

# Is Fund Management Skill More Valuable in Noisy Times?

## ABSTRACT

Is fund management skill more valuable in noise trading times—a natural setting to detect skill—when asset prices drift from intrinsic values, short-selling is limited, and value-relevant information is costlier? Our results demonstrate that skilled fund managers generate persistent excess risk-adjusted returns especially in high sentiment and stock mispricing states. We find that fund managers with the highest (lowest) skill create, on average, \$7.71 (\$5.64) million of added value (loss) conditional on high sentiment periods, relative to \$3.74 million for the entire sample period, while they experience a value loss of \$0.18 (\$30.32) million in low sentiment periods. This pattern persists after we control for lucky bias, using the “false discovery rate” approach, which permits to disentangle manager “skill” from “luck”.

*JEL Classification:* G11, G14, G20, G23

*Keywords:* Mutual fund performance; investor sentiment; fund manager skill

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*“...noise creates the opportunity to trade profitably, but at the same time makes it difficult to trade profitably.”*

- Fisher Black, 1986

## **1. Introduction**

Does noise trading affect the performance of skilled mutual fund managers? Undoubtedly, noise trading is more likely to be prevalent when markets are crowded by noise trading. While noise trading activity has been held responsible for much of the market uncertainty during the last two decades, its impact on actively managed mutual fund performance remains unknown.<sup>1</sup> We address this question by investigating whether noise trading, observed during high investor sentiment periods, influences fund alphas, as noted by Miller (1997), which, in turn, makes it difficult to carry out profitable trades, as discussed in Black (1986). Specifically, we examine the capacity of U.S. domestic equity fund managers in adding value during periods of heightened noise trading, used as an “acid” test of management skill, when market sentiment is high, and it is more difficult to identify profitable stocks. A further “headwind” for active mutual fund management is represented by investor fund flow changes, which also reflect investor sentiment.<sup>2</sup> Using stock mispricing, based on 11 market anomalies (Stambaugh, Yu, and Yuan, 2012), as an alternative state of noise trading, we also examine whether skilled fund management delivers added value in states of stock mispricing. If high-skill fund managers exploit their informational advantage, one would also expect them to outperform their low-skill counterparts in states of increased market volatility triggered by pessimistic investor emotions.

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<sup>1</sup> Campbell and Vuolteenaho (2004) separate stock market returns into that due to changing forecasts of future cashflows (which tend to be non-mean-reverting) and changing forecasts of market discount rates (which are related to investor sentiment and is mean-reverting). They find that changes in discount rate forecasts (i.e., changes in investor sentiment) is a major driver of market volatility.

<sup>2</sup> Ben-Rephael, Kandel, and Wohl (2012) document that investor flows negatively forecast future market returns; thus, mutual funds face outflows before a several-month upturn in market prices, and inflows before a downturn (on average).

A large body of the literature, motivated by the question of whether fund managers create value, arrives at the conclusion that actively managed funds, on average (and, unconditionally over time), underperform passively managed funds. However, while recent papers find that funds with certain characteristics, such as concentrated portfolio holdings or a large deviation of holdings away from a benchmark, can outperform such a benchmark, net of expenses (Kacperczyk, Sialm, and Zheng, 2005; Cremers and Petajisto, 2009; and Cremers, Ferreira, Matos, and Starks, 2016) they do not examine whether fund managers create added value when markets are crammed by noise, identified by high investor sentiment, changes in investor fund flows, and stock mispricing, and it is hard to carry out profitable trades. Other studies document that active fund manager skill varies over time with macroeconomic conditions (e.g., Christopherson, Ferson, and Glassman, 1998; and Avramov and Wermers, 2006). This literature emphasizes that fund managers may have particular skills in managing stocks during a certain phase of the business cycle; for instance, a technology manager may produce a higher alpha when short-term interest rates are high, and the credit spread is low, while a consumer staples manager may produce alphas when short rates are low, and the credit spread is high. Whereas these studies show that fund alpha in various industry sectors is related to real economic forces, such as cycles in industry sales and an industry's ability to borrow to finance growth, they do not shed light on the important question whether fund alpha is linked to fund managers' skill, particularly, in noise trading states of the market when it is difficult to execute profitable trades.

Unlike the previous literature, this paper aims to quantify whether fund management skill delivers high alpha when market noise is more prevalent and hard to find valuable investment opportunities. That is, when the costs of gathering and processing private information is higher, and the signal-to-noise ratio is lower. While a higher level of trading noise, due to investor sentiment, extraordinary capital flow changes, or stock mispricing, presents a more difficult

environment for all active managers to pick valuable stocks and sectors, it should not apply to skilled fund managers who possess the ability to discern noise from real information.

As explained by Black (1986), noise trader participation in the market, which can be triggered by investor optimism, can move asset prices away from fundamental values, making it difficult for professional managers to produce risk-adjusted excess returns. Further, noise trader participation varies with time, and is related to the state of investor sentiment. Since investor sentiment has been shown to influence noise trader investment behavior and, in turn, asset prices (Hirshleifer and Shumway, 2003; Dowling and Lucey, 2005; Edmans, Garcia, and Norli, 2007; Kaplanski and Levy, 2010; and Bialkowski, Etebari, and Wisniewski, 2012), it stands to reason that skilled fund managers would outperform their low skilled counterparts by being able to better discern information from noise when the signal-to-noise ratio is lower during high investor sentiment states. Grinblatt and Keloharju (2001) and Lamont and Thaler (2003) report that unsophisticated investors are more likely to enter the stock market during prosperous periods and periods of heightened investor exuberance. Hence, noise trader activity is not expected to be symmetric across optimistic and pessimistic sentiment periods. It is more likely to be more prevalent during optimistic times. Therefore, the above arguments could have implications about the performance of fund managers across different sentiment times. Specifically, if skilled fund managers trade more on (private) information about the true value of financial assets under management, in contrast to their low skill counterparts, they are expected to deliver more value during high sentiment periods, which is detectable by an above-average sentiment index, when financial asset prices are noisier than in low sentiment periods when financial markets are not crowded by unsophisticated (noisy) investors. In sum, previous findings raise the important question of whether fund managers' performance is affected by investor sentiment, a natural

setting to detect if fund managers possess skill, when noise trading activity is much more prominent.

Moreover, in contrast to the previous literature that examines whether fund managers try to exploit investor sentiment by deploying sentiment-based (timing) strategies in order to attract capital flows (Massa and Yadav, 2015) or whether funds tilt their portfolios toward better performing stocks when they buy (sell) stocks that are highly sensitive to market sentiment, measured by sentiment betas, preceding an increase (decrease) in investor sentiment (Cullen, Gasbarro, Le, and Monroe, 2013), we treat sentiment as a market condition, not as a risk factor where skilled managers actively time investor sentiment by modifying fund strategies based on their sentiment prediction.<sup>3</sup> While our evidence is consistent with the previous literature showing that skilled fund managers outperform their low skill peers (Amihud and Goyenko, 2013; Berk and van Binsbergen, 2015), we distinctly document that fund managers' stock-selectivity skill is more profitable during high than low sentiment periods when noise trading is more widespread and impactful on asset prices, due to short selling limitations (Shleifer and Vishny, 1997) and value-relevant information is costlier. We also find that high-skill fund managers outperform their low-skill counterparts in low sentiment periods, when increased market volatility might be present, suggesting that they exploit their informational advantage across both states of noise. Unlike Kacperczyk, Van Nieuwerburgh, and Veldkamp (2016), who argue that the time-varying fund performance is caused by fund managers' optimally choosing to process information about aggregate shocks in recessions and idiosyncratic shocks in booms, because uncertainty is high in high sentiment times and investors find it harder to assess true value, we treat investor sentiment as a noisy market condition which allows us to determine whether skilled fund managers are able

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<sup>3</sup> 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.

to outperform both their average and low-skilled counterparts. We find that, in high sentiment periods, skilled fund managers generate significantly and economically higher alpha than the average-skill and low-skill fund managers. When we treat sentiment as risk factor, we find that sentiment-based (timing) strategies are associated only with low skilled fund managers, realizing significant risk-adjusted fund losses.

Another interesting question, which has received little attention in the literature (e.g. Baks, Metrick, and Wachter, 2001), is what percentage of the active fund managers is consistently associated with higher excess risk-adjusted returns under different states of investor sentiment. The answer to this question, which is addressed in this study, is very important because more and more capital is flowing from individual investors to professional investment managers. Conducting a lucky bias analysis that allows us to examine what percentage of significant fund performance (alpha) is due to management skill, and not to luck alone, we find that the percentage of skilled fund managers decreases substantially in high sentiment periods.

To examine these two questions, we employ two different management skill and fund performance measures over the 1990–2014 period. First, we use the Amihud and Goyenko (2013) selectivity method to assess fund management skill, which does not require the use of fund portfolio holdings (i.e., does Daniel, Grinblatt, Titman, and Wermers, 1997), and examine the relation between fund selectivity and performance across different states of investor sentiment.<sup>4</sup> Consistent with our hypothesis, our results based on the selectivity measure demonstrate that fund managers with superior skills generate significantly high risk-adjusted returns during noisy periods.

