –0.07 |
| | [1.00] | [0.43] | [–0.33] | [1.82] | [1.18] | [2.36] | [1.00] | [0.47] | [–0.06] |
| Difference | 0.51 | 0.67 | 0.69 | 0.21 | 0.26 | 0.15 | 0.37 | 0.53 | 0.53 |
| | [1.45] | [2.23] | [2.27] | [0.73] | [0.89] | [0.49] | [1.25] | [1.89] | [1.88] |

*Note.* This table shows performance measures for the CAPM optimal portfolio and an equal-weight portfolio of the funds in the top 5% of CAPM alpha during the prior year. Each measure is calculated over the period January 2000 through December 2016 using daily returns, but each measure is annualized in the table to ease interpretation. Panel A shows standard performance evaluation measures for the portfolios. Panel B shows percentage alphas for the portfolios estimated using nine different models. The models include the capital asset pricing model (CAPM), the Fama and French three-factor model (FF3), the FF3 model augmented with a momentum factor (FF4), the FF4 model augmented with the profitability and investment factors (FF6), the FF4 model augmented with the mispricing factors (FFSY), the FF4 model augmented with the "betting against beta" factor and the "quality minus junk" factor (FFAQR), the Hou-Xue-Zhang four-factor q-model (Q4), and the Cremers-Petajisto-Zitzewitz four- and seven-factor models (CPZ4 and CPZ7). *t*-statistics are in square brackets below each measure of alpha. Panel C repeats Panel B but during portfolio formation, assumes zero correlations between funds' residuals.

**TABLE 4** Performance of optimal portfolios formed using different factor models

| | | Evaluation model | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | | CAPM | FF3 | FF4 | FF6 | FFSY | FFAQR | Q4 | CPZ4 | CPZ7 |
| Formation model | CAPM | 3.90 | 3.14 | 2.40 | 3.76 | 3.42 | 4.27 | 3.47 | 3.05 | 2.46 |
| | | [2.94] | [2.71] | [2.24] | [3.71] | [3.32] | [4.27] | [3.04] | [2.62] | [2.55] |
| | FF3 | 2.96 | 1.84 | 1.71 | 2.80 | 2.94 | 3.00 | 2.59 | 2.48 | 2.23 |
| | | [2.51] | [2.33] | [2.17] | [3.79] | [4.05] | [3.97] | [3.24] | [2.98] | [3.01] |
| | FF4 | 2.79 | 1.68 | 1.62 | 2.42 | 2.51 | 2.44 | 2.21 | 2.31 | 2.14 |
| | | [2.54] | [2.31] | [2.21] | [3.45] | [3.61] | [3.42] | [2.99] | [2.90] | [3.01] |
| | FF6 | 1.25 | 0.40 | 0.48 | 2.27 | 2.15 | 2.22 | 1.57 | 1.25 | 1.24 |
| | | [0.98] | [0.45] | [0.55] | [2.97] | [2.74] | [2.69] | [1.82] | [1.40] | [1.64] |
| | FFSY | 2.17 | 1.09 | 1.08 | 2.41 | 2.60 | 2.45 | 2.01 | 1.85 | 1.74 |
| | | [1.77] | [1.34] | [1.31] | [3.19] | [3.52] | [3.10] | [2.50] | [2.13] | [2.29] |
| | FFAQR | 2.04 | 0.95 | 0.96 | 2.18 | 2.35 | 2.38 | 1.87 | 1.65 | 1.51 |
| | | [1.71] | [1.16] | [1.18] | [2.86] | [3.28] | [3.13] | [2.36] | [1.86] | [2.05] |
| | Q4 | 2.72 | 1.61 | 1.34 | 3.13 | 2.82 | 3.34 | 2.59 | 2.21 | 1.83 |
| | | [2.11] | [1.65] | [1.39] | [3.65] | [3.13] | [3.75] | [2.76] | [2.15] | [2.07] |
| | CPZ4 | 3.84 | 2.38 | 1.88 | 2.56 | 2.14 | 2.63 | 2.37 | 2.62 | 2.34 |
| | | [3.06] | [2.86] | [2.42] | [3.39] | [2.76] | [3.46] | [2.81] | [3.07] | [3.13] |
| | CPZ7 | 3.00 | 1.69 | 1.46 | 2.33 | 2.06 | 2.55 | 2.09 | 2.18 | 1.75 |
| | | [2.58] | [2.35] | [2.06] | [3.42] | [2.99] | [3.78] | [2.83] | [2.78] | [2.98] |

*Note*. This table shows annualized percentage alphas for optimal portfolios of funds. The funds included in the portfolios are those in the top 5% of alpha during the prior year. The "Formation Model" is the model used to calculate the prior year alphas and residuals, which are used to identify the top 5% and to calculate the optimal weights. The "Evaluation Model" is the model used to measure the alphas of the resulting optimal portfolios. The models and time period are the same as those described in Table 3. *t*-statistics are in square brackets below each measure of alpha.

**TABLE 5** Performance of equal-weight portfolios formed using different factor models

| | | Evaluation model | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | | CAPM | FF3 | FF4 | FF6 | FFSY | FFAQR | Q4 | CPZ4 | CPZ7 |
| Formation model | CAPM | 1.97 | 0.66 | –0.45 | 2.20 | 1.52 | 2.89 | 1.52 | 0.66 | –0.07 |
| | | [1.00] | [0.43] | [–0.33] | [1.82] | [1.18] | [2.36] | [1.00] | [0.47] | [–0.06] |
| | FF3 | 0.37 | –0.07 | –0.14 | 2.74 | 2.94 | 2.86 | 1.84 | 0.77 | 0.52 |
| | | [0.21] | [–0.05] | [–0.10] | [2.36] | [2.57] | [2.25] | [1.41] | [0.59] | [0.49] |
| | FF4 | 0.66 | 0.09 | 0.19 | 2.68 | 2.65 | 2.74 | 1.76 | 1.02 | 1.03 |
| | | [0.41] | [0.07] | [0.15] | [2.57] | [2.51] | [2.45] | [1.50] | [0.87] | [1.05] |
| | FF6 | –0.96 | –1.11 | –0.76 | 2.67 | 2.14 | 2.51 | 1.21 | 0.05 | 0.26 |
| | | [–0.53] | [–0.81] | [–0.56] | [2.49] | [1.83] | [2.04] | [0.93] | [0.04] | [0.27] |
| | FFSY | –0.45 | –0.98 | –0.75 | 2.32 | 2.28 | 2.38 | 1.19 | 0.11 | 0.11 |
| | | [–0.25] | [–0.75] | [–0.57] | [2.16] | [2.09] | [2.00] | [0.97] | [0.09] | [0.11] |
| | FFAQR | –1.01 | –1.35 | –1.08 | 1.75 | 1.91 | 1.92 | 0.67 | –0.36 | –0.40 |
| | | [–0.57] | [–1.01] | [–0.81] | [1.54] | [1.77] | [1.60] | [0.53] | [–0.28] | [–0.40] |
| | Q4 | 1.20 | 0.49 | 0.26 | 3.58 | 2.77 | 3.64 | 2.47 | 1.26 | 0.86 |
| | | [0.67] | [0.35] | [0.19] | [3.21] | [2.22] | [2.94] | [1.90] | [0.94] | [0.82] |
| | CPZ4 | 3.03 | 1.77 | 1.18 | 2.98 | 2.20 | 3.32 | 2.34 | 2.07 | 1.81 |
| | | [1.95] | [1.68] | [1.19] | [3.37] | [2.31] | [3.72] | [2.16] | [1.94] | [2.14] |
| | CPZ7 | 1.81 | 0.68 | 0.60 | 2.44 | 2.25 | 2.77 | 1.79 | 1.43 | 1.41 |
| | | [1.21] | [0.70] | [0.62] | [2.80] | [2.57] | [3.14] | [1.84] | [1.42] | [1.84] |

*Note.* This table shows annualized percentage alphas for equal-weight portfolios of funds. The funds included in the portfolios are those in the top 5% of alpha during the prior year. The "Formation Model" is the model used to calculate the prior year alphas. The "Evaluation Model" is the model used to measure the alphas of the resulting equal-weight portfolios. The models and time period are the same as those described in Table 3. *t*-statistics are in square brackets below each measure of alpha.

