Fund Management Skill and Noise Trading

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Abstract

In this research authors show that institutional investors' skill matters the most during high sentiment periods when market signals are noisy. The results reveal that fund managers with the highest (lowest) skill add (lose) $7.71 ($5.64) million of value during high sentiment periods, compared with $3.74 million gain realized by the average manager during the entire sample period. When the market sentiment is low, high-skilled fund managers incur a value loss of only $0.18, much smaller than the $30.32 million loss realized by their low-skilled counterparts.

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While investor sentiment has been held largely responsible for the dramatic rise and fall in financial asset prices during the last two decades, its impact on the performance of actively managed mutual funds' remains unknown. To address this question, we examine whether variations in fund profitability can be explained by variations in investor sentiment, since sentiment affects the amount of noise trading which, in turn, makes it difficult to carry out profitable trades, as discussed in Black [1986].

A large body of the literature shows that actively managed funds outperform passively managed funds.[1] This superior performance is often attributed to management skills possessed by active fund managers such as stock-picking and market-timing talents. However, only a few studies have addressed the question of whether active fund managers' skills vary with time.[2] Fund management skill, as with people's skills in general, grows with experience and its efficiency to generate profits should be highly affected by financial market information especially in recent decades, since more information is available in the market and the speed of trades is much faster than before due to new technological developments. Additionally, economic and capital market conditions, which are changing with time, can also influence the profitability of fund management skill. Furthermore, the few studies addressing this question rely on the assumption that market participants behave rationally, which has been challenged by many recent behavioral finance studies.[3]

Indeed, noise traders' participation in the market, coupled with short-selling limitations, forces asset prices to deviate from their fundamental values, making it difficult to produce risk adjusted excess-returns.[4] Noise trading activity is also known to vary with time and being related to investor sentiment. There are reasons to believe that noise trader's activity is not symmetric between optimistic and pessimistic sentiment periods, and is more prevalent during optimistic times.[5] If fund managers' skill is based on their superior insight and analytical ability, as argued in previous studies, the ability of skilled fund managers to create value in high sentiment states is expected to arise from their analytical valuation talents and insights to make investment decisions than being attracted to overvalued stocks which are preferred by naïve investors. Therefore, skilled fund managers are expected to produce and trade more on (private) information about the true value of financial assets under management, and deliver more value during high sentiment periods when financial asset prices are noisier than in low sentiment periods. In contrast to the previous literature that examines whether fund managers try to exploit investor sentiment by deploying sentiment-based (timing) strategies [Massa and Yadav, 2015], we consider investor sentiment as a market condition, not as a risk factor that skilled managers attempt to predict so that they can actively modify their fund strategies accordingly.[6]

There are two reasons that skilled fund managers are more likely to deliver higher value (adjusted *alpha*) during high sentiment periods. First, the level of investor sentiment can affect both overall market returns and individual stock returns.[7] Stocks during high sentiment periods are driven away from their fundamental values by naïve investors. Additionally, short-selling impediments of institutional investors, especially mutual funds, are also major obstacles to eliminating price overvaluation. Thus, asset prices are more likely to be noisy and as a result, more difficult to identify good investment opportunities during high sentiment times. Hence, if fund managers' selectivity skill is based on their firm-specific information and analytic abilities, it should be able to produce superior fund performance during high sentiment periods when stock prices are exposed to greater noise than during low sentiment periods.

Second, fund performance can be influenced by investor sentiment due to market anomalies

[Stambaugh, Yu, and Yuan, 2012]. Combined with short-sale constraints, mutual fund managers are more likely to bet on positive information. Because stocks tend to be overvalued due to the momentum effect during high sentiment periods, sophisticated fund managers can take advantage of the momentum driven asset pricing drift to generate superior returns.

While our evidence is consistent with the findings reported in the literature that high-skill fund managers outperform their low-skill peers, our main focus is on the power of fund management skill to generate abnormal returns during high sentiment periods when noise trading is more pronounced and impactful on asset prices due to short selling limitations [Shleifer and Vishny, 1997]. The practical implication of this analysis is to show that skilled fund management matters and aid investors to make superior investment decisions through funds run by skilled managers, especially when markets are populated by noise traders.

To examine this question, we use the Berk and van Binsbergen [2015, 2017] measures of fund performance (i.e., the product of the gross abnormal return (*alpha*) and fund size (the value extracted by a fund from capital markets)) and management skill (i.e., skill ratio). We find that high investor sentiment harms fund performance, but managers with above-average stock- picking skill manage not only to protect fund performance from the adverse effect of high sentiment, but even to create value for funds under their management. Specifically, fund managers with the highest skill create $7.71 million of added value during high sentiment periods, exceeding the average realized fund gain of $3.74 million during the entire sample period, and incur a negligible loss of $0.18 million in value during low sentiment periods.[8] Whereas, fund managers with the lowest skill experience value-losses of $5.64 million during high sentiment periods, while $30.32 million during low sentiment periods.

In addition, using alternative sentiment measures such as the University of Michigan

Consumer Sentiment (UM) index, the Financial and Economic Attitudes Revealed by Search (FEARS) index, and the credit market sentiment index, we obtain qualitatively similar results with our main findings. Jointly, the evidence that skilled managers generate higher profits in high sentiment periods suggests that they can create value for fund investors when markets are populated by noisy investors.