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<sup>4</sup> Amihud and Goyenko (2013) find better performance among funds that have lower  $R^2$  with respect to a multifactor model, which is supported by the literature on fund trading activity and its impact on performance (e.g. Kacperczyk, Sialm, and Zheng, 2005; Cremers and Petajisto, 2009, 2016; Wermers, 2003; Kacperczyk, Sialm, and Zheng, 2005; Cremers, Ferreira, Matos, and Starks, 2016; Kacperczyk and Seru 2007; Cohen, Polk, and Silli, 2010). Additionally, Pastor, Stambaugh, and Taylor (2017) establish a time series relation and show that funds deliver better performance after increasing their trading activity.

Second, following Berk and van Binsbergen (2015), we reexamine the validity of our original results by using their measures of management skill (i.e., skill ratio) and performance (i.e., the mean of the product of the gross abnormal return (alpha) and fund size (the value extracted by a fund from capital markets)). Unlike the fund management selectivity skill metric, this measure assesses fund managers' skill based on the additional capital the managers can extract from the equity markets (Berk and van Binsbergen, 2016; Berk, van Binsbergen, and Liu, 2017). Our evidence, based on this fund management skill measure, consistently shows that noisy states of the market harm fund performance, but managers with above-average stock-picking skill manage to protect fund performance from the adverse effects of high investor sentiment and noisy due to investor fund flow changes and stock mispricing. Fund managers, however, create added value in noisy periods if they are endowed with superior management skill. Specifically, fund managers with the highest skill create \$7.71 million of added value during high sentiment periods which exceeds the average realized fund gains (\$3.74 million), while they incur a small value loss of \$0.18 million in low sentiment periods.<sup>5</sup> However, fund managers with the lowest skill experience a values loss of \$5.64 million during high sentiment periods which is far lower than the average realized fund gains (\$3.74 million), while they incur a substantial value loss of \$30.32 million in low sentiment periods.<sup>6</sup> We also find that skilled fund managers have lower exposure to overvalued (mispriced) stocks and their performance does not appear to be adversely affected by dramatic investor capital flow changes.

To address the second question, following Barras, Scaillet, and Wermers (2010), we conduct a lucky bias analysis that allows us to determine if significant fund performance (alphas)

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<sup>5</sup> The \$3.74 million per year of added value created annually by the average fund manager is consistent with Berk and van Binsbergen (2015), who document that the average manager is skilled, adding \$3.2 million per year.

<sup>6</sup> The correlation between the number of mutual funds in our sample and BW investor sentiment is -0.021 (with P-value equals 0.716), suggesting that our results are not sensitive to the number of active mutual funds in different sentiment periods.

is due to luck alone, and not management skill. The results show that, even though the percentage of skilled fund managers decreases considerably after controlling for lucky bias, a portion (around 2%, i.e., under the 5% significant level) of fund managers appears to possess skill capable of delivering significant alphas during high sentiment periods.

Using stock mispricing as an alternative setting of noise trading, we also examine whether the superior performance of skilled fund managers comes through exploiting the stock mispricing. Cross-sectional analysis on the relation between fund performance and stock mispricing, using a set of 11 market anomalies to identify overpriced stocks (Stambaugh et al., 2012), reveals a negative association between fund alpha and skilled fund management indicating that skilled fund managers' investments are not associated with overvalued stocks. On the contrary, skilled fund managers' performance is linked to undervalued stocks. Having used sentiment and stock mispricing as alternative states of market noise, we consistently find that skilled fund managers create value by their ability to carry out profitable trades.

Furthermore, we check the sensitivity of our results by carrying out several robustness tests and document that our results remain unchanged. First, we examine mutual funds' sentiment market timing strategy by estimating sentiment beta, as in Massa and Yadav (2015), and find that only low-skilled fund managers time investor sentiment by employing a sentiment-momentum strategy. Skilled fund managers, however, do not appear to time investor sentiment. In addition, we examine the influence of net capital flows and the volatility anomaly on the relation between fund alpha and management skill across different states of noise and find that our results remain essentially unchanged.

Finally, employing alternative measures of noise trading, such as the Financial and Economic Attitudes Revealed by Search index (FEARS) (Da, Engelberg, and Gao, 2015), the credit market sentiment index, the Chicago Board Options Exchange Volatility Index (VIX), and



the New York Stock Exchange based Arms Index (TRIN), we obtain qualitatively similar results to our main findings. Jointly, the evidence that skilled managers generate high alphas in high sentiment periods and stock mispricing states suggests that they can create value for fund investors when markets are populated by noisy investors (signals).

The rest of the paper is organized as follows. Section 2 describes the related literature and hypothesis development. Section 3 describes the data and empirical methodology. Section 4 presents empirical results. Section 5 provides a robustness test. Section 6 concludes.

## **2. Related literature and hypothesis development**

Carhart (1997) shows that, when measured with a four-factor risk model, the average active U.S.-domiciled domestic equity mutual fund has experienced negative net-of-expense alpha. In addition, Daniel, Grinblatt, Titman, and Wermers (DGTW; 1997), who employ characteristics-based benchmarks, find that the average active U.S. equity fund can beat its benchmarks, gross of fees and trading costs. Further, DGTW finds that some active equity fund managers outperform their benchmarks, pre-costs, by a wide margin; other, more recent papers provide further insights into the characteristics of skilled funds (Brands, Brown, and Gallagher, 2005; Kacperczyk et al., 2005; Cremers and Petajisto, 2009; and Cremers et al., 2016).

From another perspective, Kacperczyk, Van Nieuwerburgh, and Veldkamp (2014) show that fund manager skill comes from the managers' ability to anticipate micro- and macro-fundamentals. In addition, the previous literature shows that a fund attains superior performance if its manager focuses on the assets that s/he has specialized knowledge of. For example, Kacperczyk et al. (2005) found that funds focusing on some specific industries have better performance than the ones holding more diversified portfolios. Cohen, Frazzini, and Malloy (2007) showed that if fund managers and corporate board members have a close connection via shared

education networks, fund managers prefer to place larger bets on those firms that such corporate board members serve and find that those funds perform significantly better on these holdings relative to their non-connected holdings. Kacperczyk and Seru (2007) reported that changing portfolio allocation based on public information decreases fund performance, which supports the argument that fund manager skill is coming from private information rather than public information.

While the most of this literature has focused on the stock-picking ability of fund managers, the findings on managers' market-timing ability are ambiguous. Jiang, Yao, and Yu (2007), employing a single-index model using measures of market timing based on mutual fund holdings, find that, on average, active fund managers have positive market-timing abilities. However, as shown by Elton, Gruber, and Blake (2012), there is no evidence that market-timing strategy increases fund performance when a multi-index model is used. Interestingly, there might be a negative market-timing effect on fund performance due to the sector rotation decisions with respect to high-tech stocks. By adding timing-related variables to the basic model, which is proposed by Fama and French (1993) and Carhart (1997), denoted as the FFC model, Amihud and Goyenko (2013) found no evidence that high selectivity funds possess any market-timing skill. Meanwhile, few studies have focused on the question of whether the active fund managers' skill varies with time. Von Reibnitz (2015), 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 (Moskowitz, 2000; Glode, 2011; Kosowski, 2011; Kacperczyk, Van Nieuwerburgh, and Veldkamp 2014, 2016).

Unlike previous studies, we argue that the activities of investors are not consistently rational and, thus, fund profitability can be affected by noise traders (signals). There are two reasons to suggest that noise trading, which is heightened in the presence of investor sentiment, can influence the profitability of a fund manager's insight and analytical ability. First, the level of investor sentiment can affect both overall market returns and individual stock returns (Miller, 1977; Daniel, Hirshleifer, and Subrahmanyam, 1998; Hong and Stein, 1999; Amromin and Sharpe, 2009; and Antoniou, Doukas, and Subrahmanyam, 2015). Stocks during high sentiment periods are driven away from their fundamental values by naïve investors. Antoniou et al. (2015) find that the CAPM only holds during pessimistic periods when investor sentiment is low and asset prices are more likely to be close to their intrinsic values, which reveals that the effect of more unsophisticated investors entering the market during high sentiment states is dramatic. In optimistic times, however, the opposite is true with noise traders focusing on risky stocks, and thus overvaluing high beta stocks. As argued by Barberis and Thaler (2003), rational investors or arbitrageurs do not aggressively force prices back to fundamentals because betting against sentimental investor activities is costly and risky. Additionally, short-selling impediments of institutional investors, especially mutual funds, are also major obstacles to eliminating price overvaluation. Since more irrational and unsophisticated traders participate in financial markets during high sentiment periods, asset prices are more likely to be noisy and consequently more difficult to identify good investment opportunities. Hence, on average, stock-picking ability during high sentiment periods might be limited, thus resulting in fund underperformance. If fund managers' skills, however, are based on firm-specific analytic abilities and information rather than noise, fund managers with high selectivity skill 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. The ability of skilled fund managers to create value in high

sentiment states is expected to depend on their analytical valuation skill to make profitable investment decisions and not by investing in overvalued stocks which are preferred by naive investors. In contrast, unsophisticated investors keep away from the equity market during low sentiment periods (Grinblatt and Keloharju, 2001; Lamont and Thaler, 2003; Amromin and Sharpe, 2009; and Antoniou et al., 2015), with asset prices reverting to fundamental values. In low sentiment periods, stocks are traded at close to fundamental values, and this leaves less room for fund managers to realize significant high alphas. Taken together, these arguments lead us to expect that fund managers with high selectivity skill are more likely to outperform their low selectivity skill counterparts in high sentiment periods.