**TABLE 6** Difference in performance between the optimal and equal-weight portfolios formed using different factor models

| | | Evaluation model | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | | CAPM | FF3 | FF4 | FF6 | FFSY | FFAQR | Q4 | CPZ4 | CPZ7 |
| Formation model | CAPM | 1.93 | 2.47 | 2.85 | 1.56 | 1.90 | 1.38 | 1.95 | 2.39 | 2.53 |
| | | [1.90] | [2.96] | [3.53] | [2.10] | [2.40] | [1.78] | [2.31] | [3.22] | [3.55] |
| | FF3 | 2.59 | 1.91 | 1.85 | 0.06 | 0.01 | 0.14 | 0.75 | 1.72 | 1.70 |
| | | [2.53] | [2.09] | [2.00] | [0.07] | [0.01] | [0.16] | [0.88] | [2.10] | [2.33] |
| | FF4 | 2.13 | 1.59 | 1.44 | –0.26 | –0.15 | –0.30 | 0.44 | 1.28 | 1.11 |
| | | [2.29] | [1.92] | [1.73] | [–0.37] | [–0.20] | [–0.40] | [0.57] | [1.76] | [1.69] |
| | FF6 | 2.21 | 1.51 | 1.24 | –0.40 | 0.01 | –0.29 | 0.36 | 1.19 | 0.98 |
| | | [2.46] | [1.93] | [1.61] | [–0.60] | [0.02] | [–0.41] | [0.49] | [1.76] | [1.70] |
| | FFSY | 2.63 | 2.07 | 1.83 | 0.08 | 0.31 | 0.07 | 0.82 | 1.73 | 1.63 |
| | | [2.87] | [2.55] | [2.27] | [0.12] | [0.44] | [0.09] | [1.09] | [2.44] | [2.67] |
| | FFAQR | 3.04 | 2.30 | 2.04 | 0.43 | 0.45 | 0.46 | 1.20 | 2.00 | 1.91 |
| | | [3.16] | [2.76] | [2.48] | [0.60] | [0.62] | [0.59] | [1.51] | [2.76] | [2.98] |
| | Q4 | 1.52 | 1.12 | 1.08 | –0.45 | 0.05 | –0.30 | 0.12 | 0.95 | 0.97 |
| | | [1.77] | [1.48] | [1.43] | [–0.69] | [0.08] | [–0.42] | [0.17] | [1.41] | [1.65] |
| | CPZ4 | 0.81 | 0.61 | 0.70 | –0.41 | –0.06 | –0.69 | 0.03 | 0.55 | 0.54 |
| | | [1.26] | [1.05] | [1.20] | [–0.81] | [–0.11] | [–1.34] | [0.05] | [1.02] | [1.12] |
| | CPZ7 | 1.19 | 1.01 | 0.86 | –0.11 | –0.19 | –0.22 | 0.30 | 0.74 | 0.33 |
| | | [1.87] | [1.79] | [1.52] | [–0.22] | [–0.37] | [–0.42] | [0.55] | [1.43] | [0.68] |

*Note*. This table shows annualized percentage alphas for portfolios long an optimal portfolio from Table 4 and short the matching equal-weight portfolio from Table 5. The "Formation Model" is the model used to form the optimal portfolio and the equal-weight portfolio. The "Evaluation Model" is the model used to measure the alphas of the resulting long/short portfolios. The models and time period are the same as those described in Table 3. *t*-statistics are in square brackets below each measure of alpha.

**TABLE 7** Future performance as a function of CAPM optimal weight

| Dependent perf | CAPM | FF3 | FF4 | FF6 | FFSY | FFAQR | Q4 | CPZ4 | CPZ7 |
|---|---|---|---|---|---|---|---|---|---|
| Alpha | 0.18 | 0.25 | 0.15 | 0.15 | 0.15 | 0.14 | 0.16 | 0.13 | 0.14 |
| | [0.86] | [3.38] | [2.43] | [3.05] | [2.97] | [2.31] | [1.89] | [3.34] | [3.79] |
| Top 5% Dummy | –0.69 | –3.07 | –3.06 | –2.28 | –2.77 | –3.19 | –0.24 | –1.45 | –1.36 |
| | [–0.13] | [–2.71] | [–2.79] | [–2.77] | [–2.43] | [–3.11] | [–0.14] | [–1.34] | [–1.34] |
| Alpha x Top 5% | –0.06 | 0.09 | 0.13 | 0.12 | 0.13 | 0.16 | –0.01 | 0.02 | 0.03 |
| | [–0.25] | [1.42] | [2.35] | [2.13] | [2.00] | [3.17] | [–0.12] | [0.31] | [0.54] |
| Weight | 0.34 | 0.12 | 0.18 | 0.11 | 0.15 | 0.18 | 0.20 | 0.31 | 0.21 |
| | [2.53] | [1.14] | [2.07] | [1.35] | [1.83] | [1.75] | [1.95] | [4.04] | [2.50] |
| Active Share | 0.00 | –0.03 | 0.00 | 0.02 | 0.01 | 0.03 | –0.01 | 0.00 | 0.00 |
| | [–0.05] | [–1.58] | [0.04] | [1.28] | [0.75] | [1.74] | [–0.51] | [0.19] | [–0.15] |
| Active Weight | 0.03 | 0.00 | 0.00 | 0.01 | 0.01 | 0.02 | 0.01 | 0.00 | 0.01 |
| | [1.10] | [0.32] | [0.09] | [1.24] | [0.42] | [1.12] | [0.81] | [0.47] | [1.20] |
| Selectivity | 0.15 | 0.03 | 0.00 | –0.03 | –0.01 | 0.00 | 0.04 | 0.06 | 0.06 |
| | [2.41] | [0.67] | [0.00] | [–1.17] | [–0.33] | [–0.02] | [1.06] | [1.41] | [1.83] |
| Fixed Effects | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 213,799 | 213,799 | 213,799 | 213,799 | 213,799 | 213,799 | 213,799 | 213,799 | 213,799 |

*Note*. This table shows results from the following model:

$$\text{Perf}_{i,t+1} = \gamma + \beta * \text{Alpha}_{i,t} + \delta * \text{Top 5\%}_{i,t} + \pi * \text{Alpha}_{i,t} * \text{Top 5\%}_{i,t} + \varphi * \text{Weight}_{i,t} + \mu * \text{Active}_{i,t} + \text{Fixed Effects} + \varepsilon_{i,t}$$

where $\text{Perf}_{i,t+1}$ is the annualized percentage alpha of fund *i* in month *t* + 1. It is estimated from daily returns using each of the models described in Table 3. $\text{Alpha}_{i,t}$ is the annualized percentage alpha of fund *i* measured using the CAPM and daily returns over the 12 months ending in month *t*. $\text{Top 5\%}_{i,t}$ is a dummy variable equal to one if $\text{Alpha}_{i,t}$ for fund *i* is among the top 5% across all funds at the end of month *t*. $\text{Weight}_{i,t}$ is the percentage CAPM optimal weight of fund *i* calculated using daily returns over the 12 months ending in month *t*. $\text{Active}_{i,t}$ is a vector of variables related to the activeness of fund *i* at the end of month *t*. It includes active share, active weight, and selectivity. The full sample of funds with values available for all three measures of activeness is used. Lipper class fixed effects and year-month fixed effects are included in the model. *t*-statistics calculated from standard errors clustered by fund and year-month are reported below the coefficients in square brackets.