Data and Sample Selection

Our data were extracted from the Bloomberg Fund Dataset, which was originally built for institutional investors in 1993 and is currently widely used in the finance industry. Our sample includes 1,873 mutual funds, covering a period of 145 months from December 2002 to December 2014.[9] Since we use 24-month windows to estimate fund managers' skill, the actual data trace back to December 2000. We collected monthly raw returns for each fund if the fund had full return data for the 24-month estimation period. We also collected fund-level control variables that may be associated with the fund's performance from the same database.

To make sure that our sample does not suffer from survivorship bias, we collected data from funds with both alive and dead status. We also used several criteria to restrict our sample to actively managed U.S. domestic equity mutual funds: 1) the geographical focus of the mutual funds is United States; 2) the asset class focus of the mutual funds is Equity; 3) the country of domicile is United States; 4) the inception date is before December 31, 2012; 5) the fund type is open-end mutual fund; and 6) fund description does not contain any of the partial words: *index*, *ind*, *S&P*, *DOW*, *Wilshire*, *Russell*, *global*, *fixed-income*, *international*, *sector*, or *balanced*. Following Reibnitz [2013], we required funds to have TNA of at least $15 million in December 2013. We set an estimation period of 24 months followed by a test month, and during the estimation period, we regressed monthly fund excess return (over the T-bill rate) on the FFC model factors and moved the window a month at a time. Exhibit 1 shows the summary statistics of the mutual funds in our sample.

[Insert Exhibit 1 here]

The main sentiment measure used in this paper is based on Baker and Wurgler [2006] sentiment (BW) index.[10] The BW index, which has been widely used in the finance literature, is constructed using six proxies of investors' propensity to invest in stocks: trading volume (total NYSE turnover); the premium for dividend paying stocks; the closed-end fund discount; the number and first-day returns of IPOs; and the equity share in new issues. For the whole 145- month sample period, if month *t*'s BW index is higher (lower) than the median number of all the monthly BW index numbers, month *t* is defined as a high (low) investor sentiment month.[11]

Empirical Methodology

We use the method, introduced by Berk and van Binsbergen [2015], to deduce fund management skill based on the extra value added to the fund (i.e., the product of the gross abnormal return and fund size at the beginning of the period) divided by its standard error, measured over the period from December 2002 to December 2014. As discussed in Berk and Green [2002], gross *alpha* is not a suitable performance measure for mutual funds because of their unique investment mechanism. Specifically, a value measure, rather than a return measure, is more appropriate in measuring fund performance. This measure requires that the gross abnormal return should be adjusted for fund size. Unlike prior studies that have measured fund performance using risk models (FFC model, Fama–French three-factor model, CAPM model, etc.), Berk and van Binsbergen [2015] evaluate fund performance by benchmarking it against an alternative investment opportunity set–the 11 Vanguard index funds.[12] Their argument is that the evaluation of the mutual fund performance requires comparing a fund's performance with the next best investment opportunity available to investors at that time. The benchmark should have two characteristics: the return of the benchmark should be known to investors and the benchmark can be traded. Unfortunately, the benchmarks used in the factor models do not meet these criteria. Therefore, Berk and van Binsbergen [2015] suggest using the set of passively managed index funds offered by Vanguard as the alternative investment opportunity set, and they define the fund benchmark as the closest portfolio formed by those index funds.

We follow Berk and van Binsbergen [2015] and use the 11 Vanguard index funds to form the alternative investment opportunity set as the benchmark. However, we test, conducting a rolling window regression method, whether management skills vary over time instead of focusing on the cross-sectional skill difference among fund managers as in their analysis. We collect data only when all the 11 index funds have available data, giving us a final sample that covers 145 months from December 2002 to December 2014. We then construct an orthogonal basis set out of these index funds by regressing the n^{th} fund on the orthogonal basis produced by the first n-1 funds over the 145-month period. The orthogonal basis for index fund n is calculated by adding the residuals collected from the prior regression and the mean return of the n^{th} index fund for the entire period.

Next, as shown in Eq. (1), we regress the excess returns of each fund *f* on the 11 Vanguard index funds' orthogonal bases for the whole sample period from December 2002 to December 2014, using 24-month rolling window regression and moving forward 1 month each time.

$$Return_{f,t} = \sum_{j=1}^{11} \beta_p^j R_t^j + \alpha_f \quad (1)$$

The performance measure we use is the abnormal capital inflow a fund experiences in the test month (denoted as BvanB *alpha*), which is calculated as the fund's gross abnormal return (real raw return over its expected return) multiplied by the TNA of the fund at the beginning of the current month. The fund expected return is attained by multiplying the coefficients between each

Vanguard index fund's orthogonal basis and fund excess return from the 24-month preceding estimation period by the real numbers of each Vanguard index fund's orthogonal basis in the current month.