Second, fund performance can be influenced by market noise due to market anomalies, which are created by irrational investor trading activities that are more pronounced in high sentiment periods (Stambaugh, Yu, and Yuan, 2012). Momentum is one of the most significant market anomalies, and it is described as the tendency of past winners (losers) to outperform (underperform) the market benchmark in the near future. Antoniou, Doukas, and Subrahmanyam (2013) find a strong connection between sentiment and momentum. They argue that during high sentiment periods, information signals that oppose the direction of sentiment travels slowly due to investors' cognitive dissonance, and they show that the momentum strategy works only during optimistic (high sentiment) periods. In addition, due to short-sale constraints, mutual fund managers are more likely to bet on positive information. While stocks tend to be overvalued due to the momentum effect during high sentiment periods, stock prices will drift away from their intrinsic values and sophisticated fund managers should generate superior returns by taking advantage of this drift from true value during high sentiment times. That is, active fund managers with superior insight and analytical skill are expected not only to protect a fund's performance from this price to value drift, but also produce a higher fund alpha in high investor sentiment

periods when noise investor participation in the market is high. On the other hand, their inability to generate high alphas during low sentiment periods when asset prices are less noisy and near fundamental values may suggest that their superior insight and analytical skill is most relevant during high sentiment and noisy periods. Unlike previous studies, the novelty of this investigation is to shed light on whether fund managers' performance varies across different states of investor sentiment and particularly whether fund investors benefit the most from their selectivity skill during high sentiment periods when market signals are noisy.

### **3. Data and empirical methodology**

#### *3.1 Data and sample selection*

Unlike most previous studies, which use the CRSP Survivor-Bias-Free Mutual Fund Database, we use the Bloomberg Fund Dataset, which is originally built for institutional investors in 1993 and is widely used in the finance industry nowadays. The dataset receives pricing and performance information from the fund management companies, administrators, and trustees directly, in the form of a feed or, more commonly, via automated email distribution channels with the entities. The exchange traded information comes directly from the exchange on which the mutual fund is listed. In addition, if one data point cannot pass the volatility threshold, which varies for each mutual fund based upon its past accepted volatility and the market in which the entity trades or prices, the data point will be rejected. These features, make Bloomberg fund data reliable for academic studies and not suffering from the standard sample bias. Our data sample period covers 24 years from January 1990 to December 2014. We use 24-month time windows to estimate selectivity and past fund alphas, so the data were collected from December 1987. 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: turnover, which is the minimum of aggregated sales or aggregated purchases of securities divided by the total net assets of the fund, age, expense ratio, which is the annual expense ratio of each fund, and total net assets (TNA).

To make sure our sample does not suffer from survivorship bias, we collected data from funds with both alive and dead statuses. We also used several criteria to restrict our sample to actively managed U.S. domestic equity mutual funds. We only collected fund data if a fund met all the following standards: 1) geographical focus is the United States, 2) country of domicile is the United States, 3) asset class is equity, and 4) fund type is an open-ended mutual fund. Because we needed 24 months' estimation periods and our sample period ended in December 2014, all observations were removed if the fund had an inception date later than December 2012. We further eliminated other types of funds, such as index funds, balance funds, international funds, and sector funds, by deleting funds whose name contained the word "index," "ind," "S&P," "DOW," "Wilshire," "Russell," "global," "fixed-income," "international," "sector," and "balanced." Following Von Reibnitz (2015), we required funds to have TNA of at least \$15 million in December 2013. Overall, our sample contained 2190 mutual funds over the period from January 1990 to December 2014, with 273,557 observations. 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. A detailed data collection comparison between this paper and the previous literature (Amihud and Goyenko, 2013; and Von Reibnitz, 2015) is presented in Appendix I.

Table I shows the summary statistics of the mutual funds in our sample.  $R^2_{t-1}$  estimations range from 0.219 to 0.991, with a mean value of 0.883 and a median value of 0.922.<sup>7</sup> This shows

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<sup>7</sup> Consistent with Amihud and Goyenko (2013), the top 0.5% and the bottom 0.5%  $R^2$  observations were deleted. The argument here is that funds with the highest  $R^2$  should be "closet indexers," which have not been limited out by the sample selection criteria. Funds with the lowest  $R^2$  may be caused by estimation error.

a clear negatively skewed distribution, which indicates that around 90% of the funds' excess return variance can be explained by the market indexes variance.

[Insert Table I here]

The main sentiment measures used in this paper is the Baker and Wurgler (2006) sentiment index (BW)<sup>8</sup> and the University of Michigan sentiment index (UM)<sup>9</sup>. Even though both optimistic and pessimistic beliefs, induced by high and low market sentiment, respectively, can affect asset prices, noise trading is more likely to be triggered by high market sentiment since in pessimistic times, noisy (optimistic) investors, as a major source of noise trading activity, are expected to exit the market. Additionally, investors holding pessimistic views are generally unwilling to sell short (Barber and Odean 2008), which contributes to the asymmetry effect of market sentiment on asset pricing. Thus, high sentiment index (i.e. above-average BW sentiment index or UM sentiment index) is used as a reliable proxy to pinpoint periods when financial markets are populated with noise trading. The BW index has been used widely in the finance literature and 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. We collect the BW index data from January 1990 to December 2014, and for the whole 300-month sample period. If the month  $t$ 's BW sentiment index is higher (lower) than the median number of all the monthly BW sentiment index numbers, month  $t$  is defined as a high (low) investor sentiment month. The UM index is another sentiment index measured outside of the financial market and used widely in finance studies. The results are consistent with those using BW sentiment index. Furthermore, our findings are also

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<sup>8</sup> The BW sentiment data are available on Jeffrey Wurgler's website <http://people.stern.nyu.edu/jwurgler/>.

<sup>9</sup> The UM sentiment data can be found on University of Michigan Surveys of Consumers website <http://www.sca.isr.umich.edu/>.

supported by using four alternative sentiment measures: credit market sentiment index, FEARS index, VIX index, and NYSE based TRIN index, as reported in the robustness tests.

### 3.2 Empirical methodology

#### 3.2.1 Fund management selectivity and alpha measures

To examine whether the positive relationship between fund performance and management skill varies with time and particularly if it is more pronounced during high sentiment periods, we first assess fund management selectivity by employing the method of Amihud and Goyenko (2013). Selectivity is calculated using a fund's  $R^2$  from regressing its returns on multifactor benchmark models. The main benchmark model used is the FFC model, which contains market excess return (RM-Rf), small minus big size stocks (SMB), high minus low book-to-market ratio stocks (HML), and winner minus loser stocks (MOM), and all the data are accessible online through the *Kenneth French data library*. According to Amihud and Goyenko (2013), a low  $R^2$  and indeed a low level of co-movement with the benchmark model applied, indicates fund management's superior selectivity ability because highly skilled fund managers manage funds based on private information, which makes the fund less sensitive to variations in public information. Selectivity, in Amihud and Goyenko (2013), is measured as:

$$Selectivity = 1 - R^2 = \frac{RMSE^2}{Total\ Variance} = \frac{RMSE^2}{Systematic\ Risk^2 + RMSE^2} \quad (1)$$

where  $RMSE^2$  is the variance of the error term from the regression, which denotes the idiosyncratic risk of a fund,  $Total\ Variance$  is the overall variance of a fund's excess return, and  $Systematic\ Risk^2$  is the return variance that is due to the benchmark indexes' risk. As Equation (1) demonstrates, selectivity is higher when the fund's strategy is based more on firm-specific information, rather than market information. More importantly, unlike other fund selectivity measures, such as the well-known DGTW measure (DGTW, 1997), which use the characteristics of stocks within each



fund to estimate the fund manager selectivity skill, the Amihud and Goyenko (2013) method does not require the knowledge of fund holdings or the benchmark index that the fund is using. The fund performance measure we use in our analysis is the fund gross *alpha*, which is the average fund abnormal return before fees. The reason for using the fund gross alpha rather than the net alpha is that, as Berk and Green (2004) argue, if skill is detectable by investors, the significant positive net fund alpha will vanish due to the competition among investors. In that case, gross alpha is a more appropriate way to measure the fund managers' performance.

One may argue that by randomly selecting stocks, a manager can achieve an extremely low  $R^2$  without possessing any skill. However, Amihud and Goyenko (2013), in the same spirit of addressing a similar concern in the active share method of Cremers and Petajisto (2009), argue that actively managed funds by unskilled managers with low  $R^2$  should be eliminated by the highly competitive market in the short run. To further ensure that low  $R^2$  funds in our sample represent the funds managed by skilled managers, we only use funds with data for more than two years. Our results confirm the validity of this methodology by showing a significant positive relation between fund selectivity ( $1-R^2$ ) and fund performance.