**TABLE 8** Idiosyncratic volatility of the funds with the maximum CAPM optimal weight

| | Evaluation model | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | CAPM | FF3 | FF4 | FF6 | FFSY | FFAQR | Q4 | CPZ4 | CPZ7 |
| Portfolio | 3.75 | 2.70 | 2.43 | 2.16 | 2.18 | 2.16 | 2.65 | 2.49 | 1.98 |
| | [17.2] | [24.3] | [24.5] | [24.2] | [24.2] | [25.1] | [24.2] | [23.3] | [24.2] |
| Individual Funds | 5.57 | 4.46 | 4.11 | 3.70 | 3.71 | 3.72 | 4.30 | 4.06 | 3.41 |
| | [19.9] | [23.2] | [23.0] | [22.9] | [23.0] | [23.1] | [23.8] | [22.8] | [23.0] |
| Difference | –1.83 | –1.76 | –1.68 | –1.54 | –1.53 | –1.56 | –1.65 | –1.57 | –1.42 |
| | [–19.9] | [–17.2] | [–17.4] | [–17.4] | [–17.9] | [–17.0] | [–17.6] | [–17.6] | [–17.2] |

*Note.* This table reports average annualized idiosyncratic volatilities in percent for an equal-weight portfolio of funds with the maximum weight in the CAPM optimal portfolio (10%) and for the individual funds with the maximum weight. For the portfolio, idiosyncratic volatility is estimated every year-month using daily returns. The reported value in the table is the average of those monthly values. For the individual funds with the maximum weight, idiosyncratic volatility is first estimated every fund-year-month using daily returns. The idiosyncratic volatilities for a given year-month are then averaged across the funds. The reported value in the table is the average of those monthly averages. The difference between the portfolio-level and the fund-level results is also reported. The models and time period that are used to estimate the idiosyncratic volatilities are the same as those described in Table 3. *t*-statistics associated with a test of whether a given value is different from zero are reported below each value in square brackets.

**TABLE 9** Long-run performance of the CAPM optimal portfolio

| | Evaluation model | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | CAPM | FF3 | FF4 | FF6 | FFSY | FFAQR | Q4 | CPZ4 | CPZ7 |
| *t* + 1 | 3.31 | 2.60 | 2.24 | 2.19 | 2.28 | 2.70 | 2.37 | 2.83 | 2.03 |
| | [3.49] | [2.99] | [2.74] | [2.70] | [2.89] | [3.34] | [2.76] | [3.29] | [2.79] |
| *t* + 2 | 2.19 | 1.47 | 1.12 | 1.22 | 1.33 | 1.65 | 1.30 | 1.73 | 1.01 |
| | [2.28] | [1.69] | [1.36] | [1.49] | [1.65] | [2.04] | [1.51] | [2.00] | [1.36] |
| *t* + 3 | 2.37 | 1.70 | 1.43 | 1.74 | 1.85 | 2.22 | 1.72 | 2.05 | 1.40 |
| | [2.43] | [1.90] | [1.64] | [2.05] | [2.25] | [2.62] | [1.97] | [2.25] | [1.76] |
| *t* + 4 | 1.41 | 0.82 | 0.58 | 0.92 | 1.12 | 1.40 | 0.92 | 1.17 | 0.50 |
| | [1.42] | [0.90] | [0.65] | [1.05] | [1.34] | [1.61] | [1.02] | [1.25] | [0.62] |
| *t* + 5 | 0.24 | –0.25 | –0.42 | 0.03 | 0.29 | 0.40 | –0.01 | 0.14 | –0.49 |
| | [0.24] | [–0.27] | [–0.45] | [0.03] | [0.33] | [0.44] | [–0.01] | [0.14] | [–0.58] |
| *t* + 6 | 0.17 | –0.28 | –0.34 | 0.26 | 0.62 | 0.50 | 0.13 | 0.22 | –0.31 |
| | [0.16] | [–0.29] | [–0.34] | [0.27] | [0.69] | [0.52] | [0.14] | [0.22] | [–0.34] |
| *t* + 7 | 0.16 | –0.31 | –0.27 | 0.27 | 0.64 | 0.57 | 0.14 | 0.29 | –0.24 |
| | [0.16] | [–0.32] | [–0.28] | [0.29] | [0.73] | [0.61] | [0.15] | [0.29] | [–0.28] |
| *t* + 8 | 0.22 | –0.23 | –0.14 | 0.35 | 0.68 | 0.64 | 0.25 | 0.40 | –0.07 |
| | [0.22] | [–0.25] | [–0.15] | [0.40] | [0.80] | [0.71] | [0.27] | [0.42] | [–0.09] |
| *t* + 9 | –0.07 | –0.51 | –0.39 | 0.23 | 0.49 | 0.31 | 0.04 | 0.16 | –0.29 |
| | [–0.06] | [–0.55] | [–0.41] | [0.25] | [0.57] | [0.33] | [0.05] | [0.16] | [–0.34] |
| *t* + 10 | 0.15 | –0.33 | –0.15 | 0.41 | 0.59 | 0.53 | 0.27 | 0.40 | –0.05 |
| | [0.15] | [–0.36] | [–0.17] | [0.46] | [0.70] | [0.59] | [0.30] | [0.42] | [–0.06] |
| *t* + 11 | –0.11 | –0.59 | –0.31 | 0.38 | 0.60 | 0.49 | 0.20 | 0.25 | –0.08 |
| | [–0.11] | [–0.61] | [–0.33] | [0.41] | [0.68] | [0.52] | [0.21] | [0.26] | [–0.10] |
| *t* + 12 | –0.70 | –1.18 | –0.87 | –0.08 | 0.13 | –0.06 | –0.31 | –0.28 | –0.55 |
| | [–0.66] | [–1.22] | [–0.92] | [–0.09] | [0.15] | [–0.07] | [–0.33] | [–0.28] | [–0.65] |
| *t* + 13 | –0.47 | –0.94 | –0.59 | 0.38 | 0.65 | 0.27 | 0.08 | 0.04 | –0.09 |
| | [–0.44] | [–0.96] | [–0.63] | [0.43] | [0.78] | [0.29] | [0.08] | [0.04] | [–0.11] |

*Note***.** This table shows annualized percentage alphas for the CAPM optimal portfolio estimated using nine different models. The models used are the same as in Table 3. The time period is January 2001 through December 2016. Alpha is calculated in the first month after optimal portfolio formation ($t + 1$) and in each of the subsequent 12 months ($t + 2$ through $t + 13$). $t$-statistics are in square brackets below each measure of alpha.