To capture fund management skill, we use the skill ratio measure as in Berk and van Binsbergen [2015], denoted as the BvanB fund skill. As shown in Eq. (2), the BvanB fund skill for each fund in each month is the product of a fund's abnormal return (fund *alpha*) and the fund's size at the beginning of the month prior to the test month, divided by the standard error of the fund *alpha*. Fund *alpha*s and standard errors are obtained from the 24-month rolling window regression of fund excess return on the alternative investment opportunity. Fund size is the inflation-adjusted total net assets of the fund.

$$BvanB\ Fund\ Skill_{f,t} = \frac{alpha_{f,t-1} * TNA_{f,t-2}}{SE_{f,t-1}} \qquad (2)$$

This fund skill measure, estimated over the 24-month estimation period, allows us to infer fund selectivity based on the extra value added to the fund (i.e., the mean of the product of the gross abnormal return and fund size at the beginning of the period divided by its standard error). The advantage of this metric is that it permits to gauge the success of a fund manager based on the added value of an investment opportunity (i.e., the net present value (NPV) of an investment) rather than the return a fund earns (i.e., the internal rate of return (IRR)), as bigger funds could generate more value even if they have lower *alpha*s. Next, we form fund portfolios based on each fund skill and past performance. We first rank all funds within each month based on their prior month's BvanB fund skill, as described in Eq. (2), and sort them into five quintiles. Within each quintile, we sort funds into five portfolios based on their previous performance, i.e., the BvanB fund $alpha_{t-1}$. The BvanB fund $alpha_{t-1}$ of each fund in each month is the product of fund $alpha_{t-1}$ and fund inflation-adjusted TNA at the beginning of the last month in the 24-month estimation period, where fund $alpha_{t-1}$ is obtained by regressing each fund's monthly excess returns on the 11 Vanguard index funds' orthogonal bases. This procedure produces 25 (5x5) portfolios with a different BvanB fund skill and BvanB fund $alpha_{t-1}$, and each portfolio contains 4% of the total mutual funds within the same month.

Previous literature has shown that the presence of dispersion in stock returns and the state of the economy can influence the market environment which, in turn, provides the opportunity for skilled fund managers to outperform the market [Reibnitz, 2013; and Kacperczyk et al., 2014, 2016). Active opportunity in the market, captured by cross-sectional dispersion in stock returns, as argued by Reibnitz [2013], could influence fund performance by the variation in the arrival of firm-specific information. During a high market-dispersion period, the market price is affected more by firm-specific information than market conditions. If this is true, the impact of active bets is expected to be more pronounced during this time, and managers possessing skill in identifying, interpreting, and acting on firm-specific information will significantly outperform their low-skilled peers. As in Reibnitz [2013], we calculate market dispersion for each month. This is estimated as the average diversion between the equally weighted average return on S&P 500 constituents in each month and the return of each S&P 500 constituent in the same month. The stock return dispersion in month t (MD_t) is calculated as follows:

$$MD_t = \sqrt{\frac{1}{n-1}\sum_{i=1}^{n}(R_{i,t} - R_{m,t})^2} \quad (3)$$

where n is the number of S&P 500 constituents in month t, $R_{i,t}$ is the return of each constituent i in this month, and $R_{m,t}$ is the equally weighted average return of all S&P 500 constituents in month t. We collect the list of S&P 500 constituents and their monthly returns from Bloomberg database. Exhibit 2 shows a time series plot of monthly stock return dispersion over the 2002– 2014 sample period.

[Insert Exhibit 2 here]

The second element that can have an impact on the profitability of skilled fund managers is the state of the economy. Kacperczyk et al. [2016] built an information choice model by assuming fund managers have a finite mental capacity (attention) and skilled managers are the ones who allocate their capacity efficiently. Since the optimal allocation strategy is changing with the state of the economy, the efficiency of fund managers' investment strategy and fund return are expected to vary with time. Kacperczyk et al. [2014] decomposed manager skill into stock picking and market timing and report that managers balance those two strategies based on the state of a business cycle. The previous literature has also suggested that skilled managers devote more time and resources in managing a fund actively during recessions to protect the fund's performance from economic downturns [Wermers, 2000; Glode, 2011; Kosowski, 2011; and Reibnitz, 2013]. Thus, one can argue that the effect of investor sentiment on mutual fund performance is caused by the correlation between the cyclical variation in sentiment and economic cycles. For that reason, we use the Chicago Fed National Activity Index 3 month average (CFNAI MA3), following Kacperczyk et al. [2014], to capture the effects of the business cycle on fund performance.[13] The CFNAI is a coincident indicator of national economic activity comprising 85 existing macroeconomic time series.

Empirical Results

In this section, we present univariate and multivariate fund performance results and check the robustness of our results using alternative investor sentiment measures.

We begin by reporting the results based on the Berk and van Binsbergen [2015] fund selectivity measure, i.e., BvanB fund skill. First, for every month following the 24-month estimation period, we calculate the average monthly excess return for each fund portfolio, and we regress the test period average portfolio returns on the alternative investment opportunity market benchmark. For each portfolio, we present the portfolio BvanB fund *alpha*, which is the product of the intercept from the above regression and the average inflation-adjusted TNA of all funds within the portfolio at the beginning of the current month, in Exhibit 3.

