In Search of Under-Appreciated Skill: Passive Indexation of Active Funds*

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May 9, 2018

Abstract

Identifying skilled managers is not the only way to achieve above-market returns from investing in active funds. Despite limited evidence of outperformance at the fund level, we document that a passive "indexation" strategy of actively managed sector funds earns an annual benchmark-adjusted return of 5.70%, and a monthly alpha of 27 basis points over next-best investable passive funds. The strategy's outperformance is present in market downturns (i.e., resilient to tail risk) and robust to different rebalancing frequencies and inclusion of expenses. We provide an alpha arithmetic as explanation for strategy's success and as principle for creating similar portfolio strategies.

JEL Classification Numbers: G11, G20, G23.

Keywords: alpha, managerial skill, mutual funds, passive investing.

*We are grateful to Rajesh Aggarwal, Stephen Brown, Martijn Cremers, Eric Jacquier, Timothy Johnson, Jianjun Miao, Ronnie Sadka, Gustavo Schwenkler, and Lucian Taylor for helpful comments and suggestions.

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The irony in entrusting your capital to active managers is you also need to be an active manager. Instead of picking securities, you pick fund managers, and a poor fund selection leads to underperforming benchmarks. Like any other active manager, you face decreasing returns to scale: it is a daunting task to avoid putting too much capital into too few funds, and it only gets harder with more assets under management. Is it worth considering to be a passive manager at the top level? This paper is the first to investigate the fit of passive "indexation" of active funds as an alternative to allocate capital to active managers. Our results provide a new perspective to institutional investors who also invest in active funds to outperform the market, such as university endowments, pension funds, and multi-manger investment funds.

Passive indexation of active funds means top-level investors treat active funds as securities and trade them following simple rules — for example, periodically rebalance a group of active funds to equal weights. Hence it economizes on costs associated with in-depth analysis necessary to identify the best funds or managers. The key is to embrace passiveness at the institutional investor level by minimizing (or even completely forgoing) security selection and market timing — that is, curtailing fund selection and short-term tactical reallocation of capitals. Rather, the investor holds a group of active funds to track a benchmark and outperform it whenever the underlying active funds deliver alphas.

This paper's idea is that active risk is fund-specific and hence diversifiable. By indexing a group of active funds, the volatility of alpha at the top level soon declines and information ratio rises. Given that active manager's alpha is notoriously hard to forecast, managing active risk through diversification is a more practical and attainable goal. Once sufficient *risk reduction* in active risk is achieved, passive indexation of active funds delivers reliable alpha as long as the underlying active funds have *outperformance potential* — that is, on average, at least a marginally positive alpha.

Panel A of Figure 1 charts the cumulative portfolio value of $1,000 initial investment in active sector funds with equal weights, which we refer to as *Equal Weighted Sector* (EWS) strategy, and in the S&P 500 index over 1998 to 2016 period, while Panel B shows the drawdown of the EWS strategy compared to S&P 500 index.[1] Table 1 documents the annual return comparison between the EWS strategy and S&P 500 index. The consistent outperformance of this passive and simple strategy, i.e., investing in active sector funds with

[1]The sector-based approach assumes that returns vary across industries and time so that sectors provide risk premiums to investors that differ from the market risk premium. Academic research supports the idea that sector allocation serves as important consideration to active managers. Kacperczyk, Sialm, and Zheng (2005) find the investment skill is more evident among managers who hold portfolios concentrated in a few industries. Cavaglia, Brightman, and Aked (2000) find industry factors dominate country factors and should be important inputs for active managers of global equity portfolios. Roll (1992) find country's industrial structure is important to explain disparate behavior of international stock indices.

Industry factors/risks are widely accepted by practitioners (see, e.g., Barra's Integrated Model, Northfield's Global Equity Risk Model, Morningstar's Global Risk Model, which all recognize sector/industry exposures). Ibboston Associates publishes industry risk premium data in its annual *Stocks, Bonds, Bills, and Inflation (SBBI) Yearbook.*

equal weights, highlights that skill in mutual fund industry has been largely under-appreciated.

[Insert Figure 1 and Table 1]

Despite the recent trend of large capital flow from active funds to passive funds and the ongoing debate on the merit of active investing, active funds did add value to investors in the past few decades.[2] Recent developments in academic society have shown, contrary to earlier research, strong evidence of managerial skills among active funds. (Pástor, Stambaugh, and Taylor (2015) and Berk and van Binsbergen (2016)) More generally, active and passive investors can coexist in equilibrium where active investors are rewarded from their efforts to make markets close to efficient. (Pedersen (2018)).

However, it is hard to predict the next high-alpha fund, because alpha is not persistent (Carhart, 1997) and, more importantly, there is no easy link between alpha and skill unless decreasing returns to scale in active management are also taken into account. For example, a successful manager who specializes in small-cap stocks will not be able to deliver high-alpha if the fund size dramatically increases. To see this, consider active managers with an ability to create superior risk-reward trade-offs are a scarce resource. Investors therefore compete for their scarce alphas, putting more and more capital into skilled mangers' hands. Due to decreasing returns to scale in active management, incoming fund flow will drive net alpha down to (or even below) zero. In short, the risk-adjusted expected excess return to investing with a skilled active manager equals zero in an equilibrium with rational, value-maximizing investors (Berk and Green, 2004).

The performance drag due to increased assets under management is well known among practitioners.[3] Thus, neither managers without alpha are definitely not skilled nor managers with alpha are clearly skilled. This non-equivalence between alpha and skill implies that finding a skilled manger does not guarantee alpha. As such, less money should be spent on manager selection.

The relevant question is how to collect any net alpha from a fund after its performance drag from size and management fee are considered. We call it "skill at the right price." When high-alpha funds are hard to predict, investors better focus on minimizing costs, including operational cost for researching active funds, trading cost associated with reallocation of capital, and management fees paid to active managers. The low-cost advantages of passive investing are another motivation for passive indexation of active funds.

Although alpha-enhancement is not the focus of this paper, it suggests to target funds where above equilibrium is more likely to fail. This could be due to (1) slow learning of investors about skill and cor-

[2]For example, Berk and van Binsbergen (2016) show active managers are skilled and add 3 millions per year in value, on average, in a sample of 5,974 funds from January 1977 to March 2011.

[3]For example, Warren Buffett concluded "A fat wallet, however, is the enemy of superior investment results." (see Berkshire Hathaway Shareholder Letter 1994).

responding slow reaction to bad performance (Pástor and Stambaugh, 2012); (2) marketing effort causing investors to make ill-informed decisions (Roussanov, Ruan, and Wei, 2017); or (3) behavioral patterns of investors to overweight salient and obvious information (Barber, Odean, and Zheng, 2005). When mangers are not rewarded enough for good performance, fund size is *under-adjusted* and investors can earn positive net alphas.[4] This generally means one should research funds that are smaller, younger, and more specialized.

In an influential paper, Moskowitz and Grinblatt (1999) shows that investors can earn significant alpha by investing in the past top-performing industry portfolios. In this vein, we start with a simple idea: construct a portfolio of sector funds with equal weights and rebalance periodically to maintain equal weights. Obviously, some industries tend to outperform others for some period of time. Although these outperforming industries (or sectors) are easily discernible ex post, we do not assume that investors can predict which industries (or sectors) will outperform in the future. Moreover, a potentially high turnover ratio and associated transaction costs from dynamic rebalancing strategies, such as momentum, could limit outperformance of a more passive strategy that recognizes the findings in Moskowitz and Grinblatt (1999). Therefore, we explore portfolios that contain every sector and do not tilt weights towards any industry, risk factor, etc.

This naive diversification (1/N rule) assumes only passive indexing and excludes market timing or security selection abilities. Comparing the out-of-sample performance of 14 competing optimal portfolio models across seven empirical datasets, DeMiguel, Garlappi, and Uppal (2007) show that none of the theoretically sound models performs consistently better than the naive 1/N rule. Their results show that the out-of-sample performance of portfolios are impeded by the poor estimation of expected returns, and because of its low cost and simplicity, the 1/N naive-diversification rule should serve as a natural starting point. The EWS strategy is consistent with their argument.

Perhaps surprisingly, while forgoing security selection and market timing, our strategy consistently generates positive net alpha. In particular, the EWS strategy matches market exposure (market beta around one) while other factor exposures are largely zero, so it effectively tracks the market. Moreover, although only a handful sector funds have significant positive alphas in our sample, the EWS strategy benefits from diversification of active risk, which results in a higher information ratio. Further analysis using investable benchmarks as risk adjustment factors reveals economically and statistically stronger result for the EWS strategy's outperformance and its moderate tilt towards small size stocks.

[4] Rational and perfectly informed investors cause fund size to adjust such that net alpha are zero. However, imperfect information and costly search cause fund flows to be slow and insufficient, which makes certain funds too small (i.e., under-adjusted relative to equilibrium implied fund size that drives net alpha to zero). Recently, Goldstein, Jiang, and Ng (2017) find, for example, a convex flow-performance relation for stock funds.

1 Data

Our analysis requires us to choose a group of sector funds that are both actively managed and have full coverage of sectors or industries. Only actively managed funds have the potential to carry a component of managerial skill, and a full coverage sectors and industries provides better diversification and allows us to conclude that the results are not driven by a subset of sectors or industries. A few other criteria also come to mind. First, we require all the sector funds to reside under a single fund family. This allows us to control for the organizational diseconomies of scale in active fund management industry (see Chen, Hong, Huang, and Kubik (2004)). Second, we only consider mutual funds, which face tighter regulatory scrutiny and report audited performance. Third, we prefer older funds, so that we have longer data sample for analysis and initiation or selection bias is limited. Last, we prefer a fund family whose sector classification is finer, which makes it more likely for fund managers to have specialized knowledge that adds value to her investment process. Given these criteria, we identify forty sector funds from Fidelity (for a list of fund tickers and sectors, see Appendix A). There are no reliable substitute for these forty funds. Most sector funds are passively managed ETFs. Among the active sector funds, Vanguard offers a much smaller number (some of them have overlapping targeting sectors, and most of them are not initiated until 2004). T.Rowe Price and American Century each provide less than five sector funds. Notably, our sample selection strategy is similar to that of O'Neal (2000), who examines Moskowitz and Grinblatt's (1999) results for mutual funds.

The monthly return data of active sector funds range from September 1998, to June 2016. As benchmarks, we include the S&P 500 index and ten passively managed sector ETFs from SPDR, which are constructed in such a way that their underlying stocks reconstitute S&P 500 index.[5] The monthly return data for SPDR sector ETFs start from January 1999, and end at June 2016.

To examine factor exposures, we employ three linear asset pricing models: (1) the five-factor model from Fama and French (2015); (2) the four-factor model from Carhart (1997); and (3) the investable-index four-factor model proposed by Cremers, Petajisto, and Zitzewitz (2013).[6] The Fama-French factor data and momentum factor data of Carhart model are taken from Ken French's website and span the same period as the sector funds. The index-based factor model data are taken from Antti Petajisto's website with data coverage from September 1998 to December 2013.