**TABLE 10** Net flows as a function of CAPM optimal weight

| Dependent variable | Net flow | | | | | |
|---|---|---|---|---|---|---|
| Low Performance | 0.05 | 0.05 | | 0.05 | | 0.05 |
| | [16.61] | [16.21] | | [16.28] | | [16.25] |
| Mid Performance | 0.02 | 0.02 | | 0.02 | | 0.02 |
| | [17.46] | [18.83] | | [18.88] | | [18.89] |
| High Performance | 0.08 | 0.06 | | 0.06 | | 0.06 |
| | [19.55] | [14.22] | | [14.11] | | [14.11] |
| Top 5% Dummy | | 0.55 | | 0.38 | | 0.38 |
| | | [7.04] | | [4.58] | | [4.57] |
| Weight | | | 0.37 | 0.11 | | |
| | | | [16.35] | [5.09] | | |
| Weight ≥ 1% | | | | | 2.57 | 0.65 |
| | | | | | [17.77] | [4.47] |
| Controls | Yes | Yes | Yes | Yes | Yes | Yes |
| Fixed Effects | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 244,111 | 244,111 | 244,111 | 244,111 | 244,111 | 244,111 |

*Note.* This table shows results from the following model:

$$\text{Net Flow}_{i,t+1} = \gamma + \beta * \text{Weight}_{i,t} + \delta * \text{Perf}_{i,t} + \pi * \text{Control}_{i,t} + \text{Fixed Effects} + \varepsilon_{i,t}$$

where $\text{Net Flow}_{i,t+1}$ is the percentage net flow of fund *i* in month *t* + 1. $\text{Weight}_{i,t}$ is either the percentage CAPM optimal weight of fund *i* calculated over the 12 months ending in month *t* (Weight) or a dummy variable equal to one if that weight is greater than 1% (Weight ≥ 1%). $\text{Perf}_{i,t}$ is a vector that includes piecewise performance variables (Low, Mid, and High) created following Sirri and Tufano (1998) and a dummy variable equal to one if a fund is in the top 5% of performance. Performance is based on CAPM alpha measured using daily returns over the 12 months ending in month *t*. $\text{Control}_{i,t}$ is a vector of control variables for fund *i* as of the end of month *t*. It includes assets, age, turnover ratio, expense ratio, selectivity, CAPM beta, and CAPM idiosyncratic volatility. The coefficients associated with the controls are not reported in the table for brevity. Lipper class fixed effects and year-month fixed effects are included in the model. I estimate the model using the full sample of funds, including those not in the top 5% of CAPM alpha. *t*-statistics calculated from standard errors clustered by fund and year-month are reported below the coefficients in square brackets.

**Portfolios of Actively Managed Mutual Funds**
**Internet Appendix**

The goal of this appendix is to document the sensitivity of the performance of the CAPM optimal portfolio to changes in (i) the optimization settings and (ii) portfolio evaluation methods.

To provide a baseline, Table A1 shows the alpha of the original CAPM optimal portfolio estimated using nine different factor models. The performance of that portfolio is compared to the CAPM equal-weight portfolio, which is an equal-weight portfolio of the funds in the top 5% of CAPM alpha during the prior year. As shown, regardless of the evaluation model, the optimal portfolio has a large, positive, statistically significant alpha that is greater than the alpha of the equal-weight portfolio. Further, the alpha *t*-statistics of the optimal portfolio are multiple times those of the equal-weight portfolio.

## IA.1 Optimization settings—Varying the cutoff for top-performing funds

I originally set to zero the optimal weight on any fund not in the top 5% of CAPM alpha during the prior year. In Table A2, I form the CAPM optimal portfolio with that percentage set at either 2.5% or 10%. The results using these alternative cutoffs are similar to the baseline results, although using the 10% cutoff, the difference in alpha between the optimal portfolio and the equal-weight portfolio is not statistically significant on a consistent basis.

## IA.2 Optimization settings—Varying the maximum weight

I originally set the maximum optimal weight for any fund at 10%. In Table A3, I form the CAPM optimal portfolio with the maximum weight set at either 5% or 15%. As a whole, the results using these alternative maximum weights are similar to the baseline results.

## IA.3 Optimization settings—Varying the daily return window

I originally used the previous 12 months of daily returns to calculate the alphas and residuals. In Table A4, I form the CAPM optimal portfolio using either the previous six months of daily returns or the previous 24 months of daily returns.

The optimal portfolio formed using the previous six months of daily returns has large, positive alphas across all evaluation models, but those alphas are not statistically different from the alphas of the equal-weight portfolio. The alpha *t*-statistics for this optimal portfolio are larger than those of the equal-weight portfolio, but overall, these optimal weights add relatively limited value relative to equal weighting.

In comparison, the optimal portfolio formed using the previous 24 months of daily returns has large, positive alphas that are statistically greater than those of equal-weight portfolio across all evaluation models. The alpha *t*-statistics for this optimal portfolio are likewise greater than those of the equal-weight portfolio. Nonetheless, the alphas and alpha *t*-statistics for this optimal portfolio are less than those of the baseline optimal portfolio.

The totality of these results suggests that the optimal weights still have value if a daily return window other than 12 months is used but that the optimal weights have the most value using a 12-month window.

### IA.4 Optimization settings—Using monthly returns instead of daily returns

I originally used daily returns over the previous 12 months to calculate the alphas and residuals. In Table A5, I form the CAPM optimal portfolio using monthly returns over the previous 12, 36, and 60 months.

These optimal portfolios only have alphas that are large, positive, and statistically significant if the evaluation models with nontraditional factors (FF6, FFSY, and FFAQR) are used to evaluate performance and the return window is set at either 12 or 36 months. Optimal portfolio alpha generally decreases as the return window increases. Further, these optimal portfolios only have alphas that are statistically different from the equal-weight portfolios using a 36-month return window. Compared to the baseline, the improvement in the alpha *t*-statistics when switching from the equal-weight portfolios to the optimal portfolios is small.

As shown in Table A6, if the alphas of these optimal portfolios are measured using monthly returns instead of daily returns, the results are similar, except that the statistically significant alphas from the evaluation models with nontraditional factors disappear.

Taken as a whole, these results indicate that using monthly returns to calculate the alphas and residuals fails to produce outcomes similar to those from using daily returns.

### IA.5 Optimization settings—Using no factor model

I originally performed tests that used several different factor models to calculate the alphas and residuals. In Table A7, I form an optimal portfolio using total daily net returns.

This optimal portfolio tends to have a large and positive alpha regardless of the evaluation model, but many of those alphas are statistically insignificant. Moreover, those alphas are statistically different from those of the equal-weight portfolio only in four out of nine cases. Compared to the baseline results, the alpha *t*-statistics of this optimal portfolio are only a modest improvement over those of the equal-weight portfolio.

In short, imposing no model on the returns produces weaker results than using the CAPM.

### IA.6 Optimization settings—Excluding share classes with front- or back-end loads

I originally did not consider when building the sample whether a share class of a mutual fund had a front- or back-end load. In Table A8, I form the CAPM optimal portfolio after excluding from the sample all share classes with such loads. If every share class of a fund has a load, then the fund will drop entirely from the sample. The exclusion of load-based share classes decreases the number of unique funds in the sample from 2,298 to 1,961 (a decrease of about 15%). In general, the results using this alternative sample are slightly weaker than but consistent with the baseline results.

### IA.7 Optimization settings—Separating mutual funds by distribution channel

I originally did not consider the distribution channel of a mutual fund when building the sample. In Table A9, I form the CAPM optimal portfolio using either only direct-sold funds or only broker-sold funds. I first follow Sun (2014) to approximate the distribution channel at the share class level and then follow Del Guercio and Reuter (2014) to aggregate share classes and approximate at the fund level. About 45% of funds in the original sample are direct-sold and about 43% are broker-sold (with the remaining 12% indeterminant). The results for these alternative samples are generally consistent with the baseline results.