### *3.2.2 BvanB fund management added value and BvanB alpha measures*

As our second fund management skill measure, we use the method of Berk and van Binsbergen (2015), who deduce fund management skill 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, measured over the period December 2002 to December 2014. Mutual funds share the same investment mechanism, and a value measure, besides the return measure, is argued to be an appropriate approach to measure fund performance. To measure fund performance, the gross abnormal return is adjusted by fund size. On the other hand, 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) evaluated fund performance by comparing fund performance with an alternative investment opportunity set – 11 Vanguard index funds.<sup>10</sup> Their argument is that, in order to evaluate the performance of a mutual fund, one should compare its performance with the next best investment opportunity ( benchmark) 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. 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 closet portfolio formed by those index funds.

We then follow Berk and van Binsbergen (2015) and use the 11 Vanguard index funds to form the alternative investment opportunity set as the benchmark. Unlike their analysis, which focuses on the cross-sectional skill difference within fund managers, we use a rolling window regression method to test whether management skills vary with time. We collected data only when all the 11 index funds had available data, and finally, our data period covered 145 months, from December 2002 to December 2014. We then constructed an orthogonal basis set out of these index funds by regressing the  $n^{\text{th}}$  fund on the orthogonal basis produced by the first  $n-1$  funds over the whole 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  $n^{\text{th}}$  index fund of the whole period.

Next, as shown in Equation (2), we regress the excess returns of each fund  $f$  on the 11 Vanguard index fund orthogonal bases for the whole sample period from December 2002 to

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<sup>10</sup> The list of the 11 Vanguard index funds and their inception dates are shown in Appendix II.

December 2014, using 24-month rolling window regression and moving forward 1 month each time.

$$Return_{f,t} = \sum_{j=1}^{11} \beta_p^j R_t^j + \alpha_f \quad (2)$$

The performance measure we use is the abnormal capital inflow a fund experiences in the test month (denoted 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 the product of multiplying the coefficients between each Vanguard index fund orthogonal basis and fund excess return from the 24-month preceding estimation period by the real numbers of each Vanguard index fund orthogonal basis in the current month.

To capture fund management skill, we use the skill ratio measure introduced by Berk and van Binsbergen (2015), denoted as the BvanB fund skill. As shown in Equation (3), the BvanB fund skill for each fund in each month is the product of a fund's abnormal return (fund alpha) times the fund's size at the beginning of the month before the test month, divided by the standard error of the fund alpha. Fund alphas and standard errors are obtained from the 24-month rolling window regression of fund excess return over the alternative investment opportunity. Fund size, which is the total net assets of the fund, is inflation-adjusted.

$$BvanB \text{ Fund Skill}_{f,t} = \frac{\alpha_{f,t-1} * TNA_{f,t-2}}{SE_{f,t-1}} \quad (3)$$

### 3.2.3 Stock return dispersion and business cycle measures

The 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 of skilled fund managers to outperform the market (Von Reibnitz, 2015; and Kacperczyk et al., 2009, 2016). Active opportunity in the market, captured by cross-sectional

dispersion in stock returns, as argued by Von Reibnitz (2015), 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 so, during high market-dispersion times, the impact of active bets is expected to be more pronounced, and managers with skill in identifying, interpreting, and acting on firm-specific information will significantly outperform their low-skilled peers. As in Von Reibnitz (2015), 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:

$$MD_t = \sqrt{\frac{1}{n-1} \sum_{i=1}^n (R_{i,t} - R_{m,t})^2} \quad (4)$$

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 collected the list of S&P 500 constituents and their monthly returns from Bloomberg database. Bloomberg reports these historical data since February 1990, so our dataset for market dispersion ranges from February 1990 to December 2014. Figure I, shows a time series plot of monthly stock return dispersion over the 1990–2014 sample period.

[Insert Figure I 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 is expected to vary with time. Kacperczyk et al. (2009) decomposed manager skill into stock picking

and market timing and report that managers balance those two strategies based on the state of the 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 (Moskowitz, 2000; Glode, 2011; Kosowski, 2011; and Von Reibnitz, 2015). 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. (2009), to capture the effects of the business cycle on fund performance.<sup>11</sup> The CFNAI is a coincident indicator of national economic activity comprising 85 existing macroeconomic time series.

#### *3.2.4 Lucky bias measurement*

Even though we employ two different measures to proxy fund manager skill to ensure that our results are not sensitive to a specific measure, it is reasonable to argue that fund performance may be due to luck rather than skill. To disentangle luck from skill, we used the “false discovery rate” approach developed by Barras et al. (2010) to estimate the fraction of mutual funds that truly outperform the benchmarks. This approach assumes that there are three mutual fund performance categories in the market: zero-alpha funds (performance is not different from 0), skilled funds (performance is significantly better than the benchmark), and unskilled funds (performance is significantly worse than the benchmark). The fund performances within each category are normally distributed. For a given significant level  $\gamma$ , the lucky (unlucky) funds within the skilled funds category and unskilled funds category are the same, and are calculated as:

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<sup>11</sup> 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. In addition, based on the NBER business-cycle dates, 200 months out of 234 sample months (1990–2009) were in expansions periods.

$$F_{\gamma} = \pi_0 * \gamma/2 \quad (5)$$

where  $\pi_0$  is the true proportion of the zero-alpha fund category, and  $\gamma$  is the significance level we choose. Then, the true proportions of skilled funds,  $T_{\gamma}^+$ , and unskilled funds,  $T_{\gamma}^-$ , adjusted by the presence of lucky funds,  $F_{\gamma}$ , are measured as:

$$T_{\gamma}^+ = S_{\gamma}^+ - F_{\gamma} = S_{\gamma}^+ - \pi_0 * \gamma/2 \quad (6)$$

$$T_{\gamma}^- = S_{\gamma}^- - F_{\gamma} = S_{\gamma}^- - \pi_0 * \gamma/2 \quad (7)$$

Next, we implement the procedure of Barras et al. (2010) with a rolling window regression analysis. A fund will be considered only if the fund has full data during the whole 24-month estimation period. Within each month, we count the total number of funds and P-value from each regression. Then, the true proportion of the zero-alpha fund category in each month is estimated as:

$$\pi_{0,t} = \frac{W_{\lambda^*,t}}{M_t} * \frac{1}{1-\lambda^*} \quad (8)$$

where  $\lambda^*$  is a sufficiently high P-value threshold (we use  $\lambda^* = 0.6$ , as suggested in Barras et al., 2010).  $W_{\lambda^*}$  equals the number of funds with a P-value exceeding  $\lambda^*$  within this month, and  $M_t$  is the total number of funds considered in this month.

## 4. Empirical Results

### 4.1 Fund management selectivity performance results

We begin our examination of whether the performance of active mutual funds of differing management skills is sensitive to investor sentiment by predicting fund performance based on the fund's lagged  $1-R^2$  and the lagged excess return from the multifactor model, i.e., the fund alpha. We estimate  $R^2$  using rolling regressions of the FFC model with a 24-month window.  $R^2$  is used only if the fund has 24 months' continuous data. After each fund's  $R^2$  is calculated for each month,

we rank all the funds within each month based on their prior month's selectivity ( $1-R^2_{t-1}$ ) and sort all the funds into five quintiles based on their selectivity ranking. Within each quintile, we sort funds into five portfolios based on their prior one month's alpha ( $\alpha_{t-1}$ ), which is the intercept of the rolling regressions. This procedure produces 25 (5x5) portfolios with different selectivity and fund alphas, and each portfolio contains 4% of total mutual funds within the same month.

For each month, we calculate the monthly average excess raw returns (over the T-bill rate) of the funds that are included in each portfolio sorted by selectivity ( $1-R^2_{t-1}$ ) and past performance ( $\alpha_{t-1}$ ), and these average excess returns are regressed on the FFC model over the whole 25 years (1990–2014, 300 months) to obtain the abnormal risk-adjusted excess return, i.e., the portfolio fund alpha. The annualized alpha and P-value for each portfolio are reported in Panel A of Table II. Next, we examine whether fund selectivity skill varies with time and mainly whether high selectivity is associated with higher (lower) fund performance during high (low) states of sentiment. We address this question by examining whether variations in fund performance can be explained by variations in sentiment in line with the underlying hypothesis of this paper predicting that fund managers endowed with high selectivity skill should be associated with higher risk-adjusted excess returns during high investor sentiment periods. We used the BW sentiment index to measure the investor sentiment and separate our sample into high/low sentiment subgroups based on the investor sentiment, and each subgroup contains 150 months' observations. Then we repeat the previous analysis for high and low sentiment periods by sorting funds in each month by fund selectivity and past performance and present in Table II the annualized alpha and P-value for each portfolio for high (Panel B) and low (Panel C) sentiment periods.