[Insert Exhibit 3 here]

The results in Exhibit 3 reveal that funds with superior management skill, as measured by BvanB fund skill, have better performance. Specifically, the results in row “All” of Panel A, show that fund portfolio performance (BvanB fund *alpha*) decreases as we move from the high BvanB fund skill portfolio to the low BvanB fund skill portfolio, i.e., greater fund skill produces higher BvanB fund *alpha*s. The highest annualized BvanB fund *alpha* is 3.74 (P = 0.337) for the fund portfolio with the highest BvanB fund skill and the best past performance. While highly skilled fund managers with high past performance, Q5, do not outperform the benchmark significantly every month, the low-skilled ones realize significant losses of -4.80 (P = 0.048). The results for the hypothetical portfolio of a long position in a high BvanB fund skill portfolio and a short position in a low BvanB fund skill portfolio for each lagged *alpha* quintile, presented in the rightmost column of Panel A under “High-Low,” indicate that the return from this strategy is positive and significant in all *alpha* quintiles. For example, the high BvanB skill fund portfolio outperforms the low BvanB skill fund portfolio by 5.30 (P = 0.044). For the highest and second- highest BvanB *alpha* quintiles, the hypothetical portfolio yields an annualized *alpha* of 4.27 (P = 0.061) and 3.33 (P = 0.053), respectively. On average, the high BvanB fund skill portfolio adds $5.30 million more capital than the low BvanB fund skill portfolio every month (P = 0.044). Overall, these results confirm that funds with the best past performance are associated with the most highly skilled managers.

The results in Panels B and C of Exhibit 3 demonstrate that highly skilled managers do better during high sentiment periods than in low sentiment periods. In high sentiment periods (Panel B), consistent with the previous evidence, the highest annualized BvanB fund *alpha* is $7.71 million (P = 0.337) for the fund portfolio with the highest BvanB fund skill and the best past performance. Though the difference is not significant, it is much higher than the added value of $3.74 million (P = 0.337) that they create during the entire sample period. This indicates that the performance of skilled fund managers is pronounced when financial markets are populated with noisy investors. In the other words, they can double a fund's added value in high sentiment periods (Panel B) compared with the entire sample period (Panel A). While highly skilled managers with high past performance, Q5, do not significantly outperform the benchmark every month, the low-skilled ones do not realize losses (P = 0.656) in high sentiment periods. This probably because highly skilled managers, due to their high past performance, experience high capital inflow and—under the pressure to invest the extra capital received from investors—they are forced to make suboptimal investment decisions due to limited optimal investment opportunities in the market. This, in return, lowers the profitability of their skill.

However, in low sentiment periods (Panel C), the highest annualized BvanB fund *alpha* is -0.18 (P = 0.969) for the fund portfolio with the highest BvanB fund skill and the best past performance. This is substantially lower than the parallel BvanB fund *alpha* in the high sentiment periods of 7.71 (P = 0.219). The row "All" in Panel C shows that fund portfolio performance (BvanB fund *alpha*) is significantly below the benchmark and in contrast with the corresponding row "All" for high sentiment periods (Panel B). The rest of the funds in this group realize significant negative BvanB fund *alpha*s. The results for the hypothetical portfolio of a long position in a high BvanB fund skill portfolio and a short position in a low BvanB fund skill portfolio for every lagged *alpha* quintile, presented in the rightmost column of Panel C under "High-Low," suggest that the high BvanB skill fund portfolio realizes significantly lower losses than the low BvanB skill fund portfolio by 9.69 (P = 0.006). For the highest and second-highest BvanB *alpha* quintiles, the hypothetical portfolio yields an annualized *alpha* of 5.49 (P = 0.074) and 5.70 (P = 0.017), respectively, suggesting that the high BvanB skill fund portfolio consistently realizes significantly lower losses than the low BvanB skill fund portfolio. Taken together, these results are in line with our contention that the performance of skilled fund managers is greater in high sentiment periods than in low sentiment periods, suggesting that fund management skill is of higher value to investors when there is greater noise in the market.

Since the BvanB skill and performance measures are adjusted by fund size, one may argue that these measures are not stationary. To solve this concern, we put all the funds in each month into high and low BvanB skill portfolios based on their BvanB skill ratios, and estimate the average fund size in each portfolio. The time series plot of the average fund size in each portfolio, as shown in exhibit 4, remains roughly the same over the whole sample period.

[Insert Exhibit 4 here]

As discussed earlier, equity market dispersion and the state of the economy can influence the performance of skilled fund managers. To examine their impact on fund portfolio performance, we first repeat our portfolio sorting analysis based on the market dispersion. In line with our sentiment analysis, we divide our sample into high and low market-dispersion periods based on the median number of the market-dispersion index. The results indicate that skilled fund managers outperform their unskilled peers and the market benchmark, especially during high market-dispersion periods. This pattern, which is consistent with our high sentiment results, suggests that skilled fund managers can add value to fund investor portfolios when the market is subject to considerable uncertainty and more difficult than normal times for fund investors to interpret financial price signals.[14]

Using CFNAI MA3 to split the sample into recession and expansion periods, we repeat the portfolio sorting analysis using the same sample period as in the previous section (1990– 2014). Our results reveal that funds with high selectivity skill realize positive risk-adjusted excess returns in economic expansions than in economic recessions. In addition, the performance dispersion between the highest selectivity fund and the lowest selectivity fund is more pronounced in economic recessions than in expansions, which is consistent with the previous literature's finding that skilled active funds provide an insurance mechanism against recessions [Kacperczyk et al., 2011].[15]

Jointly, these results—while in line with previous studies—also demonstrate that skilled fund managers have superior performance during states of high equity market dispersion and economic expansion. However, one may argue that it is essentially market dispersion or business cycle, rather than investor sentiment that determines the fund performance difference between the high and low sentiment states. In response to this argument, as shown later in Exhibit 4, we account for the stock market dispersion and business cycle effects in our analysis and find that funds with skilled managers continue to have a significantly better performance during high investor sentiment periods.