[5] S&P 500 and Russell 2000 are the two most common benchmarks for US mutual funds. We choose S&P 500 because it has a higher explanatory power for out strategy's return — S&P 500 index alone could account for 92% variations in the EWS strategy. This approach of choosing benchmark, when it is unknown, as the investable index closest to a portfolio's return, is advocated by Berk and Van Binsbergen (2015) and also used by Cremers and Petajisto (2009).

[6] We use CPZ's four-factor version (IDX4) that replaces size factor with the return differences between the Russell 2000 and S&P 500 and and the value factor with the differences between the Russell 3000 Value and Growth indices.

2 Equal-Weighted Sector (EWS) Strategy

The EWS strategy is simple: invest in equal weights among a group of actively managed sector funds and rebalance to keep constant weights. While it is easy to implement and provides satisfactory return at first glance, we need to address some practical issues. First, funds have expenses (including management fee, 12B-1 fee etc.) and early redemption fees if frequent rebalancing is needed. These costs will limit the superiority of EWS strategy. Second, rebalancing is akin to synthetic short-volatility position (out-of-money put writing) that could increase tail risk in downturns. Third, its risk exposure might reveal results are due to a certain value-size-momentum tilt, which enables it to benefit from alternative betas. In that case the higher return of EWS is a result of higher or alternative risks. This section investigates these issues.

2.1 Trading EWS with Cost

The first issue is if annual fees, including 12b-1 fees, management fees, administrative fees, etc., eat up a majority of benchmark-adjusted return of EWS. We collect the annual expense ratios of the active sector funds in our sample and use their mean as expense ratio. Admittedly, by taking the mean we assume the EWS keeps its equal-weighting most of the time during the year. But we also do not see much dispersion in expense ratios, because funds are from the same fund family. Hence averaging expense ratios is reasonable. Table 1 gathers the results in the last two columns. A clear trend emerges from the expense ratio column. Over time, the expense ratio of EWS has been declining and has settled to 81 basis points recently. This is a reflection of the asset management industry's effort to reduce its charge, especially for active funds, who are striving to keep their fees low to compete with low-cost passive funds. On a going-forward basis, we have no strong reason to believe the expense ratio will spike in the future.

The last column reports after-fee excess returns. Because the expense ratios in column 5 are generally low compared to the excess return in column 4, we see little change. In only 4 of 19 years EWS does worse than the S&P 500 index (or 5 years if we deduct fees).[7] The 2006 underperformance is small, and becomes negligible when expenses for passive funds are also taken into account.[8] Because passive funds also charge fees, our reported net excess returns are lower than they should be. A $t-$test shows the outperformance of EWS is statistically significant both before fees ($t-$statistic 3.69) and after fees ($t-$statistic 3.09).

The numbers in Table 1 assume monthly rebalancing for the EWS strategy. That rebalancing frequency

[7] In 2006, the before-fee excess return is 75 basis point, while the after-fee excess return is negative 27 basis points.

[8] For example, it will cost the investor 18 basis points to invest in Vanguard's S&P 500 tracking fund in 2006, that narrows down the underperformance to 9 basis point. Vanguard's S&P 500 tracking ETF, which has a even lower expense ratio of 4 basis points, is not available to investors until late 2010.

may appear too high to some investors, especially when the transaction costs are not accounted for in the expense ratio. As a matter of fact, there are no transaction fees involved with buying these funds. However, investors still need to pay some short-term trading or redemption fees. Therefore, we consider whether it is plausible to rebalance in a lower frequency, say rebalance at each quarter, as many passive funds do, or rebalance at each year. Such infrequent rebalancing eliminates most of the short-term redemption fees and will benefit investors even if there are additional transaction fees. We consider rebalancing frequencies in Table 2.

[Insert Table 2]

Specifically, we examine four rebalancing frequencies, monthly, quarterly, yearly, and never. The last case corresponds to a buy-and-hold EWS strategy in which the funds are bought with equal weights at the beginning but are never rebalanced. For now, we focus on the outputs for EWS and EWS − S&P 500 only, and we explain later the role of SSE (SPDR Sector ETF).

The table reveals two messages. First, the cumulative return of investing in EWS or a long-short portfolio of longing EWS while shorting S&P 500 index (essentially this is the cumulative outperformance of EWS) is fairly insensitive to the rebalancing frequency. The buy-and-hold generates the smallest cumulative return, which is not surprising, because the weights drift over time and we lose the efficient diversification. But the numbers for the other rebalancing frequencies are close. This means the investor could choose to rebalance in a much slower fashion if she wishes to reduce or eliminate short-term redemption fee.[9] Second, the average annual returns for EWS and EWS − S&P 500 are both statistically significant across all rebalancing frequencies. That is, the outperformance of EWS strategy is robust to rebalancing frequency used.

We next address the question whether an 1/N portfolio of indexed or passive sector funds (i.e, ETFs) can deliver the same result. If it does, then investors are better off investing in a purely passive portfolio due to its lower cost. It also could mean our results so far are driven by different weighting, i.e. equal-sector weighting, to get an alternative performance. To this end, we consider trading EWS strategy using passive sector ETFs provided by SPDR. Nine out of ten of these sector ETFs are initiated in the end of 1998 — this coincides with the time when MSCI and Standard & Poor's developed Global Industry Classification Standard (GICS) as a standard to classify stocks in different sectors and industries. The last ETF for Real Estate is initiated in late 2015, after GICS was updated to include a Real Estate sector. The ten SPDR sector ETFs track ten S&P Select Sector Indices, which are constructed in such a way that their underlying stocks reconstitute S&P 500 index. Given our choice of benchmark, i.e. S&P 500 index, these tradable sector ETFs

[9] In untabulated results, we find the EWS strategy's fund weights do not change or diverge quickly over time. Because there are forty funds in our EWS portfolio and their initial weights are 2.5%, it is hard for the weight of any particular fund to dominate.

are the best candidates to demonstrate what an equal-sector strategy with passive investment vehicles could deliver.[10] We call this equal-sector strategy with indexed investments SSE (SPDR Sector ETF).

Table 2 considers two cases: (1) SSE's outperformance relative to S&P 500; and (2) EWS's outperformance relative to SSE. The former will demonstrate what equal-sector weighting alone could deliver. The latter will inform us of whether equal-weighting could explain the outperformance of EWS. Indeed, Panel A shows that SSE outperforms S&P 500, while it underperforms EWS across all rebalancing frequencies. This means equal-weighting alone is not able to explain all of the outperformance of EWS. Again, results are similar across rebalancing frequencies, except for the buy-and-hold strategy. A closer look at Panel B reveals that the outperformance of SSE relative to S&P 500 is statistically significant, while the statistical significance of EWS $-$ SSE is weaker. For the latter one, we still marginally reject the null hypothesis of no outperformance at 5% level, except for the case of buy-and-hold, which is insignificant statistically. Although lack of more data limits the statistical power, we do not want to overstate statistical significance. Yet, the sizable cumulative return of EWS $-$ SSE underscores the unexplained economic significance. Overall, our results indicate the equal-sector weighting alone does not account for the outperformance of EWS. Finally, Panel C shows the turnover of EWS and SSE, the results shown that both strategies require limited turnover at a comparable level across all rebalancing frequencies. Notably, both quarterly and monthly turnover could be further decreased by reasonable bounds around target weights.

Overall, the EWS strategy's outperformance is significant and is not sensitive to rebalancing frequency. Quarterly or yearly rebalancing best balances its benefits against transaction costs and portfolio turnover.

2.2 Risk of Rebalancing

The second issue is the strategy's periodical rebalancing to equal weights increases tail risk during market downturns. Buying past losers and selling past winners is like writing out-of-money calls and puts for winners and losers respectively and hence creates a synthetic short on volatility (Ang, 2014). This short-volatility nature might entail an amplified downside risk (due to the synthetic out-of-money put positions) compared to value-weighted market indices. Through various examinations, we show EWS actually performs better during market turmoils: it has shorter and shallower drawdowns, and it earns a higher average benchmark-adjusted return during down markets.

In Table 3, we take three different approaches to examine the downside risk for EWS strategy. Panel A

[10] ALPS Financial Services provides an equal-sector ETF with ticker EQL that does the same thing. However, it's not initiated until mid 2009, and it rebalances the SPDR sector ETFs at each quarter. We want to have enough data coverage and consider different rebalancing frequency.

compares the drawdowns of EWS with S&P 500 index during two of the well-known distressed periods in our sample, i.e., the Dot-com bubble and the Great Recession. We consider the maximum drawdown, the drawdown duration and the time to recovery. The drawdown duration is the time difference between the time of most recent peak prior to the maximum drawdown and the time of first recovery to this peak (i.e., the time to recovery is time difference between the time of maximum drawdown to first time of recovery to former peak). They provide slightly different sense of how persistent a severe drawdown could be. In both cases, EWS has shallower and much shorter drawdowns. For a visualization of this result, see Panel B of Figure 1.

[Insert Table 3]

In Panel B, we consider the return of EWS in panic states. Similar to Daniel and Moskowitz (2016), we define a given month as bear market when the trailing two-year cumulative return of S&P 500 is negative, and bull market otherwise. This measure captures the two aforementioned distressed periods and is more flexible. Consistent with our definition, both EWS and S&P 500 index earn a lower average monthly return in bear market. A closer inspection, however, reveals that EWS's relative performance to S&P 500 index is in fact better during bear market than during bull market. This additional benchmark-adjusted return shows EWS is a hedge for the value-weighted index like S&P 500. After all, contrarians trade against momentum followers, they are natural hedge for each other.

To make sure the result is not confounded by change of systematic risk exposure during the bear market, we consider a bear market timing regression, where we regress the excess return of EWS (over one-month T-Bill rate) on the excess return of S&P 500 index in Panel C:

$$R^e_{\text{EWS},t} = \alpha + \alpha_B I_{B,t-1} + (\beta + \beta_B I_{B,t-1}) R^e_{\text{SPX},t} + \varepsilon_t$$

where the $I_{B,t-1}$ is the ex-ante bear market indicator which equals to 1 in bear market and 0 otherwise. α_B and β_B are bear alpha and bear beta respectively: they are supposed to capture the additional outperformance and risk-exposure for EWS in bear market. Similar to results in panel B, EWS earns a bear-alpha, and has a negligible bear beta, both are not statistically significant. The high R^2 indicates our specification has good explanatory power for the variation of EWS's return.

In contrast to above-mentioned concerns, we find the EWS strategy provides downside protection, this could arise from three sources. First, the equal-weight rebalancing makes EWS more of a contrarian strategy that alleviates the impacts of market runs. Second, the low turnover ratio of EWS in Panel C of Table 2 implies the synthetic short-volatility position is small and hence its impact is also limited. Third, managers of the underlying fund might have skills to take less risk during market downturns.