### IA.8 Optimization settings—Selection based on the information ratio

I originally selected funds for inclusion in the optimal portfolio based on whether they were in the top 5% of alpha during the previous 12 months. In Table A10, I form the CAPM optimal portfolio after selecting instead the funds in the top 5% of information ratio during the previous 12 months. Among this set of funds, the optimal weights add little value relative to equal weighting—none of the differences in alpha between the optimal portfolio and equal-weight portfolio are statistically significant. Notably, untabulated tests show that the differences in alpha between the baseline optimal portfolio and the information-ratio-based equal-weight portfolio are statistically significant using eight out of the nine evaluation models (the CAPM is the exception).

### IA.9 Portfolio evaluation methods—Performance using monthly returns

In the baseline results, I measured the performance of the CAPM optimal portfolio using daily portfolio returns. Table A11 shows that switching to monthly portfolio returns produces similar results.

### IA.10 Portfolio evaluation methods—Accounting for the LVH factor

In the baseline results, I measured the performance of the CAPM optimal portfolio without accounting for the Jordan and Riley (2015) LVH (Low Volatility versus High Volatility) factor. Table A12 shows that including that factor in each of the evaluation models has only a minor effect on the results. Note that because the LVH factor is only available at a monthly frequency (https://sites.google.com/view/timbriley/home), I estimate the alphas in this table using monthly portfolio returns.

**TABLE A1** Performance of the CAPM optimal portfolio—Base model

| | Evaluation model | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | CAPM | FF3 | FF4 | FF6 | FFSY | FFAQR | Q4 | CPZ4 | CPZ7 |
| Optimal | 3.90 | 3.14 | 2.40 | 3.76 | 3.42 | 4.27 | 3.47 | 3.05 | 2.46 |
| | [2.94] | [2.71] | [2.24] | [3.71] | [3.32] | [4.27] | [3.04] | [2.62] | [2.55] |
| Equal Weight | 1.97 | 0.66 | –0.45 | 2.20 | 1.52 | 2.89 | 1.52 | 0.66 | –0.07 |
| | [1.00] | [0.43] | [–0.33] | [1.82] | [1.18] | [2.36] | [1.00] | [0.47] | [–0.06] |
| Difference | 1.93 | 2.47 | 2.85 | 1.56 | 1.90 | 1.38 | 1.95 | 2.39 | 2.53 |
| | [1.90] | [2.96] | [3.53] | [2.10] | [2.40] | [1.78] | [2.31] | [3.22] | [3.55] |

*Note***.** This table shows alphas from nine different models for the CAPM optimal portfolio and CAPM equal-weight portfolio used in the paper. The difference in alpha between the portfolios is also presented. The models used to estimate alpha include the capital asset pricing model (CAPM), the Fama and French three-factor model (FF3), the FF3 model augmented with a momentum factor (FF4), the FF4 model augmented with the profitability and investment factors (FF6), the FF4 model augmented with the mispricing factors (FFSY), the FF4 model augmented with the "betting against beta" factor and the "quality minus junk" factor (FFAQR), the Hou-Xue-Zhang four-factor q-model (Q4), and the Cremers-Petajisto-Zitzewitz four- and seven-factor models (CPZ4 and CPZ7). Alpha is estimated using daily returns over the period January 2000 through December 2016. To ease interpretation, alpha is annualized and reported in percent. *t*-statistics are in square brackets below each measure of alpha.

**TABLE A2** Performance of the CAPM optimal portfolio—Fund subsample sensitivity

*Panel A. Top 2.5% of CAPM alpha*

| | Evaluation model | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | CAPM | FF3 | FF4 | FF6 | FFSY | FFAQR | Q4 | CPZ4 | CPZ7 |
| Optimal | 3.60 | 2.66 | 1.82 | 3.83 | 3.28 | 4.39 | 3.37 | 2.64 | 1.97 |
| | [2.19] | [1.91] | [1.40] | [3.21] | [2.65] | [3.68] | [2.46] | [1.93] | [1.72] |
| Equal Weight | 1.79 | 0.42 | –0.70 | 2.19 | 1.43 | 3.07 | 1.47 | 0.49 | –0.30 |
| | [0.85] | [0.25] | [–0.46] | [1.64] | [1.01] | [2.28] | [0.90] | [0.32] | [–0.23] |
| Difference | 1.81 | 2.24 | 2.52 | 1.65 | 1.85 | 1.33 | 1.90 | 2.15 | 2.27 |
| | [2.21] | [3.20] | [3.68] | [2.53] | [2.79] | [2.02] | [2.69] | [3.32] | [3.58] |

*Panel B. Top 10% of CAPM alpha*

| | Evaluation model | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | CAPM | FF3 | FF4 | FF6 | FFSY | FFAQR | Q4 | CPZ4 | CPZ7 |
| Optimal | 3.14 | 2.54 | 1.95 | 3.06 | 2.69 | 3.55 | 2.84 | 2.50 | 2.03 |
| | [2.86] | [2.55] | [2.09] | [3.46] | [3.00] | [4.08] | [2.90] | [2.42] | [2.32] |
| Equal Weight | 1.92 | 0.67 | –0.39 | 2.03 | 1.35 | 2.64 | 1.38 | 0.65 | –0.07 |
| | [1.05] | [0.47] | [–0.31] | [1.84] | [1.14] | [2.36] | [0.98] | [0.50] | [–0.07] |
| Difference | 1.22 | 1.87 | 2.34 | 1.03 | 1.34 | 0.91 | 1.45 | 1.85 | 2.10 |
| | [1.10] | [2.13] | [2.82] | [1.36] | [1.69] | [1.17] | [1.63] | [2.43] | [2.98] |

*Note*. This table shows alphas from nine different models for alternative versions of the CAPM optimal portfolio and CAPM equal-weight portfolio. The difference in alpha between the portfolios is also presented. The evaluation models used are the same as those described in Table A1. Alpha is estimated using daily returns over the period January 2000 through December 2016. To ease interpretation, alpha is annualized and reported in percent. *t*-statistics are in square brackets below each measure of alpha. In Panel A, I set the optimal weight on any fund not in the top 2.5% of CAPM alpha during the prior year to zero before I calculate the optimal weights. In Panel B, I set the optimal weight on any fund not in the top 10% of CAPM alpha during the prior year to zero before I calculate the optimal weights.

**TABLE A3** Performance of the CAPM optimal portfolio—Maximum weight sensitivity

*Panel A. Maximum weight of 5%*

| | Evaluation model | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | CAPM | FF3 | FF4 | FF6 | FFSY | FFAQR | Q4 | CPZ4 | CPZ7 |
| Optimal | 3.31 | 2.50 | 1.64 | 3.44 | 2.89 | 3.92 | 2.99 | 2.40 | 1.73 |
| | [2.23] | [1.99] | [1.43] | [3.28] | [2.64] | [3.72] | [2.42] | [1.95] | [1.73] |
| Equal Weight | 1.97 | 0.66 | –0.45 | 2.20 | 1.52 | 2.89 | 1.52 | 0.66 | –0.07 |
| | [1.00] | [0.43] | [–0.33] | [1.82] | [1.18] | [2.36] | [1.00] | [0.47] | [–0.06] |
| Difference | 1.34 | 1.84 | 2.10 | 1.24 | 1.37 | 1.03 | 1.47 | 1.74 | 1.80 |
| | [1.73] | [2.94] | [3.45] | [2.15] | [2.30] | [1.75] | [2.32] | [3.07] | [3.24] |