We re-examine the effect of fund management skill and its interaction with sentiment on fund performance using the BvanB fund skill (ratio) and performance (*alpha*) measures, controlling for other effects, and estimate the following model:

$$BvanB\ Fund\ Alpha_{f,t} = \alpha_f + \beta_1 BvanB\ Fund\ Skill_{f,t} + \beta_2 Sentiment_t + \beta_3 BvanB\ Skill_{f,t} * Sentiment_t + \sum Controls_{f,t} + \varepsilon_{f,t} \qquad (4)$$

where BvanB fund *alpha* (performance) is the product of fund inflation-adjusted TNA at the beginning of the current month and the difference between the fund excess return in the current month and the expected excess return of the same month. BvanB fund skill is measured as the product of fund $alpha_{t-1}$ and the fund TNA at the beginning of the last month in the 24-month estimation period divided by the standard error of the fund $alpha_{t-1}$, where fund $alpha_{t-1}$ is the intercept from the preceding 24-month estimation period.

[Insert Exhibit 5 here]

Basically, the regression results in Exhibit 5 show that BvanB fund skill significantly contributes to the fund performance (BvanB fund *alpha*) in all regressions. Consistent with our prediction, we find, in most of our regressions, a significant negative relationship between investor sentiment and fund performance, but a significant positive relationship between the interaction variable, *BvanB skill*Sentiment*, and fund performance. This indicates that, on average, high sentiment harms the overall fund performance, but this does not hold for skilled fund managers. In fact, skilled fund managers during high sentiment periods show significantly better performance than in low sentiment periods due to their ability to identify opportunities and make superior investments when the market is populated by noise traders. The positive and significant relationship between fund past performance (BvanB $alpha_{t-1}$) and fund performance (BvanB fund *alpha*) reveals a strong persistent performance of skilled managers. These results, as shown in the far-right regressions, remain robust after controlling for the state of the economy and stock market dispersion. In sum, the consistency between the multivariate and the univariate results, regardless of fund selectivity and performance measures used, provide strong evidence in support of the proposition that skilled fund managers realize superior risk-adjusted abnormal returns in high sentiment periods when noisy trading is more prevalent and it is more difficult to discern true (intrinsic) value.

We also ran robustness tests using three alternative sentiment measures: University of Michigan Consumer Sentiment (UM) index, credit market sentiment index, and the Financial and Economic Attitudes Revealed by Search (FEARS) sentiment index. The UM index, which is available online, is one reliable sentiment index measured outside of the financial market and used widely in finance studies. Following Lopez-Salido, Stein, and Zakrajsek [2016], we estimated the credit investor sentiment using the two-step econometric methodology. First, we calculate the spread between yields on seasoned long-term Baa-rated industrial bonds and yields on 10-year Treasury securities for each month. Next, we regress the change in the spread based on the past 24 months' spreads, and the expected spread change is used as the credit investor sentiment index. The 24-month estimation period moves one month each time. The FEARS index, as introduced by Da et al. [2015], is an index based on the internet search behavior of households. To use this index in our analysis, we convert the data into monthly observations by taking the average of the daily data in order to match our data. Untabulated results based on these three sentiment measures are qualitatively consistent with the pattern of our previous findings.[16]

Conclusion

Unlike most of the previous literature that has focused on the question of whether fund managers improve fund performance, in this paper, we examine whether skilled mutual fund managers deliver greater value (BvanB fund *alpha*) during high sentiment periods when security markets are crowded by noise traders. Using a large sample of U.S. domestic actively-managed equity mutual funds, we empirically examine this conjecture and find that managers endowed with high fund management skill realize superior fund performance during high investor sentiment periods when asset prices are noisier and information is costlier. Specifically, our result show that fund managers with the highest skill create $7.71 million of added value during high sentiment periods, compared with the average realized fund gains of $3.74 million for the entire sample period. While these highly skilled managers incur only a small value loss of $0.18 million in low sentiment periods, the fund managers with the lowest skill experience a value loss of $5.64 million.

Our findings are robust to alternative sentiment measures including UM Sentiment index, credit market sentiment and the FEARS sentiment index. Overall, this study conclusively suggests that skilled fund managers create more value during high than low sentiment periods.

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[1] For example, Brands, Brown, and Gallagher [2005], Kacperczyk, Sialm, and Zheng [2005], Cremers and Petajisto [2009], and Cremers, Ferreira, Matos, and Starks [2015].

[2] Reibnitz [2013], for example, shows that the market environment impacts on the effectiveness of active strategies, and highly skilled managers can produce superior returns in times of high cross-sectional dispersion in stock returns. Some studies have focused on the relationship between fund performance and the business cycle and report that active funds, on average, have a better performance in recessions than in expansions [Kacperczyk, Van Nieuwerburgh, and Veldkamp 2014, 2016].

[3] Such as DeBondt and Thaler [1985], Shiller and Pound [1989], Barber and Odean [2001], and Barberis and Thaler [2003].

[4] Noise information can also be transmitted into stock prices through new asset classes, such as exchange-traded funds [Da and Shive 2017].

[5] For instance, Grinblatt and Keloharju [2001] and Lamont and Thaler [2003] report that unsophisticated investors are more likely to enter the stock market during prosperous and investor exuberant periods.