2.3 Factor Exposure of EWS

Finally, a third concern is that the EWS strategy generates more return by taking more risks. More specifically, EWS's performance might be explained by an alternative-beta exposure. Anticipating, different factor exposures do not explain EWS's performance either. To examine the risk profiles of EWS strategy and its underlying funds, we utilize linear asset pricing models. We choose three factor models from existing literature, the five-factor model from Fama and French (2015), the four-factor model from Carhart (1997), and the index-based four-factor model from Cremers, Petajisto, and Zitzewitz (2013).[11]

While Fama-French-Carhart (FFC) factors are calculated from factor mimicking portfolios, they do not represent actual investable alternatives available to investors, nor do they represent passively managed benchmark portfolios.[12] Cremers, Petajisto, and Zitzewitz (2013) suggest that FFC model could produce biased evaluation of fund performance. They propose a four-factor index-based factor model, which uses the returns of different indices to replace the factors in Carhart model. CPZ model uses S&P 500 index minus one-month T-Bill rate to replace MKT factor, return difference between Russell 2000 index and S&P 500 index to mimic SMB, and return difference between Russell 3000 Value index and Russell 3000 Growth index as alternative to HML factor. Finally, CPZ keeps the UMD factor.

[Insert Table 4]

Table 4 shows regression results for monthly-rebalanced EWS returns on three sets of factors. In panel A, we use CAPM, Fama-French five-factor and the Carhart four-factor model, these are the common factor models in the Fama-French-Carhart (FFC) methodology. The surprisingly high R^2's suggest that factor risk premiums explain almost all the variations of monthly return of our strategy. Because our strategy is an equal weighted index of a pool of active funds, we believe this reflects that more and more active managers are using factor models to manage their risk exposures.

Our relative small data sample might concern readers. To demonstrate that our results of statistical significance are credible, we consider three different estimators of standard errors for beta and alpha. The first is ordinary least squares (OLS) standard errors, which is used by academics and practitioners. Assuming i.i.d residuals, OLS gives good estimates in large samples. Some authors use White standard errors to control for heteroskedasticity, we use Newey West standard errors from Newey and West (1994) to control for both

[11] Fama-French five-factor model and Carhart four-factor model have three common factors, namely market factor (MKT), size factor (SMB) and value factor (HML) from Fama and French (1996). Beyond these three factors, Fama-French five-factor model introduces two more factors: profitability factor (RMW) and investment factor (CMA); Carhart four-factor model, on the other hand, features a momentum factor (UMD). Carhart's model is the most widely used one for fund performance attribution.

[12] Berk and Van Binsbergen (2015) argue also that FFC factor mimicking portfolios are much better investment opportunities than what is available to investors, instead, index funds should be used as benchmark portfolios.

heteroskedasticity and autocorrelation as second estimator. Finally, we use the pairwise block stationary bootstrap method of Politis and Romano (1994) with 10,000 bootstrap samples to estimate the standard errors. Hence we report three different $t-$statistics underneath each coefficient estimate for beta and alpha.

Our results in Panel A of Table 4 are similar to those from Fama and French (2010), where authors consider the equal weighted portfolio of all actively managed U.S. equity mutual funds. Among all the six factors, market factor (MKT) has an overwhelming large explanatory power. CAPM, using only market factor as explanatory variable, has a corresponding R^2 of 0.94, meaning that most of the variation of our strategy's return is captured by MKT. The beta estimate for MKT is close to 1.0, reinforcing our argument that our strategy closely tracks the market. To get a clearer picture, we report the $t-$statistic of whether MKT beta is different from 1.0 in the table. The betas for other factors are statistically but not economically significant, accounting for little return variation of our EWS strategy. This is validated by the marginal increment of R^2 with inclusion of other factors — R^2 is 0.95 in both Fama-French five-factor model and Carhart four-factor model, compared to R^2 of 0.94 in CAPM.

The current factor risk profile coincides with our previous discussion: the strategy essentially has a one to one exposure to the market while has little, if not zero, tilt towards the other risk factors — this allows the strategy to keep pace with the overall market, which is what one would achieve by simply investing in an index-tracking passive fund. The almost zero tilt towards other factors also support our argument that the alternative weighting is not driving the result. In that case the weighting would change the factor tilts towards alternative betas. Beyond that, the strategy earns Jensen's alpha from managers' skills in underlying funds. Alpha estimates are positive for both Fama-French model and Carhart model, and is statistically significant for Carhart model using all three different standard error estimators.

One might wonder why the annual, benchmark-adjusted return of 5.70%, or equivalently 46 basis points per month, drops to a Carhart alpha of 22 basis points. Apart from economically insignificant exposure to other factors, this is because it uses as market factor the Center for Research in Security Prices (CRSP) value-weighted excess return, which has outperformed S&P 500 index during our sample period.[13] This bias leads to underestimation of risk-adjusted performance.

Panel B follows Cremers, Petajisto, and Zitzewitz (2013) and Berk and Van Binsbergen (2015) and uses investable indices as factors. These indices are investable through their index-tracking passive funds, and are better reflections of investor's investment opportunity set. We first use the excess return of S&P 500

[13]CRSP index includes not only U.S. common stocks, but also non-U.S. firms, closed-end funds, real estate investment trusts (REITs), and other securities such as shares of beneficial interest (SBIs). Cremers, Petajisto, and Zitzewitz (2013) use sample from 1980 to 2005, during which the S&P 500 outperformed CRSP index, and they report a positive alpha for S&P 500 index.

index relative to one-month T-Bill as a single factor. S&P 500 index is the most common benchmark for US equity fund, so this single factor model serves as a reasonable starting point. The results for S&P 500 index are consistent with our results in Table 1. The return of S&P 500 index alone could explain 92% of return variation in EWS strategy, with a statistically significant monthly alpha of 37 basis points. The CPZ model, taken from Cremers, Petajisto, and Zitzewitz (2013), includes the return difference of Russell 2000 index and S&P 500 index (R2-S5) and return difference of Russell 3000 Value index and Russell 3000 Growth index (R3V-R3G) as investable substitutes of SMB and HML. The results strengthen our argument. First, the high R^2 of 0.95 shows that CPZ model has the same level of explanatory power as compared to FFC models. Second, the alpha is both positive and statistically significant. Third, the statistically significant R2-S5 beta of 0.30 shows our strategy slightly tilts towards small-size stocks. This moderate tilt towards small-size stocks is not surprising, as EWS overweights sectors with smaller capitalizations.

Notice the difference between Panels A and B of Table 4. Most fund performance can be factorized by common factor models; after all, these factors do a good job to explain the cross-sectional variation of stocks, and any portfolio is simply a repackaging of underlying stocks if there is no managerial skills. In addition, common factors have been widely used by fund mangers for risk management purposes. These reasons make it easy to factorize a fund's returns, but it does not necessarily indicate any fund's returns could be easily replicated. Just as the case for index-tracking funds, there are tracking errors when trading factors. Matching a desired factor exposure is often hard from scratch, it usually involves simultaneously buying and selling hundreds of stocks, which causes large transaction costs. In performance assessment, factor models based on factor mimicking portfolios are a conservative detector for alphas and skill.

Finally, we draw a few conclusions from Table 4. First, the statistically significant alpha shows the alternative beta exposure is not able to explain EWS's outperformance. Second, the close-to-one market beta and close-to-zero tilt towards other factors show that the strategy's systematic risk is similar to that of an index-tracking fund. Third, the high R^2's suggest there is little evidence that EWS outperforms the market by deviating from it, fund selectivity and activity is hardly a main contributor to the bulk of return. This last point is consistent to the passive nature of EWS.

3 Alpha Arithmetic of EWS

How can a passive portfolio of active funds outperform the market, although the investor forgoes both security selection and market timing at her level? To understand the positive and significant alpha of EWS and, more generally, passive portfolios of active funds, consider the following model. Let $\alpha_i = \phi_i + \varepsilon_i$ be the alpha of fund i from a factor asset pricing model, with mean ϕ_i and an error term ε_i for $i = 1, \ldots, N$ funds, whose mean is 0 and variance is σ_i^2. Assume that alpha is idiosyncratic to a fund, that is, the correlation of α_i and α_j is 0 if $i \neq j$. Allowing some approximation error, we can write the alpha of EWS strategy as

$$\alpha_{\text{EWS}} = \bar{\phi} + \bar{\varepsilon}$$

where $\bar{\phi} = N^{-1} \sum_i \phi_i$ is the cross-sectional average of ϕ_i, and $\bar{\varepsilon}$ is an error term with mean 0 and variance $\sigma^2 = N^{-2} \sum_i \sigma_i^2 = N^{-1} \overline{\sigma_\varepsilon^2}$, in which $\overline{\sigma_\varepsilon^2}$ denotes the average variance of error terms. The $t-$statistic of α_{EWS} is

$$t_{\text{EWS}}^{\alpha} = \bar{\phi} / \sigma = \sqrt{T} (\text{IR}_{\text{EWS}})$$

where T is the number of sample periods and IR_{EWS} is the information ratio of the EWS strategy.

For an increasingly large number of funds N, diversification reduces risk, $d\sigma/dN < 0$, and hence increases statistical significance, t_{EWS}^{α}, and mean-variance trade-off, IR_{EWS}. At the same time, only when there is potential outperformance, i.e., $\bar{\phi} > 0$, would such risk reduction be potentially valuable to investors. These two effects are separate, and apply generally to any 1/N indexing choices of active funds.[14]

In sum, risk reduction and potential outperformance — despite the latter being insignificant and small at the fund level — can explain why passive portfolios of active funds can generate reliably positive net alpha. Hence we need to both evaluate the effectiveness of diversification and understand why alphas of the underlying active sector funds are individually insignificant but, on average, positive. We address risk reduction and potential outperformance in Sections 4 and 5.

4 Risk Reduction

A naive explanation for EWS's alpha is that most funds generate statistically significant alphas and EWS simply repackages them. However, we find limited evidence for this argument.

[Insert Figure 2]

Figure 2 shows the count of funds in three different categories: the ones with insignificant alpha, the ones with significant positive alpha, and the ones with significant negative alpha. We calculate alphas using the four factor models we have used so far: CAPM, Fama-French five-factor model, Carhart four-factor model, and CPZ model. A clear pattern should be spot from the figure. Regardless of the model used, the majority

[14]Notice that there may be an optimal number, N^*, that trades off the two effects. Initially, more funds reduce risk (Effect 1) but eventually there are little or no funds with potential outperformance (Effect 2), i.e., $d\bar{\phi}/dN < 0$. In short, over-diversification could hurt performance.

of our 40 funds have insignificant alpha — only a handful of them generate significant positive alpha, a few of them even generate significant negative alpha. We can hardly argue these funds carry reliable alpha. In contrast, we argue below that diversification is the key to understanding the remarkable result of generating significant alpha for a portfolio when the underlying assets have insignificant alpha.

Diversification follows from holding a sufficient number of stocks, and that number is around thirty to fifty. This accepted practical wisdom has its roots in academic papers from 1970s. Two widely cited papers on this subject are Fisher and Lorie (1970) and Elton and Gruber (1977), drawing similar conclusions from empirical and theoretical arguments respectively. Although correlation drives diversification, number of stocks also measures diversification (Van Horne, Blume, and Friend, 1975; Goetzmann and Kumar, 2008).