[Insert Table II here]

Consistent with the findings of Amihud and Goyenko (2013), the results in Panel A of Table II show that greater fund selectivity, measured by ( $1-R^2_{t-1}$ ), yields higher fund alpha. The

results in the row “All” clearly show that fund portfolio performance (alpha) decreases as we move from the high selectivity (high  $1-R^2_{t-1}$ ) portfolio to the low selectivity (low  $1-R^2_{t-1}$ ) portfolio. The highest annualized alpha is 3.05% ( $P = 0.023$ ) for the fund portfolio with the highest selectivity and the best past performance. On average, around 8% of mutual funds outperform the benchmark significantly every month, which confirms that a relatively small fraction of active funds has selectivity skill that creates value for fund investors. In sum, the results in Panel A of Table II reveal that funds’ risk-adjusted excess return is higher for funds with greater fund selectivity skill ( $1-R^2_{t-1}$ ), which is highly consistent with the patterns in Amihud and Goyenko (2013).

As predicted, the results in Panels B and C of Table II demonstrate that high selectivity fund managers consistently outperform their low selectivity counterparts, but only beat the market benchmark significantly during high sentiment (noisy) periods. When investor sentiment level is high, as shown in Panel B, the highest past alpha quintile managers with the highest skill and second-highest skill produce 4.82% ( $P = 0.020$ ) and 2.70% ( $P = 0.073$ ) higher excess returns than the market benchmark, respectively. In sum, about 8% of active funds outperform the market benchmark during high sentiment periods. However, the results in Panel C indicate that during low sentiment periods none of the fund portfolios can beat the market benchmark significantly. These results indicate the superior performance of fund managers with the highest and the second highest selectivity skill, reported in Panel A for the entire sample period, is realized during high sentiment periods. Taken together, the results are in line with our hypothesis that high fund management selectivity produces the highest alpha mainly during high sentiment periods. Funds with higher selectivity skill deliver higher risk-adjusted returns in high sentiment periods. During low sentiment periods, they fail to outperform the market when asset prices are commonly believed to



trade near their intrinsic values due to the absence of noise traders.<sup>12</sup> Jointly, these results suggest that fund selectivity skill is far more valuable to fund investors when there is high sentiment and price signals are noisy due to the greater presence of investor hype in the market.

#### *4.2 BvanB fund management added value performance results*

In this section, we report results based on the Berk and van Binsbergen (2015) fund selectivity measure, i.e., BvanB fund skill. As noted earlier, this fund skill measure allows us to deduce the 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) measured over the 24-month estimation period. 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 alphas. To form the portfolios, we first rank all funds within each month based on their prior month's BvanB fund skill, as described in Equation (3), 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, while fund  $\alpha_{t-1}$  is obtained by regressing each fund's monthly excess returns on the 11 Vanguard index funds orthogonal bases. Then, for the following month, we calculate the average monthly excess return for each portfolio, and we regress the test period average portfolio returns on the alternative investment opportunity market benchmark. For each portfolio, we

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<sup>12</sup> To check the sensitivity of these results, we replicated our analysis using the median number of the UM index to separate high/low sentiment periods, and the results are presented in Appendix III. The results are more significant, both economically and statistically.

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, and present these results in Table III.<sup>13</sup> 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.

[Insert Table III here]

Consistent with our previous findings (Table II), the results in Table III reveal that funds with superior management skills, as measured by BvanB fund skill, have better performance. The results of Panel A in the row “All” 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 alphas. 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 reason is that 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 skills.

The results in Panels B and C of Table III demonstrate that highly skilled managers do better during high sentiment periods than in low sentiment periods. In high sentiment periods

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<sup>13</sup> We also did a similar portfolio performance analysis using the median number of the UM index to separate high/low sentiment periods, and we sort funds into portfolios based on BvanB fund skill and conventional fund  $\alpha_{t-1}$ , which is obtained from the estimation period by regressing each fund’s monthly excess returns on the factors from the alternative market benchmark, formed by the 11 Vanguard index funds orthogonal bases. The results, exhibited in Appendix IV, are consistent and more significant.

(Panel B), consistent with the previous evidence, the highest annualized BvanB fund alpha is \$7.71 million ( $P = 0.219$ ) for the fund portfolio with the highest BvanB fund skill and the best past performance. Even though this number is not significant, it is much higher than the entire sample period, i.e., \$3.74 million ( $P = 0.337$ ). This indicates that the performance of skilled fund managers is pronounced when financial markets are populated with noisy investors. This means that managers with the highest skill produce \$7.71 million added value during high sentiment periods, but only \$3.74 million for the entire period. That is, they can double a fund's added value in high sentiment periods even though they experience an increased inflow of capital because of their superior past performance. 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 performance difference shows that highly skilled fund managers do considerably better in high sentiment periods (Panel B) than in the entire sample period (Panel A). The reason that highly skilled managers with high past performance do not realize statistically significant superior performance in high sentiment periods is because they experience high capital inflows and under the pressure to invest the extra capital received from investors it lowers the profitability of their skill due to limited optimal investment opportunities.

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 counterpart fund performance in high sentiment periods (Panel B), i.e., 7.71 ( $P = 0.219$ ), and this is consistent with our view that skilled fund managers outperform their peers even in low sentiment periods. In addition, 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). While a greater fund skill produces a higher BvanB fund alpha, 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, while the parallel BvanB fund alpha in the high sentiment periods is 7.71 ( $P = 0.219$ ). The rest of the funds of this group realize significant negative BvanB fund alphas. Taken together, the 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.

#### *4.3 Fund portfolio performance and stock market dispersion*

As discussed in previous section, 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 simply based on the market dispersion. Similar to our sentiment analysis, we divide our sample into high and low market-dispersion periods based on the median number of the market-dispersion index, calculated for January 1990 to December 2014. The reported results in Table IV for the high (Panel A) and low (Panel B) market-dispersion periods 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.

[Insert Table IV here]

#### *4.4 Fund portfolio performance and economic activity*

Using CFNAI MA3 to split the sample into recession and expansion periods, we repeated the portfolio sorting analysis using the same sample period as in the previous section (1990–2014). Our results, as shown in Table V, reveal that more funds with high selectivity skill realize positive

risk-adjusted excess returns in economic expansions, which is 4.11% ( $P = 0.024$ ), than in economic recessions, which is 3.54% ( $P = 0.055$ ). The evidence is consistent with the previous literature (Kacperczyk et al., 2009) that found that skilled active funds provide an insurance mechanism against recessions.

[Insert Table V here]

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 can argue that it is essentially market dispersion or business cycle, rather than market noise that determines the fund performance difference between the high and low sentiment states. In response to this argument, as shown later in Tables VII and VIII, 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.

#### *4.5 Fund management selectivity performance regression results*

So far, we have analyzed the linear relationship between active fund performance, selectivity, and sentiment, but we want to make sure that high selectivity funds do outperform low selectivity funds using different factor models. To do so, we first formed two fund portfolios based on selectivity. In each month from January 1990 to December 2014, we formed five equally weighted fund portfolios based on their selectivity, which is estimated using rolling regressions of the FFC model with the 24-month time windows. These portfolios are rebalanced every month. Within these five portfolios, we only focus on the highest selectivity fund portfolio and the lowest selectivity fund portfolio. Within each month, we calculate the equally weighted average return for both portfolios and this provides a time series of monthly performance estimates for each

portfolio. We then calculate the risk-adjusted returns of high and low selectivity fund portfolios using the CAPM model, FF3 model, and FFC model. The results are shown in Table VI, along with the performance of the hypothetical strategy of longing the high selectivity fund portfolio and shorting the low selectivity fund portfolio, in the column labeled "High-Low".

[Insert Table VI here]

Unsurprisingly, the low-skilled fund portfolio delivers significant negative fund alphas in all three models. On the other hand, the highly skilled fund portfolio alpha is statistically insignificant in the FF3 and FFC models, which indicates that, on average, fund managers do not outperform these multifactor benchmarks. This is consistent with our earlier results demonstrating that only a small fraction of (skilled) fund managers (i.e., with the highest selectivity (Q5 quintile)), as shown in Tables II and III. The high selectivity fund portfolio outperforms its low selectivity counterpart significantly in all three models. The hypothetical strategy of a long position in the high selectivity fund portfolio and a short position in the low selectivity delivers 1.56% ( $P < 0.001$ ), 1.08% ( $P = 0.004$ ), and 0.96% ( $P = 0.031$ ) annualized alphas in each of the three models, respectively.<sup>14</sup> After adjusting for other risk factors, the spread in alpha between the high selectivity fund portfolio and the low selectivity fund portfolio decreases but continuous to remain significant. In addition, the significant negative relationship ( $-0.02$ ,  $P < 0.001$ ) between the return of the low selectivity portfolio and the momentum risk factor (MOM) indicates that low-skill managers require a lower return to invest in high-momentum-related stocks, suggesting that low-skilled managers behave like the average investor who chases momentum market anomalies by paying high prices. This confirms that they lack analytic and investment selection skills. However, this is not the case for the skilled fund managers. The insignificant coefficient between skilled fund

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<sup>14</sup> The annualized alpha is calculated as the monthly alpha (regression intercept) times 12.

portfolio and MOM (0.02, P = 0.170) means that highly skilled fund managers do not appear to make a profit by capitalizing on the momentum anomaly per se. For the rest of our analysis, we will focus on the FFC model.