*Panel B. Maximum weight of 15%*

| | Evaluation model | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | CAPM | FF3 | FF4 | FF6 | FFSY | FFAQR | Q4 | CPZ4 | CPZ7 |
| Optimal | 3.84 | 3.09 | 2.40 | 3.58 | 3.31 | 4.12 | 3.36 | 3.00 | 2.43 |
| | [3.03] | [2.76] | [2.30] | [3.57] | [3.29] | [4.20] | [3.04] | [2.65] | [2.57] |
| Equal Weight | 1.97 | 0.66 | –0.45 | 2.20 | 1.52 | 2.89 | 1.52 | 0.66 | –0.07 |
| | [1.00] | [0.43] | [–0.33] | [1.82] | [1.18] | [2.36] | [1.00] | [0.47] | [–0.06] |
| Difference | 1.87 | 2.43 | 2.86 | 1.38 | 1.79 | 1.23 | 1.84 | 2.34 | 2.50 |
| | [1.65] | [2.62] | [3.20] | [1.70] | [2.06] | [1.45] | [1.97] | [2.86] | [3.20] |

*Note.* This table shows alphas from nine different models for alternative versions of the CAPM optimal portfolio and CAPM equal-weight portfolio. The difference in alpha between the portfolios is also presented. The evaluation models used are the same as those described in Table A1. Alpha is estimated using daily returns over the period January 2000 through December 2016. To ease interpretation, alpha is annualized and reported in percent. *t*-statistics are in square brackets below each measure of alpha. In Panel A, I set the maximum weight for any fund in the optimal portfolio at 5%. In Panel B, I set the maximum weight for any fund in the optimal portfolio at 15%.

**TABLE A4** Performance of the CAPM optimal portfolio—Return window sensitivity

*Panel A. Prior six months*

| | Evaluation model | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | CAPM | FF3 | FF4 | FF6 | FFSY | FFAQR | Q4 | CPZ4 | CPZ7 |
| Optimal | 3.33 | 2.24 | 1.55 | 2.30 | 1.84 | 2.99 | 2.37 | 2.19 | 1.62 |
| | [2.40] | [1.85] | [1.35] | [2.06] | [1.62] | [2.72] | [1.97] | [1.77] | [1.47] |
| Equal Weight | 3.00 | 1.41 | 0.30 | 2.09 | 1.28 | 2.72 | 1.81 | 1.34 | 0.59 |
| | [1.57] | [0.93] | [0.22] | [1.62] | [0.95] | [2.13] | [1.19] | [0.93] | [0.47] |
| Difference | 0.33 | 0.83 | 1.25 | 0.21 | 0.57 | 0.27 | 0.56 | 0.86 | 1.03 |
| | [0.34] | [0.98] | [1.55] | [0.27] | [0.72] | [0.34] | [0.66] | [1.11] | [1.40] |

*Panel B. Prior 24 months*

| | Evaluation model | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | CAPM | FF3 | FF4 | FF6 | FFSY | FFAQR | Q4 | CPZ4 | CPZ7 |
| Optimal | 2.07 | 1.42 | 1.20 | 1.29 | 1.43 | 1.73 | 1.40 | 1.76 | 1.10 |
| | [2.32] | [1.74] | [1.49] | [1.61] | [1.86] | [2.19] | [1.71] | [2.09] | [1.57] |
| Equal Weight | 0.24 | –0.88 | –1.17 | –0.21 | 0.01 | 0.16 | –0.52 | –0.24 | –0.77 |
| | [0.18] | [–0.84] | [–1.14] | [–0.22] | [0.01] | [0.16] | [–0.49] | [–0.24] | [–0.94] |
| Difference | 1.83 | 2.30 | 2.36 | 1.50 | 1.43 | 1.58 | 1.92 | 2.01 | 1.87 |
| | [2.10] | [3.24] | [3.31] | [2.28] | [2.21] | [2.32] | [2.58] | [3.06] | [2.94] |

*Note.* This table shows alphas from nine different models for alternative versions of the CAPM optimal portfolio and CAPM equal-weight portfolio. The difference in alpha between the portfolios is also presented. The evaluation models used are the same as those described in Table A1. Each evaluation model is estimated using daily returns. To ease interpretation, alpha is annualized and reported in percent. *t*-statistics are in square brackets below each measure of alpha. In Panel A, I use the previous six months of daily returns to calculate the optimal weights. I then estimate portfolio alphas over the period January 2000 through December 2016. In Panel B, I use the previous 24 months of daily returns to calculate the optimal weights. I then estimate portfolio alphas over the period January 2001 through December 2016.

**TABLE A5** Performance of the CAPM optimal portfolio—Monthly alphas and residuals

*Panel A. Prior 12 months*

| | Evaluation model | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | CAPM | FF3 | FF4 | FF6 | FFSY | FFAQR | Q4 | CPZ4 | CPZ7 |
| Optimal | 1.94 | 1.09 | 0.49 | 2.70 | 2.06 | 3.29 | 2.12 | 1.30 | 0.60 |
| | [1.19] | [0.80] | [0.37] | [2.25] | [1.65] | [2.74] | [1.59] | [0.95] | [0.53] |
| Equal Weight | 1.65 | 0.50 | –0.43 | 2.61 | 1.90 | 3.35 | 1.78 | 0.69 | 0.00 |
| | [0.81] | [0.32] | [–0.29] | [2.08] | [1.42] | [2.61] | [1.15] | [0.47] | [0.00] |
| Difference | 0.29 | 0.59 | 0.91 | 0.09 | 0.16 | –0.06 | 0.34 | 0.61 | 0.60 |
| | [0.33] | [0.76] | [1.21] | [0.12] | [0.21] | [–0.08] | [0.43] | [0.84] | [0.84] |

*Panel B. Prior 36 months*

| | Evaluation model | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | CAPM | FF3 | FF4 | FF6 | FFSY | FFAQR | Q4 | CPZ4 | CPZ7 |
| Optimal | 0.17 | –0.08 | –0.41 | 1.98 | 1.41 | 2.04 | 1.16 | 0.28 | –0.23 |
| | [0.12] | [–0.07] | [–0.36] | [2.05] | [1.36] | [1.98] | [1.05] | [0.24] | [–0.26] |
| Equal Weight | –1.41 | –1.75 | –2.18 | 1.20 | 0.70 | 1.24 | 0.04 | –1.26 | –1.82 |
| | [–0.75] | [–1.23] | [–1.54] | [1.08] | [0.60] | [1.00] | [0.03] | [–0.95] | [–1.95] |
| Difference | 1.58 | 1.67 | 1.77 | 0.77 | 0.71 | 0.80 | 1.12 | 1.54 | 1.58 |
| | [1.85] | [2.34] | [2.49] | [1.17] | [1.09] | [1.16] | [1.59] | [2.33] | [2.58] |

*Panel C. Prior 60 months*

| | Evaluation model | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | CAPM | FF3 | FF4 | FF6 | FFSY | FFAQR | Q4 | CPZ4 | CPZ7 |
| Optimal | 0.27 | –0.45 | –0.84 | –0.25 | –0.92 | 0.07 | –0.26 | –0.27 | –1.07 |
| | [0.26] | [–0.51] | [–0.99] | [–0.30] | [–1.13] | [0.08] | [–0.30] | [–0.29] | [–1.40] |
| Equal Weight | 0.64 | –0.51 | –1.25 | 0.19 | –0.69 | 0.53 | –0.12 | –0.37 | –1.32 |
| | [0.43] | [–0.47] | [–1.25] | [0.20] | [–0.73] | [0.57] | [–0.11] | [–0.35] | [–1.65] |
| Difference | –0.37 | 0.07 | 0.41 | –0.44 | –0.23 | –0.46 | –0.14 | 0.10 | 0.25 |
| | [–0.44] | [0.10] | [0.65] | [–0.75] | [–0.38] | [–0.76] | [–0.21] | [0.17] | [0.45] |

*Note.* This table shows alphas from nine different models for alternative versions of the CAPM optimal portfolio and CAPM equal-weight portfolio. The difference in alpha between the portfolios is also presented. The evaluation models used are the same as those described in Table A1. Alpha is estimated using daily returns over the period January 2000 through December 2016. To ease interpretation, alpha is annualized and reported in percent. *t*-statistics are in square brackets below each measure of alpha. In Panel A, I use monthly returns over the previous 12 months to calculate the optimal weights. In Panel B, I use the previous 36 months of monthly returns. In Panel C, I use the previous 60 months of monthly returns.