Most mutual funds hold more than fifty stocks, so investors may think their investments are diversified. Such conclusion, although is by and large true, is subject to one problem. That is, the alpha generated by the mutual fund, is orthogonal to its systematic risk, and hence active risk remains an idiosyncratic risk that is not diversified. Admittedly, the alpha is what draws the attention of investors who are willing to deviate from a passive index fund. But one should also admit how inconsistent the alpha from an average fund is.

[Insert Figure 3]

Figure 3 plots the underlying funds' monthly alphas against their standard deviations, split by the factor model. The straight lines are the fitted lines from a regression of using alpha as single regressor and alpha's standard deviation as regressand. The feature we see here is that funds with higher alphas generally also have more volatile alphas — this is a visualization of conundrum of identifying funds with alpha ex ante. It is therefore suboptimal to either predict which fund will generate alpha, or put concentrated weights in only a few active funds. By placing active funds in an 1/N portfolio, we effectively trim the risk associated with investing in individual alpha.

Additionally, the diversification of active funds also allow EWS to have a systematic risk exposure similar to that of an index tracking fund. Looking at the factor exposure for EWS in Table 4 makes it hard to see how dispersed the factor exposures of the underlying funds are. Because each active sector fund invests in one particular sector/industry, their factor exposures vary a lot.

[Insert Table 5]

Table 5 provides additional evidence for the role of diversification. Using empirical percentiles, it reports the cross-sectional distribution of the Carhart beta estimates for the underlying sector funds. One should notice the large variations of betas. Due to different target sectors, funds load on different factors. These discrepancies are net out to roughly zero when we index them with equal weights, as shown in Table 4. Diversification helps EWS to load of market factor. Notice that means of estimated betas in Table 5 are almost indistinguishable from estimated betas in Table 4 for the strategy. This is only true when the factor model is correctly specified and hence additional evidence that managers are using factor models to manage risks.[15]

We consider next mean-variance plots similar to Markowitz (1952). Because our focus is EWS outperformance, we study benchmark-adjusted returns, as opposed to gross returns. Figure 4 plots the average benchmark-adjusted return vs. benchmark-adjusted return standard deviation for the active funds and EWS. Each triangle represents a sector fund. Solid triangles represent those funds with a statistical significant benchmark-adjusted return and the circle represents the EWS strategy.

[Insert Figure 4]

Most funds do not earn significant benchmark-adjusted returns, but many have in-sample positive average benchmark-adjusted returns. The statistical insignificance is a result of large standard deviations, a reflection of our previous discussion: the outperformance of mutual funds are hard to capture. Although some funds do earn a higher benchmark-adjusted returns compared to simply indexing all of them, it is a formidable task to predict which of them will be best in advance.

Diversification makes investors better off. Holding a pool of active funds with outperformance potential, investor could attain a better risk-return trade-off. Given the context of Figure 4, the slope of the line that connects the origin and an portfolio is the information ratio for that particular portfolio. (See Goodwin (1998)). Our EWS strategy attains the highest slope — this is not driven by a higher average excess return, but by a smaller volatility of excess returns, a result of diversification. For ease of comparison, the dotted line indicates the ex-post best risk-return trade-off an investor could get if she invests in one mutual fund only. The role of risk reduction is evident from the graph.

Risk reduction is only part of EWS. Diversification helps lowering volatility of alpha/benchmark-adjusted returns, but explaining EWS also requires, on average, fund returns to outperform the market. The next section discusses various hypotheses for the second part of EWS, i.e., why do these sector funds on average generate higher return than the market.

[15] One might be tempted to wonder which funds are, for example, behind the 99th percentile of the coefficient distributions in Table 4. Semiconductors (FSELX) have had the highest market exposure, which indicates operating rather than financial leverage is important. However, semiconductors did not perform significantly better than the S&P 500. Similar observations apply to biotechnology, banking, and biotechnology again, which are, respectively, the 99th percentile for size factor (SMB), value factor (HML), and the momentum factor (UMD).

5 Potential Outperformance

5.1 Insufficient Fund Flows

We argue the magnitude of alpha of EWS strategy is a reflection of inefficiency of fund inflow in relation to fund's skill. In line with Berk and Green (2004, henceforth B&G), other recent empirical studies document decreasing returns to scale in active fund management industry (see, e.g., Pástor, Stambaugh, and Taylor (2015) or Chen, Hong, Huang, and Kubik (2004) on size erosion of fund performance). In short, when the fund inflow is insufficient to increase the fund size to its equilibrium point — at which the net alpha is zero — the fund will have positive alpha.

B&G argue a fund's alpha is uninformative about skill. This is in contrast to early studies that use alpha as indicator of a fund's skill, for example Jensen (1968) and Carhart (1997). Given that fund's skill (i.e., the ability to identify positive net present value opportunities) is scarce in supply, rational investors will put money in those mangers who are capable. This creates fund inflow to managers who are able to generate alpha. Through fund inflow, skilled managers collect rents for providing investment services, investors take away alpha after fee, or net alpha. Eventually the fund grows in size and managers are no longer able to find enough outperformance potential, so fund ends up with generating zero net alpha in equilibrium.

Because mutual funds cannot adjust share prices to ensure the return going forward is competitive, the adjustment comes through fund flows, hence size of fund is closely related to its ability to generate alpha. Pástor, Stambaugh, and Taylor (2017), for example, have shown that a fund's net alpha is positive if and only if its size is smaller than its equilibrium size, and vice versa. Empirically, Chen, Hong, Huang, and Kubik (2004) show fund size erodes fund performance. Trading costs associated with liquidity or market impact force bigger funds to invest in stocks that are more liquid and have larger market capitalizations. Thus, bigger funds may have to invest in suboptimal stocks or take larger positions than what is optimal.

If the equilibrium argument goes through, then one should not use alpha as measure of skills of active managers. Consistent with this predication, Berk and Van Binsbergen (2015) finds that managers on average are skilled and the difference in skill is predominantly reflected in difference of fund size, not gross alpha. Additionally, they show that a value-weighted portfolio that invests in a sample of 5,974 funds (this sample is larger than most comparable studies) returns negative 95 basis points per month after fees. In other words, despite apparent skill, the economic rents are entirely collected by the fund mangers, not investors.

Although the former argument is by and large true, and has been validated by several empirical studies, one should also agree that the equilibrium is an ideal state. A couple of mechanisms could distort fund flows and, in turn, imply that fund size can be above and below its equilibrium quantity.

The first distortion comes from slow learning (Pástor and Stambaugh, 2012). Endogeneity and persistence in fund size impede learning about decreasing returns to scale of active funds and, as a result, cause investor's adjustment to fund allocation (i.e., size) to be slow too. Investors only moderately decrease their allocation to active management when underperformance continues.

The second distortion comes from marketing efforts. Barber, Odean, and Zheng (2005) show that investors are more likely to buy funds with higher marketing expenses. On average, money spent on marketing more than offsets any negative effect of expense fees on fund flows. Recent study such as Roussanov, Ruan, and Wei (2017) also stresses the importance of marketing in determining fund flows. They find marketing is nearly as important as performance and fees for determining fund size. Using portfolio of funds sorted by net skill, they find there are both over-allocation to funds with low net skill and under-allocation to funds with high net skill. They conclude that asset misallocation exists in both bad funds and good funds in the data.

Overall, investors make mistakes due to imperfect information and costly search. When the size of a given fund is smaller than its equilibrium size due to insufficient fund inflow, there will be positive net alpha available to investors, which economically explains our results.

There are several reasons why these fund flows are under-adjusted. First, sector funds are often portrayed as bearing more risk due to their lack of cross-sector diversification. Investors are hence less willing to put money into a fund with such narrow focus. Should they considered the possibility of holding a diversified portfolio of sector funds, this could change. Second, sector funds are nonstandard investment outlets and require more knowledge and studying, investors are simply attracted by funds with more salient and easy-to-interpret information.[16] Third, absence of readily available sector benchmarks make it difficult for investors to evaluate the performance of sector funds, and make the fund flow adjustment slow. Fourth, it's nearly impossible to compare a given sector fund with its competitors, including passive sector investment vehicles. Because fund managers are usually unwilling to restrict themselves to a particular sector, active sector funds are rare, and they usually have different definition for their targeting sector. As for sector ETFs, for example, they also define sectors differently and track different sector benchmarks. It is rarely useful to compare one sector fund to one of its competitors (if there is one).[17]

[16]Due to behavioral reasons, investors are more sensitive to obvious and salient information. Barber, Odean, and Zheng (2005) find that investors have grown less willing to invest in funds with higher front-end-load fees, but kept irresponsive to the difference of total operating expense ratios.

[17] Two more practical factor that contribute to the positive net alpha are related to expenses. First, being in the same fund family, the fund managers for these sector funds are constrained to set optimal fees. In some cases, probably too low. Second, competition with low-cost passive funds/ETFs has driven down active management fees.

We apply Roussanov, Ruan, and Wei's (2017) procedure to show that most active sector funds are smaller than their B&G implied equilibrium size. B&G provide a Bayesian updating scheme for investors' belief over a given fund manager's skill. Once investor observes new realized net alpha from the fund, she updates her belief about the fund's skill. In the zero net alpha equilibrium, investor's belief about a fund's skill must exactly offsets the expense she pays plus fund's unit operating cost for active management. Because a fund's unit operating cost is closely related to its size, this allows us to back out the equilibrium size of fund.[18]

Annual realized net alpha is based on the Carhart model. (Other factor models give similar results.) We first calculate monthly implied excess return over one-month T-bill rate of a fund by multiplying its Carhart betas with contemporaneous Carhart factor returns. We subtract the implied excess return from the actual excess return of a fund to get its monthly realized gross alpha. We then aggregate monthly realized gross alpha to annual realized gross alpha, and subtract fund's expense ratio to get its annual realized net alpha. Finally, we use the aforementioned procedure to get the B&G implied fund size at the end of our sample period.

Figure 5 depicts B&G implied log fund size vs. actual log fund size. We sort active sector funds into four groups on their net skills (investor's posterior belief about their skills net of expenses) from bottom to top. The line segments connect the mean log fund size of each group, where the upper and lower bars indicate 95% confidence intervals. To see how individual funds fits into the graph, we plot them with circles.

Across the net skill groups, one should notice the B&G implied mean log fund size is larger than actual mean log fund size in the data, except for the bottom-performing group. This reflects insufficient fund inflows for many of the active funds — 28 out of 40 funds have smaller sizes than those implied by equilibrium. In fact, we see limited variation in actual fund sizes for these sector funds with respect to skills. Surprisingly, the mean log size for the best-performing group is smallest. This misallocation of capital by investors hinders reward and punishment for past performance. Hence B&G's equilibrium argument fails for this particular group of active funds. In sum and consistent with Roussanov, Ruan, and Wei (2017), and Goldstein, Jiang, and Ng (2017), the figure supports the view that active sector funds are under-adjusted.