Subsequently, we use multivariate regression analysis to examine the effect of selectivity and its interaction with sentiment on active fund performance for the entire sample period. The multivariate regression results are calculated using the BW index, as an investor sentiment measure,<sup>15</sup> while we also control for the market dispersion and business cycle effects.<sup>16</sup> To test whether the profitability of fund management skill (selectivity) is higher during high sentiment periods, we estimate the following model:

$$Alpha_{f,t} = \alpha_f + \beta_1 Selectivity_{f,t} + \beta_2 Sentiment_t + \beta_3 Selectivity_{f,t} * Sentiment_t + \sum Controls_{f,t} + \varepsilon_{f,t} \quad (9)$$

where  $Alpha_{f,t}$  is calculated as the difference in the fund's excess return in each month (over the T-bill rate) and the expected excess return in the same month. The expected excess return for each fund in each month is calculated by multiplying the FFC model factor loadings from the 24-month preceding estimation period by the factors in the current month. The estimation and test periods are rolling one month at a time. Selectivity for each fund is calculated as  $1-R^2_{t-1}$ , and  $R^2$  is estimated using the FFC model with the 24-month estimation period. Control variables in the regression include  $alpha_{t-1}$ , expense ratio, log value of fund age, fund turnover, log of fund total net assets, and squared log value of the fund total net assets.  $Alpha_{t-1}$  is the intercept from the FFC model using a 24-month estimation period, and as in Amihud and Goyenko (2013), we report results with and without  $alpha_{t-1}$  as control variables. Based on the central prediction of our hypothesis that

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<sup>15</sup> 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.

<sup>16</sup> Among those variables, CFAI MA3 and the UM index have the strongest correlation coefficient of 0.565, followed by the correlation coefficient of -0.513 between CFAI MA3 and market dispersion. Our main sentiment measure, the BW index, has a -0.015 coefficient with CFAI MA3 and a 0.351 coefficient with market dispersion.

active funds run by managers with high selectivity skills are expected to produce a better performance during high investor sentiment periods, when market signals are likely to be much noisier, than in low sentiment periods, we hypothesize that  $\beta_1 > 0$ ,  $\beta_2 < 0$ , and  $\beta_3 > 0$ .

[Insert Table VII here]

Consistent with the univariate results presented earlier and the above prediction, the results in Table VII Panel A show that selectivity in all regression specifications, in accordance with the evidence in Amihud and Goyenko (2013), is positive and significantly correlated with fund alpha ( $P < 0.001$ ) while sentiment is negative and significantly related to fund alpha ( $P < 0.001$ ), suggesting that, on average, fund performance is adversely affected when the market is plagued by noisy price signals as is most likely to be the case during high sentiment periods. However, the coefficient of the interaction variable between fund management selectivity and sentiment, *Selectivity\*Sentiment*, is highly significant (0.23,  $P = 0.005$  without  $\alpha_{t-1}$ , and 0.21,  $P = 0.009$  with  $\alpha_{t-1}$ ) and positively related to fund performance. Consistent with our hypothesis, this result demonstrates that during high sentiment periods, fund managers endowed with high selectivity deliver high alphas. This implies that high selectivity managers possess the ability to identify and make superior investments to the benefit of fund investors during high sentiment periods when the market is populated by noisy investors.

Given that the distribution of  $R^2$  is negatively skewed with its mass being in the high values close to 1, the distribution of selectivity should be heavily positively skewed. Therefore, we replicated the previous estimation, using the logistic transformation of selectivity, labeled *TSelectivity*, as shown in Equation (10), instead of the original selectivity measure.

$$TSelectivity = \log\left(\frac{Selectivity}{1-Selectivity}\right) \quad (10)$$



The new results, reported in Table VII Panel B, have a similar pattern with those presented previously in Panel A. The logistic-transformed selectivity measure is positively correlated with fund alpha ( $P < 0.001$ ). As in Panel A, *Sentiment* retains its negative relation with fund alpha ( $-0.04$ ,  $P = 0.088$  without  $alpha_{t-1}$ , and  $-0.11$ ,  $P < 0.001$  with  $alpha_{t-1}$ ) and the coefficient of the new interaction variable,  $TSelectivity * Sentiment$ , and fund performance is still positive and statistically significant ( $0.04$ ,  $P < 0.001$  without  $alpha_{t-1}$ , and  $0.02$ ,  $P = 0.016$  with  $alpha_{t-1}$ ). Jointly, the results in Table VII demonstrate a positive and significant relationship between fund performance and fund management skill in high sentiment periods. A funds' risk-adjusted excess return is higher for funds run by high selectivity managers, as measured by  $1-R^2_{t-1}$ , in high sentiment periods.

#### 4.6 BvanB fund management added value regression results

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, as defined in section 3.2.2, to estimate the following model:

$$BvanB\ Fund\ Alpha_{f,t} = \alpha_f + \beta_1 BvanB\ Fund\ Skill_{f,t} + \beta_2 Sentiment_t + \beta_3 BvanB\ Skill_{f,t} * Sentiment_t + \sum Controls_{f,t} + \varepsilon_{f,t} \quad (11)$$

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 24-month preceding estimation period.

[Insert Table VIII here]

Basically, the regression results in Table VIII show that BvanB fund skill significantly contributes to the fund performance, BvanB fund alpha, in all regressions. Consistent with the previous results, we find mostly a significant negative relationship between investor sentiment and fund performance, but a positive and significant association between the interaction variable,  $BvanB\ skill * Sentiment$ , and fund performance. This indicates that, on average, sentiment harms the overall fund performance, but this does not hold for skilled fund managers. In fact, skilled fund managers during high sentiment periods experience a significantly better performance than in low sentiment periods due to their ability to identify and make superior investments in high sentiment periods when the market is populated by noisy investors. 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.<sup>17</sup> 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.

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<sup>17</sup> Avramov and Wermers (2006) argue that some macroeconomic variables can affect fund managers skill and influence fund performance. To address the sensitivity of our results, we use four macroeconomic variables, as suggested in their paper, to control economic conditions: aggregate dividend yield, which is the total cash dividends on the value-weighted CRSP index over prior 12 months divided by the current level of the index; default spread, which is the difference between Moody's BAA-rated bonds yield and AAA-rated bonds yield; term spread, which is the different between ten-year treasury bonds yield and three-month T-bills yield; and the yield on the three-month T-bill. These results, as shown in Appendix V, are consistent with our previously reported findings.

## *4.7 Lucky bias analysis*

### *4.7.1 Selectivity performance lucky bias results*

One criticism about the superior performance of skilled fund managers, particularly in high sentiment periods, as documented above, is that it could be attributed to luck rather than to the differing abilities of managers. To address this concern, we followed Barras et al. (2010) and conduct a lucky bias analysis for the entire sample and replicated the analysis for both high and low sentiment periods. As shown in Table IX Panel A, using fund risk-adjusted excess return (fund alpha) as a performance measure, with a 20% significance level, 4.41% of the total funds beat the market significantly, and within the 4.41% funds, only 1.63% of fund managers are truly skilled. This number decreases to 0.69% when we move to the 5% significance level. This indicates that some of the mutual fund managers do possess management skill, but the proportion is very low.

[Insert Table IX here]

After we take investor sentiment into consideration, the results for high (Panel B) and low (Panel C) investor sentiment are consistent with our hypothesis. On average, 5.10% of funds outperform the market benchmark with a 20% significance level during high sentiment periods. After we get rid of the lucky funds, this number decreases to 1.57%. Using a 5% significance level, the total proportion of funds with positive extra returns is 1.85%, and the skilled funds account for 1.00% of total funds. During low sentiment periods, 3.70% (1.13%) of total funds beat the market at the 20% (5%) significance level, and the true skilled-funds proportion is only 0.73% (0.39%). The explanation for observing more skilled fund managers during high than low sentiment periods is that in high sentiment periods, when the market is noisy and information is costly, the investor demand for superior fund management skills is greater, which increases the payoffs of talented managers, resulting in superior fund performance.

#### 4.7.2 *BvanB fund added value lucky bias results*

When we replicate the lucky bias analysis, using the BvanB fund alpha as the performance measure, which captures the extra capital funds absorb from the financial market, we find similar results to those reported in Table IX. Specifically, as shown in Table X Panel A, on average, 7.52% (3.73%) of funds outperform the market benchmark at the 20% (5%) significance level. The proportion drops to 5.40% (1.48%) at a 20% (5%) significance level after we remove the lucky funds. Once again, during high sentiment periods, the percentage of skilled funds goes up to 8.60% (2.71%), but in low sentiment periods, the percentage decreases to 2.24% (0.27%).