[6] Specifically, Massa and Yadav [2015] consider the preferences of fund managers for holding stocks that react in a contrary manner to the level of investor sentiment or display a contrarian sentiment behavior.

[7] Such as Daniel, Hirshleifer, and Subrahmanyam [1998], Hong and Stein [1999], Amromin and Sharpe [2009], and Antoniou, Doukas, and Subrahmanyam [2015].

[8] The $3.74 million per year of added value created annually by the average fund manager is consistent with the findings by Berk and van Binsbergen [2015], who document that the average manager is skilled, adding $3.2 million per year.

[9] The reason why our sample period begins in December 2002 is that the data to form the Vanguard index funds market benchmark [Berk and van Binsbergen 2015] are only available from December 2000 in Bloomberg database, and we used the first 24 months' data as estimation period.

[10] The BW sentiment data are available on Jeffrey Wurgler's website http://people.stern.nyu.edu/jwurgler/.

[11] We also replicate the same analysis using an orthogonalized BW index where each of the proxies has first been orthogonalized with respect to a set of macroeconomic conditions. The results are similar to the reported ones and are available upon request.

[12] The list of the 11 Vanguard index funds and their inception dates are shown in Appendix I.

[13] Most studies use NBER business-cycle dates to clarify economic recessions or expansions. However, when we collected the data for this paper, NBER business cycle dates were unavailable after 2009.

[14] These results are available upon request.

[15] These results are available upon request.

[16] These results are available upon request.

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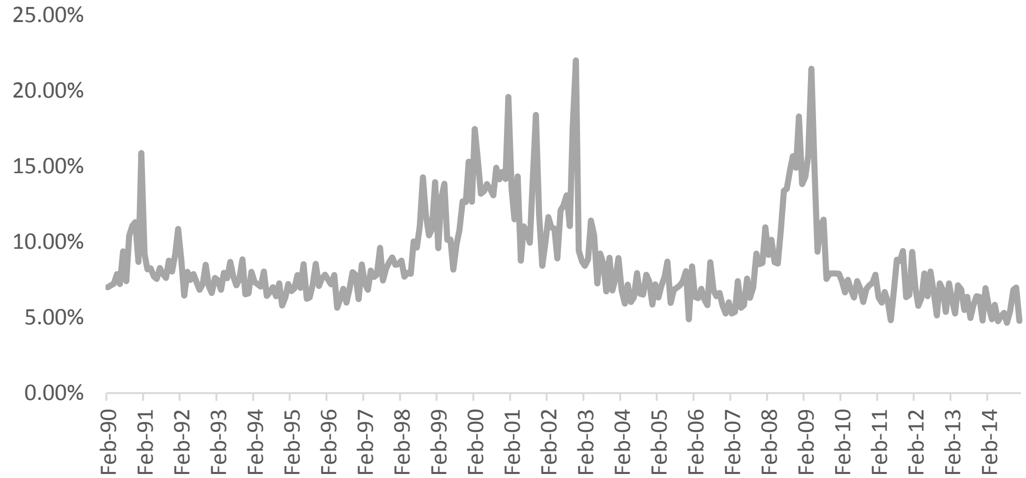
EXHIBIT 1.
Summary Statistics

	Mean	Median	Minimum	Maximum
Turnover (%)	85.64	56.00	0.00	3,452.00
Age (years)	17.44	17.00	3.00	47.00
Expense Ratio (%)	1.28	1.21	0.00	9.16
TNA (millions)	25.35	19.61	11.66	906.95

Notes: This exhibit shows descriptive statistics of individual fund estimates. Our sample contains 1,873 actively-managed U.S. equity mutual funds over the period from December 2002 to December 2014, with 185,194 observations. Turnover is the minimum of aggregated sales or aggregated purchases of securities divided by the total net assets of the fund. Expense ratio is the annual expense ratio of each fund. TNA is each fund's total net assets in millions.

EXHIBIT 2.
Time Series Plot of Monthly Market Dispersion



Notes: This figure shows the time series plot of monthly market dispersion from December 2002 to December 2014. The market dispersion is calculated using equally weighed monthly cross-return of S&P 500 index constituents.

EXHIBIT 3.
BvanB Fund *Alpha*, Sorting on BvanB Fund Skill and Lagged BvanB Fund *Alpha*

Panel A: Portfolio BvanB fund alpha for the entire sample period

	BvanB fund skill						
BvanB *Alpha*$_{t-1}$	**Low**	**4**	**3**	**2**	**High**	**All**	**High-Low**
Low	-18.06*	-3.25	-1.44	-0.22	0.77	-4.44	9.42*
	(0.074)	(0.115)	(0.353)	(0.850)	(0.609)	(0.124)	(0.056)
4	-8.61	-3.25*	-1.30	-0.42	1.03	-2.51	4.82*
	(0.103)	(0.065)	(0.324)	(0.740)	(0.563)	(0.194)	(0.069)
3	-4.84	-2.30	-0.87	0.31	1.22	-1.29	3.03*
	(0.140)	(0.138)	(0.470)	(0.796)	(0.498)	(0.393)	(0.089)
2	-4.52	-2.02	-0.64	0.14	2.14	-0.98	3.33*
	(0.120)	(0.168)	(0.575)	(0.911)	(0.308)	(0.500)	(0.053)
High	-4.80**	-1.75	-0.20	0.64	3.74	-0.48	4.27*
	(0.048)	(0.182)	(0.864)	(0.649)	(0.337)	(0.769)	(0.061)
All	-8.82*	-2.51	-0.89	0.09	1.78	-1.94	5.30**
	(0.078)	(0.115)	(0.472)	(0.943)	(0.413)	(0.280)	(0.044)
High-Low	6.63*	0.75	0.62	0.43	1.48	1.98*	
	(0.098)	(0.150)	(0.138)	(0.199)	(0.261)	(0.060)	