[18]Mathematically, investors update their belief about a fund's skill by the following equation: $\phi_t = \phi_{t-1} + \omega r_t/(\gamma + t\omega)$, where ϕ_t is investors' posterior belief about a fund's skill at time t, ω is the precision (reciprocal of variance) of excess return earned on the first dollar actively managed by the fund, γ is the precision of investor's prior over fund's skill, and r_t is fund's realized net alpha at time t. Once the prior belief over fund's belief ϕ_0 is provided, one can get ϕ_t recursively. Here we let investors update their beliefs each year. In the competitive equilibrium, investor's posterior belief over fund's skill, i.e., expected revenue from investing, equals the sum of fund's unit operating cost plus expense: $\phi_t = c(q_t) + f_t$, where $c(q_t)$ is the unit cost of actively managing a fund of size q_t, and f_t is its expense ratio at time t. $c(q_t)$ increases monotonically to capture decreasing returns to scale in active fund management. Following Roussanov, Ruan, and Wei (2017), we assume $c(q_t) = \eta \log(q_t)$, where η is a decreasing returns to scale parameter. So the B&G implied log fund size is given by: $\log(q_t) = (\phi_t - f_t)/\eta$. We use the calibrated parameter values from Roussanov, Ruan, and Wei (2017) for ϕ_0, ω, γ, and η.

5.2 Other Hypotheses

5.2.1 Short-Term Reversal

The contrarian nature of the equal-weighted strategy enables it to benefit from short-term reversal like the lead-lag effect documented in Lo and MacKinlay (1990). Because our strategy rebalances sector funds with equal weights, it is designed to sell sector/industry portfolios that have outperformed in the past (winners) and buy those that have underperformed in the past (losers), hence it is essentially a contrarian strategy. But this will not explain EWS's outperformance.

By the same logic, EWS could be hurt by the mid-term momentum documented in Jegadeesh and Titman (1993) and benefit again from long-term reversal documented in Bondt and Thaler (1985). So the EWS return would vary noticeably with the rebalancing frequency used. However, Table 2 shows the contrary, the performance of EWS is insensitive to the rebalancing frequency.

Additionally, such momentum-reversal argument requires a sufficient valuation gap between winners and losers. It will be useful, therefore, to consider how quickly does the relative valuation of different sectors/industries change over time. Unreported results (available on request) analyze the sector weights in a buy and hold strategy, so sector weights are driven over time by performance. No sector turns out to be dominating and it takes sufficient long period of time for the few winners and losers to reverse their roles. Therefore, neither frequent rebalancing is a key driver for the outperformance of EWS strategy, nor are short-term reversals an explanation for our findings.

5.2.2 Embedded Leverage

Although most mutual funds face leverage constraints, funds might be able to enhance their returns by investing in high market beta stocks, or stocks with embedded leverage. This additional risk should be adjusted by the factor models we used and will not explain EWS's alpha. To clearly reject the hypothesis that embedded leverage is driving our strategy's outperformance, we sort funds into high-beta funds and low-beta funds based on their ex-ante betas, and form an equal-weighted portfolio for high-beta funds and low-beta funds separately. The ex-ante beta is estimated with CAPM using trailing 60-month data. We redo the sorting each month to get monthly returns for the two beta-sorted portfolios. We then use CAPM, Fama-French five-factor model, Carhart four-factor model and CPZ model to estimate alpha for the beta-sorted portfolios. The result is reported in Figure 6. Regardless of the factor model used, the graph shows that high-beta funds earn a negative alpha while low-beta funds earn positive alpha.[19] This is consistent with the results of Frazzini and Pedersen (2014), in which authors argue investors with no easy access to leverage bid up high beta assets, resulting high beta assets to have lower alpha. Similarly, we conjecture investors are more easily attracted by high-beta funds, because they tend to generate higher past returns, and fund inflows soon take up fund manager's best ideas, leading to a dimmed prospect for alpha. From an alpha-enhancing perspective, investing in funds with higher embedded leverage will only hinder us; see also Christoffersen and Simutin (2017).

[Insert Figure 6]

5.2.3 Active Share and/or Value-Size Tilt

Two closely related hypotheses are holding large percentages of stocks that are not part of the S&P 500 index, and overweighting value and small-size stocks because active sector funds tend to have smaller sizes.

Inspection of the first hypothesis requires retrieval of historical fund holdings and compare them with the index composition, as done by Cremers and Petajisto (2009). However, active share is not a measure of skill but rather measures how different the fund's holdings are relative to the holdings of the particular benchmark considered. Hence it's hardly a predictor of benchmark-adjusted performance for a small sample of funds.

Another issue with active share is the determination of the passive benchmark. Using fund's self-declared benchmark is problematic in that funds are not bound to invest in their self-declared style. Active share could be misleading and sensitive to the choice of passive benchmarks used. To make things worse, the active sector funds in our sample failed to clearly state their benchmarks.

On the other hand, because active share is defined as the sum of absolute deviations of the fund's stock holdings (weights) from those of its benchmark index portfolio, it is really a measure of fund's selectivity, i.e. a measure of deviations from passive benchmarks. Amihud and Goyenko (2013) proposed to use R^2, obtained from a regression of fund's returns on a multifactor benchmark model, as an easy-to-compute substitute for active share of Cremers and Petajisto (2009). A lower R^2 implies a greater selectivity and predicts higher return. They used Fama-French three-factor model, Carhart four-factor model and CPZ model to calculate R^2, similar to what we do. Inspecting Table 4, the high R^2's across all factor models imply that fund selectivity is unlikely to be a sufficient explanation for the outperformance of EWS.

Similarly, Table 4's results reject the tilt hypothesis. We see little tilt towards either value factor or size factor in the FFC models. While see a moderate size tilt in the CPZ model, the alpha in CPZ model is still sizable and statistically significant. Thus, the value-size tilt does not explain the outperformance either.

[19] Since mutual funds are required to report their holdings and performance regularly, return-smoothing should not distort the market beta estimates.

6 Conclusion

In this article, we have established that a passive and simple strategy can outperform the market — buy sector funds with equal weights and rebalance periodically to preserve the equal weighting. This strategy earns 5.70% of benchmark-adjusted return per year relative to the S&P 500 from 1998 to 2016. The result is robust to fee, transaction cost, and tail risk. The outperformance is not driven by alternative weighting or alternative beta exposure — the strategy has a market beta close to one and only a mild exposure to the size factor.

We are the first to consider passive indexation of active funds as an alternative for investors to allocate capital to external active managers. Creating a passive indexation of active funds means to mimic a passive investor and trade active funds following simple rules, e.g., to periodically rebalance active funds to equal weights. Passive indexation suggests institutional investor to focus on the diversification of active risk and the corresponding increase in top-level information ratio and spend less operation costs on researching skilled managers. As we discussed in the paper, predicting the next high-alpha fund is cost-ineffective.

Although we have focused on one particular strategy in this paper, namely Equal-Weighted Sector (EWS) strategy, the idea of passive indexation of active funds can be applied to, e.g., style investing too. Specifically, a passive indexation of active value funds is likely to outperform a value benchmark, if alphas of underlying funds are not highly correlated. But if active managers select similar securities, their active risks are no longer fund-specific or diversifiable, which hinders increases in top-level information ratio.

Instead of equal weights, other schemes can be used. For example, if smaller funds are more likely to generate alpha, one could over-weight smaller funds in the passive indexation strategy. Similarly, younger funds are on average more likely to outperform so fund age could be another dimension to consider.

Moreover, passive indexation of active funds can accommodate an investor's 'view' on which funds are more likely to outperform. For example, a momentum strategy with sector funds has proven to be profitable (O'Neal (2000)). The takeaway from our research is institutional investor should consider whether the increase in expected alpha will be able to compensate the increase in active risk due to more activeness.

One practical aspect we did not cover in the paper is over-diversification. McKay, Shapiro, and Thomas (2018) suggests that too much diversification leads to too little active risk and a diminished chance to achieve active return objective after management fees. This is not an issue for the EWS strategy. In practice, whether there is over-diversification is always a subtle problem. Instead of blindly investing in too many funds, institutional investor should evaluate whether there is an after-cost positive marginal benefit from diversification. The alpha arithmetic of this article will be helpful for the evaluation.

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Appendix A List of Active Sector Funds

Table A.1
List of Active Sector Funds

Ticker	Sector	Ticker	Sector
FBIOX	Biotechnology	FSDPX	Materials
FBMPX	Multimedia	FSELX	Semiconductors
FBSOX	IT Services	FSENX	Energy
FCYIX	Industrials	FSESX	Energy Service
FDCPX	Computers	FSHCX	Health Care Services
FDFAX	Consumer Staples	FSHOX	Construction and Housing
FDLSX	Leisure	FSLBX	Brokerage and Investment Management
FIDSX	Financial Services	FSLEX	Environment and Alternative Energy
FIUIX	Telecom and Utilities	FSMEX	Medical Equipment and Systems
FNARX	Natural Resources	FSNGX	Natural Gas
FPHAX	Pharmaceuticals	FSPCX	Insurance
FSAGX	Gold	FSPHX	Health Care
FSAIX	Air Transportation	FSPTX	Technology
FSAVX	Automotive	FSRBX	Banking
FSCGX	Industrial Equipment	FSRFX	Transportation
FSCHX	Chemicals	FSRPX	Retailing
FSCPX	Consumer Discretionary	FSTCX	Telecommunications
FSCSX	Software & IT Services	FSUTX	Utilities
FSDAX	Defense & Aerospace	FSVLX	Consumer Finance
FSDCX	Communications Equipment	FWRLX	Wireless

Table 1
Annual Return (%) of EWS

The table reports the annual returns of Equal Weighted Sector strategy and S&P 500 index, and the expense ratio for EWS. EWS stands for Equal Weighted Sector. EWS here rebalances each month, we consider different benchmarks and different rebalancing frequencies in table 2. The data coverage is from September 1st 1998 to June 30th 2016. The annual return for 1998 is the cumulative return form September 1st to December 31st 1998; the annual return for 2016 is the cumulative return from January 1st 2001 to June 30th 2016. In calculating net excess return for 1998 and 2016, expense ratios are adjusted proportionately to time span.

		Benchmark Adjustment		Expense Adjustment	
	EWS	S&P 500	Excess Return	Expense Ratio	Net Excess Return
1998	30.24	28.41	1.83	1.61	1.43
1999	25.50	19.53	5.97	1.48	4.49
2000	9.96	−10.14	20.10	1.43	18.66
2001	−6.01	−13.04	7.03	1.36	5.67
2002	−17.82	−23.37	5.55	1.31	4.24
2003	35.97	26.38	9.59	1.44	8.14
2004	16.42	8.99	7.43	1.32	6.10
2005	13.78	3.00	10.78	1.08	9.70
2006	14.37	13.62	0.75	1.03	−0.27
2007	10.77	3.53	7.24	0.98	6.26
2008	−40.21	−38.49	−1.73	0.93	−2.65
2009	44.03	23.45	20.58	0.94	19.63
2010	22.55	12.78	9.76	0.96	8.81
2011	−3.04	0.00	−3.04	0.90	−3.94
2012	17.19	13.41	3.78	0.87	2.91
2013	33.28	29.60	3.68	0.86	2.83
2014	9.79	11.39	−1.60	0.82	−2.42
2015	−2.76	−0.73	−2.03	0.81	−2.84
2016	4.26	2.69	1.57	0.81	1.16
$t-$statistic	2.51		3.69		3.09

Table 2
Different Rebalancing Frequency for EWS Strategy

The table reports the return profile of Equal Weighted Sector (EWS) strategy. Three different rebalancing frequencies are considered. Buy and hold column reports the results for no rebalancing. SSE (SPDR Sector ETF) is an equal-weighted portfolio of indexed investments in ten S&P sectors. Average return for monthly and quarterly rebalancing are annualized. The corresponding $t-$statistics are reported in parenthesis. Turnover is the total value of trades as proportion of the portfolio value. EWS and S&P 500 data are from September 1998 to June 2016, SSE data are from January 1999 to June 2016.