[Insert Table X here]

There are three points to take away from the lucky bias analysis. First, even though the average mutual manager cannot beat the market, a small fraction of fund managers (about 0.69%, using selectivity ( $1-R^2$ ) measure and 1.48%, using BvanB value added skill measure, both of which are below the 5% significance level) with high stock-picking skills delivers persistently superior performance than their low skill peers. Second, skilled fund managers' skills are more profitable during high sentiment periods when the market is crowded with noise traders. During low sentiment periods when stocks are more likely to be traded near their intrinsic values, only a smaller portion of skilled managers produces significantly positive fund alphas for investors, which implies that selectivity skill is less valuable in low sentiment periods. Third, as argued by Berk and van Binsbergen (2015), there are more skilled fund managers in the market than we can detect using fund excess returns to capture performance because larger skilled funds may generate more value for their clients with relative low alphas. One could argue that an upward bias exists in the results due to sample selection, since good opportunities might attract more talented managers into the mutual fund industry during high sentiment periods. Conversely, there might be a

downward bias if bad funds disappear in times of low sentiment. To address this concern, we estimate the correlation between the number of funds appearing/disappearing and investor sentiment (BW Index) for each month. Interestingly, we find the number of new funds appearing to be insignificantly correlated with investor sentiment index (-0.01,  $P=0.880$ ), implying that skilled fund managers are not attracted by high investor sentiment. However, the number of funds disappearing is significantly positively correlated with investor sentiment (0.22,  $P<.001$ ), demonstrating that investor sentiment harms their performance due to lack of skill.<sup>18</sup>

#### *4.8 Stock mispricing and mutual fund performance*

We also examine whether the superior performance of skilled fund managers in high sentiment periods, when the views of optimistic (noisy) investors are more pronounced and short selling is limited, comes through investing in overvalued or undervalued stocks. To address this issue, we perform a cross-sectional analysis on the relation between fund performance and stock mispricing, using a set of 11 market anomalies to identify overpriced stocks (Stambaugh et al., 2012), and expect a negative relation to emerge for skilled fund managers.<sup>19,20</sup> Specifically, the stock mispricing data range between 0 and 100, and stocks with the highest mispricing values are the ones that are overpriced by the market, while stocks with the lowest mispricing values are underpriced. Since stocks with the highest mispricing values are identified as overpriced by the market due to noise, they should be less attractive to skilled fund managers. Consequently, we expect to observe a negative relationship between skilled fund managers' performance and highly mispriced stocks. Then, we calculate the value weighted average of stock mispricing ( $VW\_MISP$ ) for all stocks within each fund.<sup>21</sup> To check the sensitivity of our results, we replace the value

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<sup>18</sup> These results are available upon request.

<sup>19</sup> The 11 anomalies contain net stock issues, composite equity issues, accruals, net operating assets, asset growth, investment to assets, financial distress, O-score, momentum, gross profitability premium, and return on assets.

<sup>20</sup> The data are available through Yu Yuan's website <http://www.saif.sjtu.edu.cn/facultylist/yyuan/>.

<sup>21</sup> Fund holdings information is manually collected through Bloomberg Portfolio Analysis Database.

weighted average mispricing with the equal weighted average of stock mispricing ( $EW\_MISP$ ) for all stocks within each fund. Then, we break our sample into 5 quintiles based on fund management skill and estimate the relation between fund performance and stock mispricing for each quintile.

[Insert Table XI here]

Table XI presents the coefficient between fund performance and stock mispricing by regressing fund performance, for the 5 management skill quintiles, on fund level mispricing, while controlling for past fund performance ( $\text{Alpha}_{t-1}$ ), expense ratio, log value of fund age, fund turnover, log value of total net assets (TNA), and squared log value of TNA. First, as expected, the results in column “All” reveal a significant and negative relation between fund performance and stock mispricing. Furthermore, we find that the negative association between fund performance and stock mispricing is more pronounced for funds with lower management skill. For example, when sorting funds based on fund selectivity, the coefficient between fund performance and  $VW\_MISP$  ( $EW\_MISP$ ) in the lowest skill fund quintile is -0.111 (-0.111) and significant, while the coefficient in the highest skill fund quintile is -0.069 (-0.101). This pattern is even stronger when sorting funds into quintiles using BvanB fund skill measure. In sum, consistent with our previous evidence, the results of this cross-sectional analysis demonstrate that skilled fund managers’ investments are associated with undervalued stocks.

## **5. Robustness**

### *5.1 Sentiment beta analysis*

Several studies have focused on the profitability of mutual funds’ sentiment timing strategy. For example, Grinblatt, Titman, and Wermers (1995) and Carhart (1997) have showed that mutual funds tend to follow momentum. Recently, Massa and Yadav (2015) reported that mutual funds employ portfolio strategies based on market sentiment. Specifically, they find that low sentiment

*beta* funds outperform the high sentiment beta funds, even after controlling for standard risk factors and fund characteristics. This result is attributed to the sentiment-contrarian strategy rather than the sentiment-momentum strategy, which, in turn, attracts significant investor flows in comparison to the sentiment-catering strategy. In a more recent study, Chen, Han, and Pan (2016) examine whether exposure to sentiment risk can explain the cross-sectional variation in hedge fund returns and find that funds with a sentiment beta in the top decile subsequently outperform those in the bottom decile by 0.67% per month on a risk-adjusted basis. Therefore, they argue that some hedge funds can time sentiment and contribute to fund performance by increasing their exposure to a sentiment factor when the factor premium is high.

In this section, we investigate the impact of fund sentiment timing strategy on fund performance. As discussed earlier, in this study, we view investor sentiment as an economic condition, rather than as a risk factor to be exploited by its timing and argue that skilled managers invest in assets based on their superior analytic ability and private information about an asset's true value, rather than timing sentiment. This leads us to expect that the fund sentiment timing strategy is more likely to be associated with low rather than high skilled fund managers. To examine whether high (low) skilled fund managers are less (more) likely to time investor sentiment, we perform Fama–MacBeth regressions of high- and low-skilled fund portfolio returns and alphas on sentiment beta, while controlling for fund-level characteristics. The fund alpha is calculated as the intercept of the regressing portfolio excess returns on the FFC model for our entire 300-months sample period. Following Massa and Yadav (2015), we calculate each portfolio's sentiment beta by regression using the 24 months of data proceeding the current month:

$$R_{p,t} - R_{f,t} = \alpha + \beta_1(RM - Rf)_t + \beta_2SMB_t + \beta_3HML_t + \beta_4MOM_t + \beta_5Sentiment_t \quad (12)$$

where  $R_{p,t}$  is the portfolio  $p$ 's return in month  $t$ ;  $R_{f,t}$  is the risk-free rate in month  $t$ ;  $RM-Rf$  is the market excess return in month  $i$ ,  $SMB$  is the return difference of small and big size stocks in month  $i$ ,  $HML$  is the return difference of high and low book-to-market ratio stocks in month  $i$ ,  $MOM$  is the return difference of winner and loser stocks in month  $i$ , and  $Sentiment$  is the BW index for the same month.  $\beta_5$  is the sentiment beta estimated by running regression (12) with a 24-month moving window. Then, we run the following cross-sectional regression of portfolio return (13) (and portfolio alpha obtained from FFC model (14)) on the sentiment beta, with or without fund-level control variables:

$$R_{p,t} - R_{f,t} = \gamma + \omega Sentiment Beta_{t-1} + \varphi \sum Controls_t + \epsilon_{p,t} \quad (13)$$

$$alpha_{p,t} = \gamma + \omega Sentiment Beta_{t-1} + \varphi \sum Controls_t + \epsilon_{p,t} \quad (14)$$

The control variables include the equally weighted average expense ratio, fund age, turnover, and log value of fund TNA.

[Insert Table XII here]

Table XII reports the Fama–MacBeth regression results where the dependent variable is either the monthly portfolio excess return or the portfolio  $alpha$ . The only significant coefficient on sentiment beta that emerges from these regressions is for the low-skill fund portfolio's  $alpha$ , when alpha serves as a dependent variable, indicating that low-skilled funds seem to time investor sentiment by employing a sentiment-momentum strategy. Other than that, the insignificant coefficient of sentiment beta in the high-skill regressions, suggests that skilled fund managers do not appear to time investor sentiment. These results support the view that skilled fund managers do not time investor sentiment as a value-creating strategy because, as argued by Shleifer and Vishny (1997), movements in investor sentiment are in part unpredictable. Therefore, fund managers betting against mispricing during high sentiment periods run a high risk, at least in the



short run, that investor sentiment will become more extreme and prices will move even further away from fundamental values. Skilled fund managers focus more on stock selection during high sentiment periods than on timing the investor sentiment movements. Consistent with our previous results, these findings imply that skilled fund managers' superior performance relative to their low-skilled peers is mainly due to their ability to produce more (private) information about the true value of financial assets under management during high sentiment periods when asset prices are noisier than in low sentiment periods when financial markets are not crowded by unsophisticated (noisy) investors.

## *5.2 Fund capital flow analysis*

The portfolio sorting and multivariate analysis thus far, shows that skilled fund managers have a significant and persistent past performance ( $\alpha_{t-1}$ ), and this should attract capital inflows from the financial market as investors tend to make investment decisions based on the past performance of each mutual fund. Therefore, due to limited optimal investment opportunities in the market skilled fund managers under the pressure to invest the extra capital inflows will be forced to make investment decisions which consequently may weaken fund performance (fund alpha), unless they are endowed with high selectivity skills. Additionally, studies have shown that sentiment is correlated with fund flows (Ben-Raphel, Kandel, and Wohl, 2012). In this section, we address this issue by investigating whether the superior performance of skilled fund managers remains pronounced under the influence of additional capital inflows.