Panel B: Portfolio BvanB fund alpha during high market sentiment

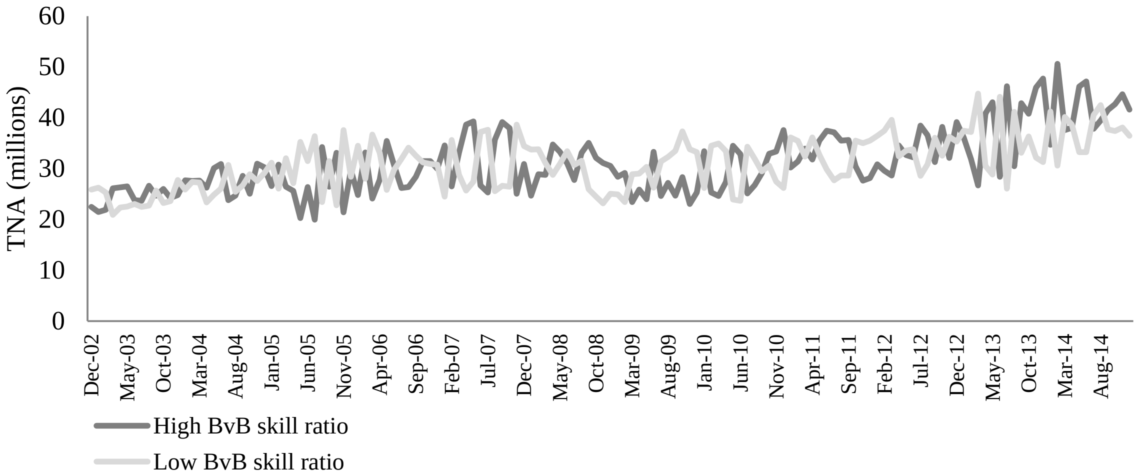
BvanB *Alpha*$_{t-1}$	**Low**	**4**	**3**	**2**	**High**	**All**	**High-Low**
Low	-5.64	2.98	3.12	3.55*	3.44	1.49	4.54
	(0.732)	(0.356)	(0.217)	(0.054)	(0.167)	(0.755)	(0.566)
4	8.97	1.80	2.60	2.99	4.51	4.17	-2.23
	(0.249)	(0.516)	(0.207)	(0.141)	(0.138)	(0.166)	(0.560)
3	4.67	2.04	2.85	3.78*	3.64	3.39	-0.52
	(0.344)	(0.416)	(0.138)	(0.055)	(0.234)	(0.169)	(0.842)
2	3.39	2.23	2.78	3.24	5.25	3.38	0.93
	(0.441)	(0.339)	(0.140)	(0.114)	(0.128)	(0.157)	(0.710)
High	1.65	1.90	3.03	3.86	7.71	3.63	3.03
	(0.656)	(0.370)	(0.122)	(0.101)	(0.219)	(0.183)	(0.373)
All	3.21	2.19	2.88	3.48*	4.91	3.21	0.85
	(0.682)	(0.387)	(0.154)	(0.082)	(0.172)	(0.276)	(0.829)
High-Low	3.64	-0.54	-0.05	0.15	2.14	1.07	
	(0.579)	(0.516)	(0.944)	(0.782)	(0.304)	(0.520)	

Panel C: Portfolio BvanB fund alpha during low market sentiment

BvanB *Alpha*$_{t-1}$	**Low**	**4**	**3**	**2**	**High**	**All**	**High-Low**
Low	-30.32**	-9.39***	-5.95***	-3.95***	-1.85	-10.29***	14.23**
	(0.011)	(0.001)	(0.001)	(0.006)	(0.284)	(0.002)	(0.017)
4	-25.96***	-8.22***	-5.14***	-3.77***	-2.40	-9.10***	11.78***
	(0.001)	(<.001)	(0.001)	(0.010)	(0.198)	(<.001)	(0.001)
3	-14.22***	-6.58***	-4.54***	-3.11**	-1.15	-5.92***	6.53***
	(0.001)	(0.001)	(0.001)	(0.018)	(0.557)	(0.001)	(0.007)
2	-12.33***	-6.20***	-4.02***	-2.92**	-0.93	-5.28***	5.70**
	(0.001)	(0.001)	(0.002)	(0.032)	(0.700)	(0.001)	(0.017)
High	-11.17***	-5.35***	-3.38***	-2.54*	-0.18	-4.53***	5.49*
	(0.001)	(0.001)	(0.007)	(0.091)	(0.969)	(0.009)	(0.074)
All	-20.68***	-7.15***	-4.61***	-3.26**	-1.30	-7.02***	9.69***
	(0.001)	(0.001)	(0.001)	(0.018)	(0.599)	(0.001)	(0.006)
High-Low	9.58**	2.02***	1.28**	0.70*	0.84	2.88**	
	(0.041)	(0.001)	(0.013)	(0.073)	(0.613)	(0.028)	