**TABLE A6** CAPM optimal portfolio monthly performance—Monthly alphas and residuals

*Panel A. Prior 12 months*

| | Evaluation model | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | CAPM | FF3 | FF4 | FF6 | FFSY | FFAQR | Q4 | CPZ4 | CPZ7 |
| Optimal | 2.07 | 0.72 | 0.22 | 2.03 | 0.62 | 2.50 | 1.72 | 1.37 | 0.68 |
| | [0.89] | [0.49] | [0.16] | [1.42] | [0.44] | [1.57] | [1.12] | [0.94] | [0.54] |
| Equal Weight | 1.72 | 0.00 | –0.79 | 1.33 | 0.22 | 2.12 | 0.78 | 0.58 | –0.10 |
| | [0.64] | [0.00] | [–0.56] | [0.95] | [0.15] | [1.37] | [0.44] | [0.38] | [–0.08] |
| Difference | 0.35 | 0.72 | 1.01 | 0.70 | 0.41 | 0.38 | 0.94 | 0.79 | 0.77 |
| | [0.43] | [1.01] | [1.49] | [0.97] | [0.55] | [0.49] | [1.21] | [1.15] | [1.04] |

*Panel B. Prior 36 months*

| | Evaluation model | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | CAPM | FF3 | FF4 | FF6 | FFSY | FFAQR | Q4 | CPZ4 | CPZ7 |
| Optimal | 0.08 | –0.39 | –0.48 | 0.38 | 0.37 | 0.79 | 0.55 | 0.01 | 0.19 |
| | [0.06] | [–0.36] | [–0.44] | [0.35] | [0.32] | [0.65] | [0.54] | [0.01] | [0.22] |
| Equal Weight | –1.56 | –1.95 | –2.29 | –0.09 | –0.08 | 0.59 | –0.53 | –1.32 | –1.53 |
| | [–0.74] | [–1.48] | [–1.81] | [–0.07] | [–0.06] | [0.44] | [–0.36] | [–1.05] | [–1.64] |
| Difference | 1.63 | 1.56 | 1.81 | 0.46 | 0.45 | 0.20 | 1.08 | 1.34 | 1.72 |
| | [1.42] | [1.90] | [2.37] | [0.57] | [0.59] | [0.21] | [1.14] | [1.80] | [2.67] |

*Panel C. Prior 60 months*

| | Evaluation model | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | CAPM | FF3 | FF4 | FF6 | FFSY | FFAQR | Q4 | CPZ4 | CPZ7 |
| Optimal | 0.23 | –0.59 | –0.66 | –0.96 | –1.47 | –0.75 | –0.80 | –0.34 | –0.95 |
| | [0.23] | [–0.69] | [–0.76] | [–1.13] | [–1.77] | [–0.88] | [–0.93] | [–0.41] | [–1.30] |
| Equal Weight | 0.59 | –0.67 | –1.04 | –0.53 | –1.45 | –0.03 | –0.58 | –0.30 | –0.86 |
| | [0.37] | [–0.69] | [–1.14] | [–0.59] | [–1.55] | [–0.03] | [–0.55] | [–0.32] | [–1.11] |
| Difference | –0.35 | 0.08 | 0.38 | –0.43 | –0.02 | –0.72 | –0.22 | –0.03 | –0.09 |
| | [–0.35] | [0.12] | [0.66] | [–0.79] | [–0.04] | [–1.21] | [–0.31] | [–0.06] | [–0.16] |

*Note.* This table shows alphas from nine different models for alternative versions of the CAPM optimal portfolio and CAPM equal-weight portfolio. The difference in alpha between the portfolios is also presented. The evaluation models used are the same as those described in Table A1. To ease interpretation, alpha is annualized and reported in percent. *t*-statistics are in square brackets below each measure of alpha. In Panel A, I use monthly returns over the previous 12 months to calculate the optimal weights. In Panel B, I use the previous 36 months of monthly returns. In Panel C, I use the previous 60 months of monthly returns. Portfolio alphas are estimated using monthly returns over the time period January 2000 through December 2016.

**TABLE A7** Performance of an optimal portfolio derived from total daily net returns

| | Evaluation model | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | CAPM | FF3 | FF4 | FF6 | FFSY | FFAQR | Q4 | CPZ4 | CPZ7 |
| Optimal | 3.74 | 2.52 | 1.01 | 2.31 | 2.03 | 2.75 | 2.18 | 1.77 | 1.49 |
| | [1.92] | [1.53] | [0.73] | [1.71] | [1.50] | [2.11] | [1.31] | [1.21] | [1.14] |
| Equal Weight | 2.27 | 0.87 | –0.75 | 1.55 | 0.69 | 1.90 | 0.90 | 0.37 | –0.16 |
| | [1.08] | [0.54] | [–0.58] | [1.33] | [0.56] | [1.63] | [0.54] | [0.27] | [–0.14] |
| Difference | 1.47 | 1.65 | 1.76 | 0.76 | 1.34 | 0.85 | 1.28 | 1.40 | 1.65 |
| | [1.57] | [1.85] | [1.98] | [0.89] | [1.53] | [0.98] | [1.44] | [1.66] | [2.04] |

*Note.* This table shows alphas from nine different models for the total daily net return optimal portfolio and the total daily net return equal-weight portfolio. The difference in alpha between the portfolios is also presented. The evaluation models used are the same as those described in Table A1. Alpha is estimated using daily returns over the period January 2000 through December 2016. To ease interpretation, alpha is annualized and reported in percent. *t*-statistics are in square brackets below each measure of alpha.

**TABLE A8** Performance of the CAPM optimal portfolio—No-load sample

| | Evaluation model | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | CAPM | FF3 | FF4 | FF6 | FFSY | FFAQR | Q4 | CPZ4 | CPZ7 |
| Optimal | 3.08 | 2.30 | 1.45 | 3.10 | 2.69 | 3.62 | 2.73 | 2.17 | 1.64 |
| | [2.10] | [1.82] | [1.25] | [2.89] | [2.43] | [3.40] | [2.19] | [1.73] | [1.58] |
| Equal Weight | 1.76 | 0.51 | –0.68 | 2.00 | 1.29 | 2.70 | 1.34 | 0.43 | –0.35 |
| | [0.88] | [0.32] | [–0.48] | [1.61] | [0.97] | [2.14] | [0.85] | [0.30] | [–0.30] |
| Difference | 1.31 | 1.79 | 2.13 | 1.10 | 1.40 | 0.92 | 1.39 | 1.74 | 1.99 |
| | [1.47] | [2.33] | [2.89] | [1.56] | [1.92] | [1.28] | [1.79] | [2.52] | [3.02] |

*Note.* This table shows alphas from nine different models for alternative versions of the CAPM optimal portfolio and CAPM equal-weight portfolio. The difference in alpha between the portfolios is also presented. The evaluation models used are the same as those described in Table A1. Alpha is estimated using daily returns over the period January 2000 through December 2016. To ease interpretation, alpha is annualized and reported in percent. *t*-statistics are in square brackets below each measure of alpha. In this sample, I exclude any mutual fund share class with a front- or back-end load.