	Rebalancing Frequency			Buy and Hold
	Monthly	Quarterly	Yearly	
	Panel A: Cumulative Return			
EWS	5.6459	5.6957	5.7888	5.2778
EWS − S&P 500	3.4533	3.5032	3.5963	3.0852
SSE − S&P 500	1.5296	1.5070	1.5205	1.3485
EWS − SSE	1.0979	1.1471	1.2189	1.0612
	Panel B: Average Annual Return			
EWS	0.1170	0.1194	0.1668	0.1612
	(2.8479)	(2.6629)	(2.2786)	(2.1856)
EWS − S&P 500	0.0570	0.0575	0.0621	0.0565
	(4.7360)	(5.2149)	(4.1097)	(3.6812)
SSE − S&P 500	0.0368	0.0360	0.0376	0.0346
	(4.2333)	(4.1613)	(4.7054)	(4.0947)
EWS − SSE	0.0198	0.0216	0.0241	0.0204
	(1.6751)	(1.9486)	(1.6814)	(1.3564)
	Panel C: Average Annual Turnover			
EWS	37.62%	22.63%	11.55%	–
SSE	30.63%	17.80%	11.75%	–

Table 3
Downside Risk Analysis

Panel A reports the maximum drawdown for two financially distressed periods in our sample, drawdown duration is the time difference between time of most recent peak before the maximum drawdown to the the first time of recovery, time to recovery is the time difference between the time of maximum drawdown to fist recovery of former peak. Panel B defines the bear market as months when the cumulative trailing two-year return of S&P 500 is negative (similar to Daniel and Moskowitz (2016)) and bull market otherwise. Panel C tests the state contingent specification for monthly excess return (over one-month T-Bill) of EWS strategy regressed on the excess return of S&P 500:

$$R^e_{\text{EWS},t} = \alpha + \alpha_B I_{B,t-1} + (\beta + \beta_B I_{B,t-1}) R^e_{\text{SPX},t} + \varepsilon_t$$

where the $I_{B,t-1}$ is the ex-ante bear market indicator, which equals to 1 in bear market, and α_B and β_B are bear alpha and bear beta respectively. The numbers in parenthesis are t-statistics. The t-test for beta tests whether the estimate is different from one.

Panel A: Drawdown

	Maximum Drawdown	Drawdown Duration (Years)	Time to Recovery (Years)
Great Recession			
EWS	-55.97%	3.23	1.82
S&P 500	-56.78%	5.47	4.05
Dot-com Bubble			
EWS	-37.30%	3.35	1.24
S&P 500	-49.15%	7.19	4.64

Panel B: Contingent Average Monthly Return

	Bull Market	Bear Market
EWS	0.88%	0.42%
S&P 500	0.54%	-0.21%
EWS - S&P 500	0.34%	0.64%
	(3.03)	(3.17)

Panel C: Bear Market Conditionality

	Alpha(%)	Bear Alpha(%)	Beta	Bear Beta	R^2_{adj}
1	0.42		1.06		0.92
	(4.26)		(2.62)		
2	0.33	0.31	1.04	0.04	0.92
	(2.69)	(1.46)	(1.12)	(0.84)	

Table 4
Factor Attribution of Returns of Equal Weighted Sector (EWS) Strategy

The table reports estimates of betas and alphas for the EWS strategy; in parentheses are $t-$statistics for each coefficient estimate. We report three different $t-$statistics based on three different methodologies for calculating the standard errors. The top $t-$statistic uses OLS estimation, the middle one uses heteroskedasticity and autocorrelation consistent standard errors from Newey and West (1994), the bottom one uses pairwise block stationary bootstrapped standard errors of Politis and Romano (1994), based on 10,000 bootstrap samples. Panel A shows the result using common linear asset pricing factors. CAPM uses market factor only, Fama-French Five stands for Fama-French five-factor model of Fama and French (2015), Carhart stands for Carhart four-factor model of Carhart (1997). MKT, SMB, HML, RMW, CMA, UMD are market factor, size factor, value factor, profitability factor, investment factor, and momentum factor, respectively. For the market beta, t–test tests whether the MKT beta is different from 1.0. Panel B uses common tradable benchmarks as factors, CPZ is the proposed IDX4 model in Cremers, Petajisto, and Zitzewitz (2013). S5 - RF is return of S&P 500 index minus one-month T-Bill rate, R2-S5 is an index-based factor of Russell 2000 minus S&P 500, R3V-R3G is return of Russell 3000 Value minus Russell 3000 Growth. R^2 is adjusted for degrees of freedom. For the beta of S5-RF, $t-$test tests whether it is different from 1.0. Regressions in Panel A use monthly data from September 1998 to June 2016, regressions in Panel B use monthly data from September 1998 to December 2013.

Panel A: Fama-French-Carhart Factors

		Factors						
Model	Alpha(%)	MKT	SMB	HML	RMW	CMA	UMD	R^2_{adj}
CAPM	0.25	1.02						0.94
	(3.04)	(1.11)						
	(2.39)	(0.66)						
	(2.04)	(0.51)						
Fama-French Five	0.14	1.05	0.12	0.08	0.09	0.02		0.95
	(1.86)	(2.45)	(4.55)	(2.50)	(2.69)	(0.52)		
	(1.37)	(1.58)	(3.54)	(1.34)	(2.51)	(0.43)		
	(1.97)	(1.88)	(2.62)	(0.89)	(1.46)	(0.35)		
Carhart	0.22	1.01	0.10	0.12			-0.03	0.95
	(2.87)	(0.55)	(4.04)	(4.99)			(-1.79)	
	(2.05)	(0.20)	(2.75)	(1.95)			(-0.83)	
	(2.41)	(0.32)	(1.82)	(1.12)			(-1.02)	

Panel B: Investable Benchmarks

		Factors				
Model	Alpha(%)	S5-RF	R2-S5	R3V-R3G	UMD	R^2_{adj}
S&P 500	0.37	1.04				0.92
	(3.50)	(1.69)				
	(3.27)	(1.28)				
	(3.06)	(1.09)				
CPZ	0.27	1.02	0.30	0.06	-0.01	0.95
	(3.44)	(1.01)	(12.41)	(2.22)	(-0.46)	
	(2.49)	(0.58)	(10.39)	(1.00)	(-0.23)	
	(3.39)	(1.14)	(8.99)	(0.53)	(-0.26)	

Table 5
Carhart Factor Exposures of Active Sector Funds

The table summarizes the cross-section of estimated betas for the 40 active sector funds in our sample, using Carhart four-factor model. All estimations use monthly data from September 1998 to June 2016.

	MKT	SMB	HML	UMD
Mean	1.01	0.10	0.11	−0.02
Standar Deviation	0.24	0.23	0.53	0.10
1st Percentile	0.53	−0.31	−1.00	−0.27
5th Percentile	0.61	−0.25	−0.88	−0.16
10th Percentile	0.70	−0.19	−0.81	−0.11
50th Percentile	0.99	0.07	0.25	−0.03
90th Percentile	1.31	0.42	0.68	0.09
95th Percentile	1.48	0.43	0.74	0.12
99th Percentile	1.48	0.61	0.86	0.19

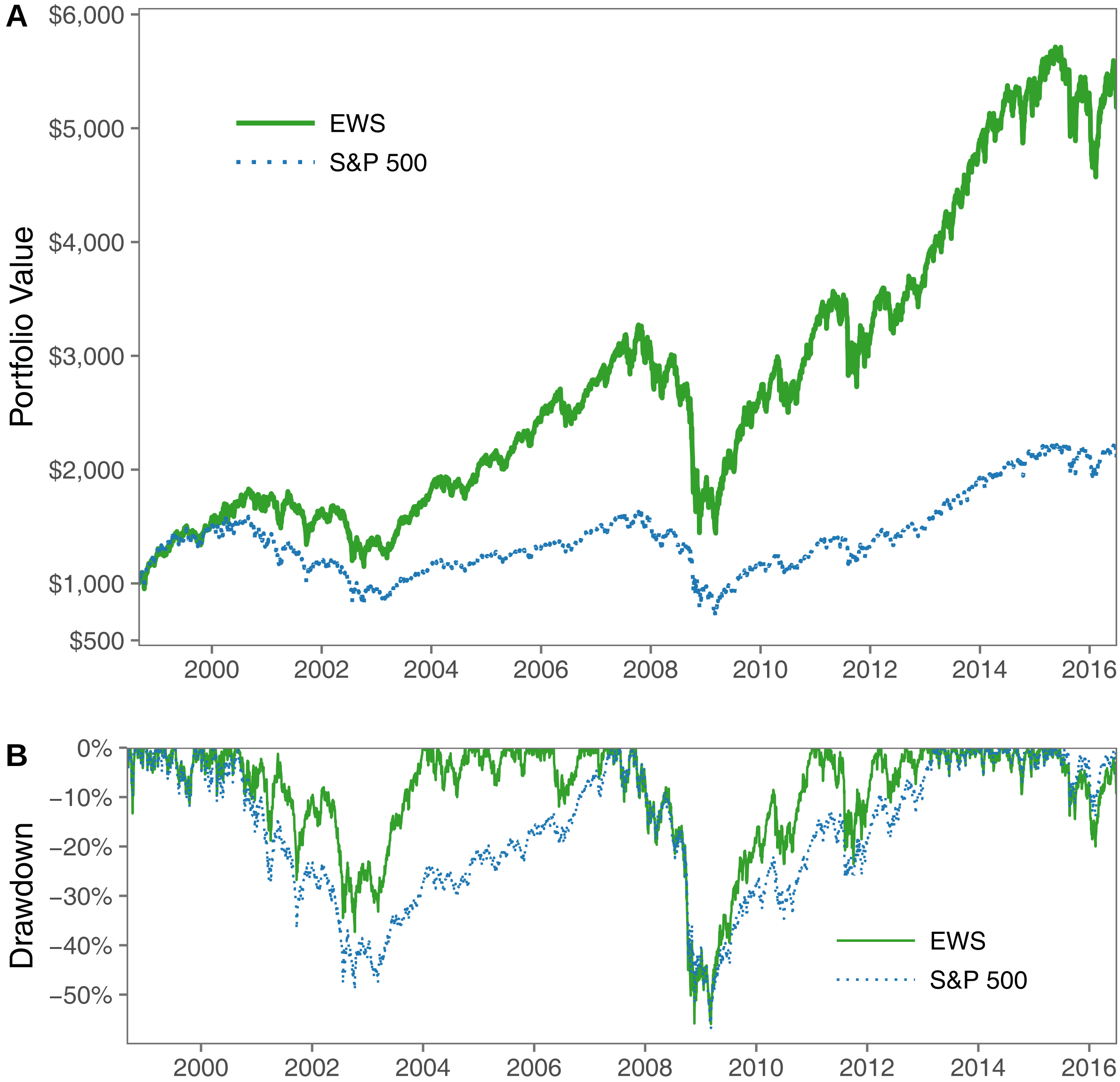

Figure 1. Growth of $1,000 Investment.