Notes: This exhibit presents the portfolio BvanB fund *alpha*, annualized, using monthly returns (145 months), from December 2002 to December 2014 (Panel A), high sentiment (Panel B), and low sentiment (Panel C) periods, based on the sentiment index data available at Jeffrey Wurgler's website. If the BW sentiment index for the test month (t) is higher (lower) than the median number of all monthly BW sentiment index numbers, we define this month as high (low) market sentiment month. Portfolios are formed by sorting all funds in each month into quintiles by BvanB fund skill (Eq. 3) and then by BvanB fund *alpha*$_{t-1}$, and both are described in detail in section III.B.2. For each portfolio cell, we present portfolio BvanB fund *alpha*, which is the portfolio *alpha* times the average TNA of funds within the portfolio at the beginning of current month (t), and the P-value. ***, **, * denotes significance at the 1%, 5% or 10% level.

EXHIBIT 4.
Time series plot of average total net assets of high and low BvanB skill fund portfolios



Notes: This figure shows time series plot of monthly average total net assets of high and low BvanB skill ratio fund portfolios from December 2002 to December 2014.

EXHIBIT 5.
The Effect of Fund BvanB Skill Ratio and Investor Sentiment on Fund Performance

	BvanB Fund *Alpha*			
Intercept	0.71***	0.72***	0.84***	0.84***
	(<.001)	(<.001)	(<.001)	(<.001)
BvanB Skill	0.03**	0.04**	0.25***	0.24***
	(0.018)	(0.014)	(<.001)	(<.001)
Sentiment		0.04***	-0.06***	-0.06***
		(<.001)	(<.001)	(<.001)
BvanB Skill*Sentiment			1.01***	1.00***
			(<.001)	(<.001)
Market Dispersion				0.01
				(0.975)
Business Cycle				-0.02**
				(0.036)
BvanB $\boldsymbol{Alpha_{t-1}}$	1.03***	1.03***	1.02***	1.02***
	(<.001)	(<.001)	(<.001)	(<.001)
Turnover	0.01	0.01*	0.01	0.01
	(0.205)	(0.092)	(0.130)	(0.243)
Expense Ratio	-0.50***	-0.50***	-0.60***	-0.60***
	(<.001)	(<.001)	(<.001)	(<.001)
log(TNA)	0.08***	0.08***	0.10***	0.10***
	(<.001)	(<.001)	(<.001)	(<.001)
[log(TNA)]^2	7.11E-05**	6.81E-05**	6.01E-05*	5.86E-05*
	(0.035)	(0.043)	(0.072)	(0.080)
Log(Age)	0.01	0.01	0.01	0.01
	(0.631)	(0.675)	(0.357)	(0.313)
Adj. R^2	0.878	0.878	0.880	0.880

Notes: This exhibit reports the results of regressing fund's BvanB *alpha* on manager's BvanB fund skill and investor sentiment controlling for other fund characteristics. The dependent variable is fund's BvanB *alpha*, which is the product of fund total net assets (TNA) in month t-1 and the difference between fund excess return (over T-bill rate) in month t and the expected excess return of the same month. The expected excess return for each fund in month t is calculated by multiplying the 11 Vanguard Index fund orthogonal bases factor loadings from the 24 month estimation period (t-24 to t-1) by the 11 Vanguard Index fund orthogonal bases factors in current month. The process repeats by moving the estimation and test period one month at a time. The main independent variables are fund BvanB skill ratio, which is measured as the product of fund $alpha_{t-1}$ and fund TNA at the beginning of the last month (t-1) in the estimation period (t-24 to t-1) divided by the standard error of the fund $alpha_{t-1}$, market sentiment (BW sentiment index, available at Jeffrey Wurgler's website), and Skill*Sentiment, which is the product of BvanB skill ratio and market sentiment. Fund-level control variables contain expense ratio, log value of fund age, fund turnover, log value of TNA, squared log value of TNA, and BvanB $alpha_{t-1}$, which is the product of fund $alpha_{t-1}$ and fund TNA at the beginning of the last month (t-1) in the estimation period (t-24 to t-1) and fund $alpha_{t-1}$ is the intercept from the 24 month estimation period (t-24 to t-1). Sample period ranges from December 2002 through December 2014 (145 months). The P-value and adjusted R^2 for each regression are also presented. ***, **, * denotes significance at the 1%, 5% or 10% level.

Appendix 1.
Vanguard Index funds

Fund Name	Ticker	Inception Date
S&P 500 Index	VFINX	08/31/1976
Extended Market Index	VEXMX	12/21/1987
Small-Cap Index	NAESX	01/01/1990
European Stock Index	VEURX	06/18/1990
Pacific Stock Index	VPACX	06/18/1990
Value Index	VVIAX	11/02/1992
Balanced Index	VBINX	11/02/1992
Emerging Markets Stock Index	VEIEX	05/04/1994
Mid-Cap Index	VISMX	05/21/1998
Small-Cap Growth Index	VISGX	05/21/1998
Small-Cap Value Index	VISVX	05/21/1998

Notes: This exhibit shows the list of Vanguard Index funds used to calculate the alternative market benchmark, which is the alternative investment opportunity set. The tickers and inception date are also included. The data for each index fund are collected from Bloomberg database ranging from December 2000 to December 2014 when all of 11 index funds' data are available.