**TABLE A9** Performance of the CAPM optimal portfolio—Distribution channel

*Panel A. Broker-sold funds*

| | Evaluation model | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | CAPM | FF3 | FF4 | FF6 | FFSY | FFAQR | Q4 | CPZ4 | CPZ7 |
| Optimal | 3.26 | 2.41 | 1.50 | 3.45 | 2.85 | 3.86 | 2.88 | 2.29 | 1.61 |
| | [2.03] | [1.77] | [1.20] | [3.00] | [2.37] | [3.32] | [2.13] | [1.75] | [1.48] |
| Equal Weight | 2.00 | 0.69 | –0.37 | 2.16 | 1.50 | 2.79 | 1.45 | 0.69 | –0.02 |
| | [1.02] | [0.46] | [–0.27] | [1.77] | [1.16] | [2.27] | [0.96] | [0.49] | [–0.02] |
| Difference | 1.26 | 1.71 | 1.87 | 1.29 | 1.35 | 1.07 | 1.43 | 1.60 | 1.63 |
| | [1.90] | [3.13] | [3.45] | [2.46] | [2.53] | [2.03] | [2.56] | [3.06] | [3.15] |

*Panel B. Direct-sold funds*

| | Evaluation model | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | CAPM | FF3 | FF4 | FF6 | FFSY | FFAQR | Q4 | CPZ4 | CPZ7 |
| Optimal | 3.20 | 2.25 | 1.35 | 3.23 | 2.71 | 3.85 | 2.87 | 2.22 | 1.56 |
| | [2.03] | [1.70] | [1.11] | [2.93] | [2.37] | [3.48] | [2.20] | [1.73] | [1.46] |
| Equal Weight | 1.73 | 0.52 | –0.64 | 2.22 | 1.46 | 2.90 | 1.47 | 0.52 | –0.17 |
| | [0.85] | [0.32] | [–0.44] | [1.74] | [1.06] | [2.22] | [0.91] | [0.35] | [–0.14] |
| Difference | 1.46 | 1.73 | 2.00 | 1.01 | 1.25 | 0.95 | 1.40 | 1.70 | 1.73 |
| | [1.91] | [2.59] | [3.08] | [1.65] | [1.96] | [1.50] | [2.07] | [2.80] | [2.93] |

*Note.* This table shows alphas from nine different models for alternative versions of the CAPM optimal portfolio and CAPM equal-weight portfolio. The difference in alpha between the portfolios is also presented. The evaluation models used are the same as those described in Table A1. Alpha is estimated using daily returns over the period January 2000 through December 2016. To ease interpretation, alpha is annualized and reported in percent. *t*-statistics are in square brackets below each measure of alpha. In Panel A, the sample includes only mutual funds that are classified as broker-sold. In Panel B, the sample includes only mutual funds that are classified as direct-sold.

**TABLE A10** Performance of the CAPM optimal portfolio—Information ratio selection

| | Evaluation model | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | CAPM | FF3 | FF4 | FF6 | FFSY | FFAQR | Q4 | CPZ4 | CPZ7 |
| Optimal | 3.22 | 2.56 | 2.03 | 2.57 | 2.35 | 3.02 | 2.58 | 2.50 | 1.99 |
| | [3.42] | [2.93] | [2.49] | [3.21] | [2.93] | [3.86] | [2.98] | [2.73] | [2.55] |
| Equal Weight | 3.25 | 2.14 | 1.16 | 2.45 | 1.80 | 3.10 | 2.30 | 1.96 | 1.15 |
| | [2.26] | [1.77] | [1.09] | [2.44] | [1.73] | [3.14] | [1.90] | [1.70] | [1.20] |
| Difference | –0.03 | 0.42 | 0.86 | 0.12 | 0.56 | –0.08 | 0.27 | 0.54 | 0.85 |
| | [–0.04] | [0.61] | [1.38] | [0.19] | [0.90] | [–0.13] | [0.40] | [0.90] | [1.49] |

*Note.* This table shows alphas from nine different models for alternative versions of the CAPM optimal portfolio and CAPM equal-weight portfolio. The difference in alpha between the portfolios is also presented. The evaluation models used are the same as those described in Table A1. Alpha is estimated using daily returns over the period January 2000 through December 2016. To ease interpretation, alpha is annualized and reported in percent. *t*-statistics are in square brackets below each measure of alpha. The funds selected for inclusion in the optimal portfolio are those in the top 5% of information ratio during the previous 12 months.

**TABLE A11** Performance of the CAPM optimal portfolio—Monthly portfolio returns

| | Evaluation model | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | CAPM | FF3 | FF4 | FF6 | FFSY | FFAQR | Q4 | CPZ4 | CPZ7 |
| Optimal | 4.11 | 2.78 | 2.07 | 3.33 | 2.26 | 3.76 | 2.83 | 3.04 | 2.19 |
| | [1.99] | [2.01] | [1.77] | [2.37] | [1.86] | [2.47] | [1.80] | [2.23] | [1.96] |
| Equal Weight | 2.10 | 0.24 | –0.68 | 1.05 | 0.27 | 2.02 | 0.65 | 0.70 | –0.02 |
| | [0.79] | [0.15] | [–0.51] | [0.77] | [0.20] | [1.36] | [0.37] | [0.46] | [–0.01] |
| Difference | 2.01 | 2.54 | 2.75 | 2.28 | 1.99 | 1.74 | 2.18 | 2.35 | 2.20 |
| | [2.06] | [3.52] | [4.05] | [3.25] | [2.80] | [2.18] | [3.11] | [3.27] | [3.13] |

*Note.* This table shows alphas from nine different models for the CAPM optimal portfolio and CAPM equal-weight portfolio. The difference in alpha between the portfolios is also presented. The evaluation models used are the same as those described in Table A1. Alpha is estimated using monthly returns over the period January 2000 through December 2016. To ease interpretation, alpha is annualized and reported in percent. *t*-statistics are in square brackets below each measure of alpha.

**TABLE A12** Performance of the CAPM optimal portfolio—LVH factor

| | Evaluation model | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | CAPM | FF3 | FF4 | FF6 | FFSY | FFAQR | Q4 | CPZ4 | CPZ7 |
| Optimal | 6.54 | 2.26 | 2.71 | 3.22 | 2.52 | 3.74 | 2.95 | 3.77 | 1.88 |
| | [2.29] | [1.50] | [1.95] | [2.28] | [1.93] | [2.45] | [1.81] | [2.53] | [1.68] |
| Equal Weight | 5.82 | –0.08 | 0.52 | 1.16 | 0.65 | 2.01 | 0.93 | 1.91 | 0.09 |
| | [1.87] | [–0.05] | [0.36] | [0.84] | [0.46] | [1.34] | [0.54] | [1.30] | [0.07] |
| Difference | 0.72 | 2.34 | 2.19 | 2.05 | 1.87 | 1.73 | 2.01 | 1.86 | 1.80 |
| | [0.83] | [3.09] | [3.07] | [2.95] | [2.58] | [2.18] | [2.82] | [2.60] | [2.52] |

*Note.* This table shows alphas from nine different models for the CAPM optimal portfolio and CAPM equal-weight portfolio. The difference in alpha between the portfolios is also presented. The evaluation models used are the same as those described in Table A1, except that the Jordan and Riley (2015) LVH factor is added to each model. Alpha is estimated using monthly returns over the period January 2000 through December 2016. To ease interpretation, alpha is annualized and reported in percent. *t*-statistics are in square brackets below each measure of alpha.