The plot displays the cumulative portfolio value from investing $1,000 in the Equal Weighted Sector (EWS) strategy and S&P 500 index (SPX). The solid line corresponds to EWS strategy, the dashed line corresponds to S&P 500 index. Panel A shows the portfolio values. Panel B shows corresponding drawdowns. The investment period is from September 1st, 1998, to June 30, 2016.

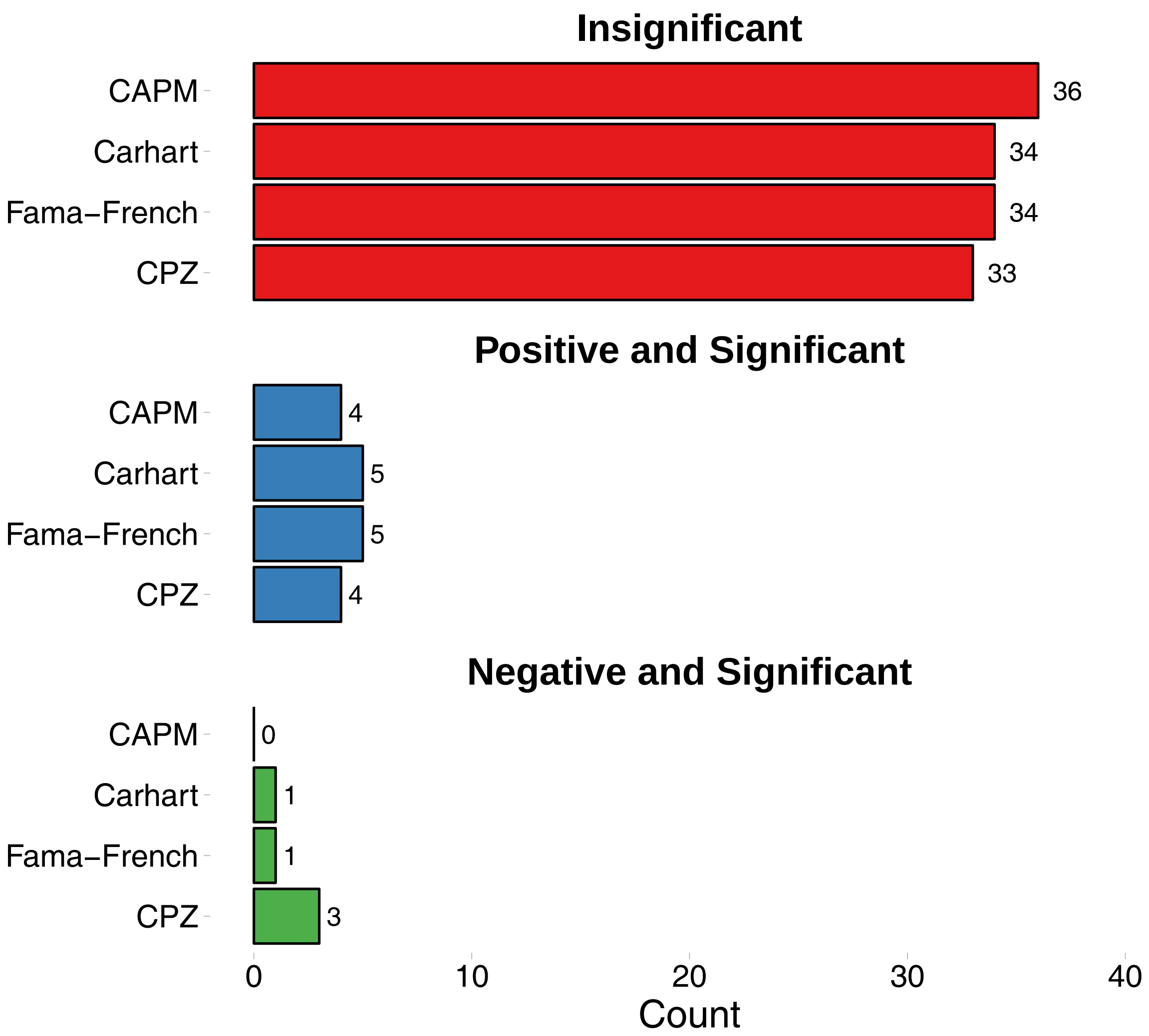

Figure 2. Alpha Significance

This figure plots the number of active sector funds in different categories of alpha significance. Four factor models are used to account for risks: CAPM, Fama-French five-factor model from Fama and French (2015), Carhart four-factor model form Carhart (1997), and CPZ four-factor model from Cremers, Petajisto, and Zitzewitz (2013)

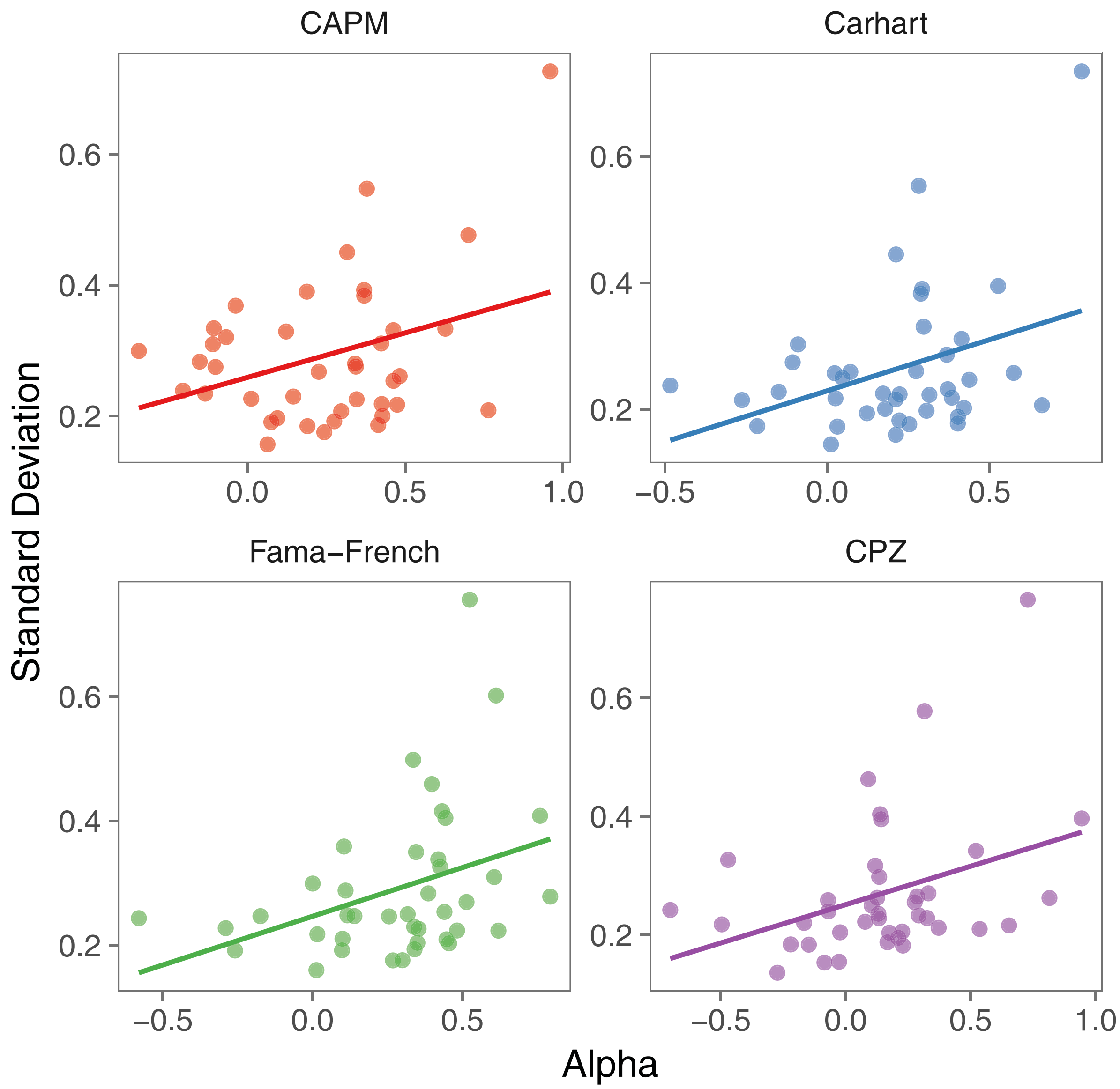

Figure 3. Alpha vs. Standard Deviation

This figure plots funds' monthly alphas against their standard deviations split by the factor model used. Each circle corresponds to an active sector fund. The fitted lines use alpha as single regressor for its standard deviation. The factor models used are, CAPM, Fama-French five-factor model from Fama and French (2015), Carhart four-factor model form Carhart (1997), and CPZ four-factor model from Cremers, Petajisto, and Zitzewitz (2013)

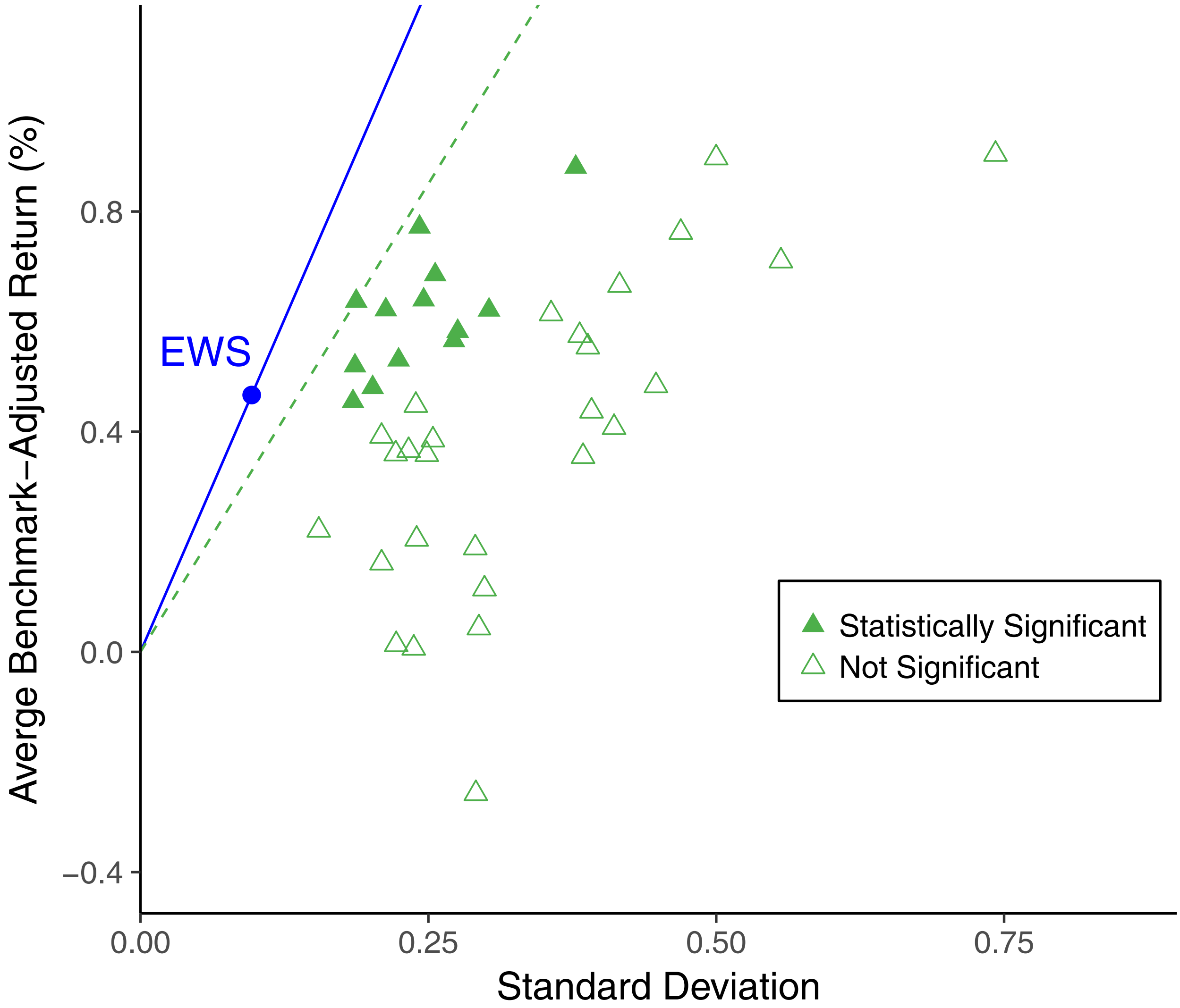

Figure 4. Mean-Variance Trade-off

Each triangle represents an active sector fund, the solid triangles represent those funds with a statistically significant benchmark-adjusted return. The benchmark used is S&P 500 monthly return. The vertical axis gives the average monthly benchmark-adjusted return, the horizontal axis gives the associated standard deviation. The solid circle indicates the coordinates for the Equal Weighted Sector (EWS) strategy. The dashed line corresponds to the ex-post optimal risk-return trade-off if invested in an individual active sector fund. The solid line corresponds to achieved risk-return trade-off for EWS. The slopes of the lines are corresponding information ratios.

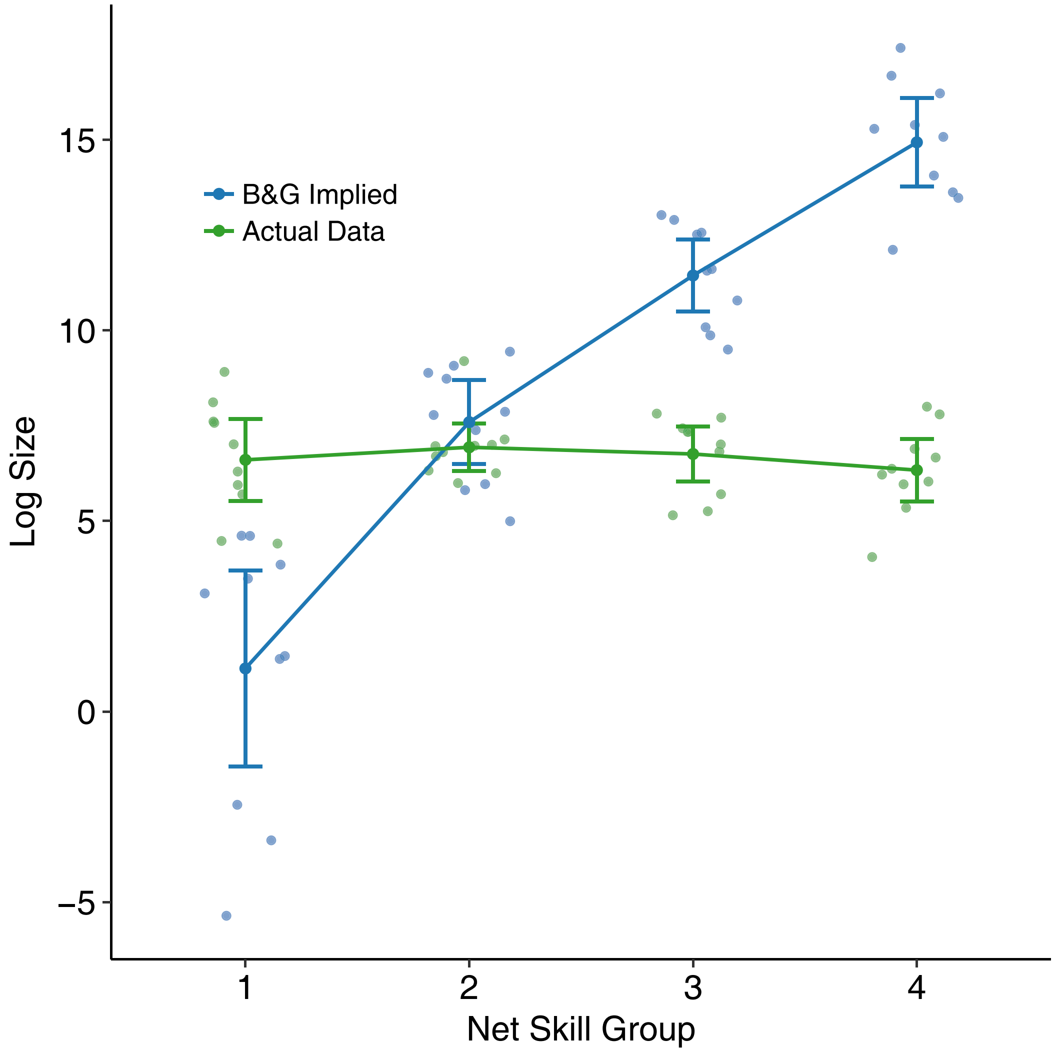

Figure 5. Under-Adjustment for Active Sector Funds

This figure plots Berk and Green (2004) implied log fund size in equilibrium versus actual log fund size. The underlying active sector funds are sorted into four net skill groups, in which net skill is defined as investors' posterior expectation of fund's skill minus fund's expense. The line connects the mean log fund size for net skill groups, the upper and lower bars indicate the 95% confidence bounds of the mean. Each circle represents an active sector fund. Net skill group 1 has the lowest skill while net skill group 4 has the highest skill.

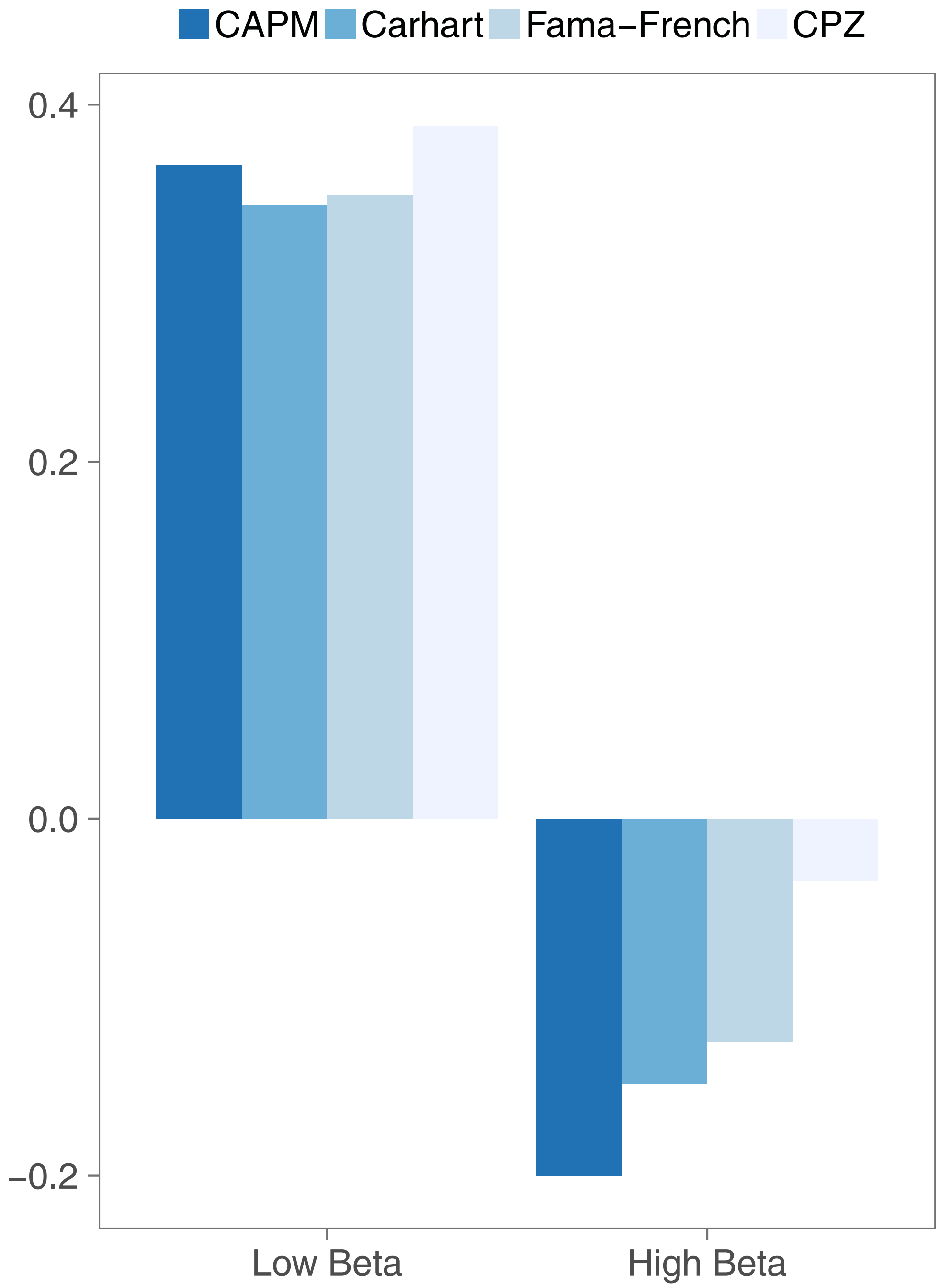

Figure 6. Alphas of Beta-Sorted Funds

Alphas(%) of beta-sorted portfolios which are constructed from active sector funds with equal weights. The funds are sorted into low-beta funds and high-beta funds according to their ex-ante market betas estimated using 60-month moving windows. The alphas are intercepts from regressions of monthly returns accounted for factor exposures. Four factor models are used, CAPM, Fama-French five-factor model from Fama and French (2015), Carhart four-factor model form Carhart (1997), and CPZ four-factor model from Cremers, Petajisto, and Zitzewitz (2013)