To inspect the influence of capital inflows, we first estimate the capital flow of each fund as follows:

$$\text{Net capital flow}_{f,t} = TNA_{f,t} - (1 + R_{f,t}) * TNA_{f,t-1} \quad (15)$$

where  $TNA_{f,t}$  is the total net assets of fund  $f$  in month  $t$ , and  $R_{f,t}$  is the fund return in month  $t$ . To test whether and how fund performance is affected by capital flows, we include net capital flows 2 months ago ( $Flow_{t-2}$ ) and 1 month ago ( $Flow_{t-1}$ ), and their interaction variables with fund selectivity and sentiment into our main multivariate regression, as presented in Equation (9).

[Insert Table XIII here]

Consistent with our prediction, the results in Table XIII column 1 show a negative and significant correlation between the previous month capital inflows ( $Flow_{t-1}$ ) with fund *alpha*, which reveals that extra capital inflows create more pressure on fund managers to invest resulting in lower fund *alpha*. The insignificant coefficients between the interaction  $Flow*Sentiment$  in t-1 and t-2 and fund *alpha* ( $P = 0.97$  and  $P = 0.62$  for capital inflows, respectively), as shown in column 2, indicate that the negative relationship between the previous months' capital inflows and fund performance is not sentiment-related. The coefficients between the interaction  $Flow*Selectivity$  in t-1 and t-2 and fund *alpha*, as reported in column 3, are positive and significant ( $P < 0.001$ ), suggesting that managers with high selectivity skill direct extra capital inflows in better investment opportunities delivering high *alpha* than their unskilled fund counterparts. Last, the positive and significant relationship between the interaction  $Selectivity*Sentiment$  and fund *alpha* (0.166,  $P = 0.04$ ), in column 4, shows that even after controlling for the negative effect of capital inflows from previous months, high selectivity managers still possess the ability to make significantly superior investments during high sentiment periods to the benefit fund investors.

### 5.3 Volatility anomaly analysis

There is also evidence in the literature suggesting that the volatility anomaly, either directly or indirectly, can lead to mismeasurement of fund manager skill (Jordan and Riley, 2015; Novy-Marx, 2014; and Fama and French, 2017). Volatility anomaly basically means that the low

volatility stock portfolio outperforms the high volatility stock portfolio significantly, and Jordan and Riley (2015) show that it has a large impact on mutual fund returns, which could create a significant bias when measuring managers' skills. Even though the volatility anomaly has been questioned by other studies, we assess the sensitivity of our results by controlling for the effect of the volatility anomaly.<sup>22</sup>

In accord with section 4.1, we sort all the funds in each month into 25 (5x5) portfolios with a different selectivity ( $1-R^2_{t-1}$ ) and past fund performance,  $\alpha_{t-1}$ . Next, we examine whether fund selectivity skill varies with time and particularly whether high selectivity is associated with a higher fund performance during high sentiment states. As before, we use the BW sentiment index to measure the investor sentiment and if the month  $t$ 's BW sentiment index is higher (lower) than the median number of all the monthly BW sentiment index numbers, we define month  $t$  as a high (low) investor sentiment month. Then, for each month, we calculate the monthly average excess raw returns of funds included in each portfolio and regress the returns on the Fama–French five-factor plus momentum factor model, which contain the profitability factor and investment factor that can explain the volatility anomaly (Jordan and Riley, 2015), to obtain the abnormal risk-adjusted excess return, i.e., portfolio fund alpha. Table XIV presents the annualized fund alpha and P-value for each portfolio in high (Panel A) and low (Panel B) sentiment periods, respectively.

[Insert Table XIV here]

These results continue to show that skilled fund managers' performance is superior during high investor sentiment periods indicating that they are not sensitive volatility anomaly. Consistent with the pattern of our main results, fund portfolio performance (alpha), as shown in row "All," decreases from the high selectivity (high  $1-R^2_{t-1}$ ) portfolio to the low selectivity (low  $1-R^2_{t-1}$ )

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<sup>22</sup> For example, Moreira and Muir (2016) showed that a volatility-managed portfolio, which decreases portfolio volatility when the expected market risk is high and increases the portfolio volatility when expected market risk is low, yields high alphas and increases the portfolio Sharpe ratio significantly.

portfolio in both high (Panel A) and low sentiment (Panel B) periods. Panel A shows that when investor sentiment level is high, the highest past alpha quintile managers with the highest skill and second-highest skill produce 6.66% ( $P = 0.002$ ) and 4.54% ( $P = 0.003$ ) higher excess returns than the market benchmark, respectively. The hypothetical strategy of a long position in the high selectivity fund portfolio and a short position in the low selectivity fund portfolio, rightmost “High-Low,” yields 1.10% ( $P = 0.087$ ) extra return than the market benchmark for the entire sample. However, during low sentiment periods, as shown in Panel B, the fund portfolio with the highest selectivity and the best past performance cannot beat the market benchmark significantly (1.93%,  $P = 0.247$ ). In addition, the hypothetical strategy fails to significantly outperform the market on average (0.64%,  $P = 0.167$ ).<sup>23</sup> Taken together, these results provide supplemental evidence indicating that skilled managers produce higher fund alphas during high sentiment periods, and this relationship is not biased by the volatility anomaly.

#### *5.4 Alternative sentiment measures*

We also ran robustness tests using several alternative sentiment measures: credit market sentiment, the FEARS sentiment index, the VIX index, and the NYSE based TRIN index. 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

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<sup>23</sup> The same analysis is re-examined using the UM index and the results are consistent with the results using the BW index.

converted the data into monthly observations by taking the average of the daily data in order to match our data. The VIX index is estimated based on a range of S&P 500 index options and reflects the expectation of the equity market volatility in the near future, which is often referred as *fear index* or the *fear gauge*. The TRIN index is a short-term technical analysis stock market trading indicator, which is widely used in the financial industry to indicate bullish ( $TRIN < 1$ ) and bearish ( $TRIN > 1$ ) market sentiment. Unreported results based on these alternative sentiment measures are qualitatively consistent with the pattern of our previous finding that skilled mutual fund managers generate greater value (alpha) during high equity market sentiment periods, identified by low credit market sentiment index, high FEARS index, low VIX index (i.e. market complacency), and low (bullish) TRIN index.

## **6. Conclusion**

In this paper, unlike most of the previous literature that has focused on the question of whether fund managers improve fund performance, we examine whether skilled mutual fund managers deliver greater value (alpha) when security markets are crowded by noise traders (signals). Our results can be construed as providing general support for the hypothesis that skilled fund managers generate persistent excess risk-adjusted returns especially during high sentiment periods, when asset prices are noisier and information is costlier, and stock mispricing states as an alternative setting of noise trading.

Using a large sample of U.S. domestic active-managed equity mutual funds, we empirically test this conjecture and find that managers endowed with high fund management skills realize superior fund performance during high investor sentiment periods. Specifically, our result show that fund managers with the highest skill create \$7.71 million of added value during high sentiment periods which exceeds the average realized fund gains (\$3.74 million), while they incur a small

value loss of \$0.18 million in low sentiment periods. However, fund managers with the lowest skill experience a values loss of \$5.64 million during high sentiment periods which is far lower than the average realized fund gains (\$3.74 million), while they incur a substantial value loss of \$30.32 million in low sentiment periods. High-skill fund managers also outperform their low-skill counterparts in states of increased market volatility triggered by pessimistic investor emotions. Assessing the performance of fund managers in stock mispricing states, as an alternative setting of noise trading, our evidence consistently shows that high-skill (low-skill) managers' performance is associated with undervalued (overvalued) stocks, indicating their ability to create value by identifying and carrying out profitable trades.

We also find that only a small subset (around 2%, under the 5% significance level) of all fund managers has superior management skills that generate persistent excess risk-adjusted returns. Our findings are robust to sentiment beta effect, stock market dispersion, state of macroeconomic environment, alternative sentiment measures, and the effect of the volatility anomaly. Overall, our findings conclusively suggest that skilled fund managers create more value during high than low sentiment periods and stock mispricing states, when noise trading is more pronounced.

## References

- Amihud, Y. and Goyenko R. (2013): Mutual fund's  $R^2$  as predictor of performance, *Review of Financial Studies* 26, 667-694.
- Amromin, G. and Sharpe, S. A. (2009): Expectations of risk and return among household investors: Are their Sharpe ratios countercyclical? *Available at SSRN 1327134*.
- Antonioni, C., Doukas, J. A., and Subrahmanyam, A. (2013): Cognitive dissonance, sentiment, and momentum, *Journal of Financial and Quantitative Analysis* 48, 245-275.
- Antonioni, C., Doukas, J. A., and Subrahmanyam, A. (2015): Investor sentiment, beta, and the cost of equity capital, *Management Science* 62, 347-367.
- Avramov, D., and Wermers, R. (2006): Investing in mutual funds when returns are predictable, *Journal of Financial Economics* 81, 339-377.
- Baker, M., and Wurgler, J. (2006): Investor sentiment and the cross- section of stock returns, *The Journal of Finance* 61, 1645-1680.
- Baks, K., Metrick, A., and Wachter, J. (2001): Should investors avoid all actively managed mutual funds? A study in Bayesian performance evaluation, *The Journal of Finance* 56, 45-85.
- Barberis, N., and Thaler, R. (2003): A survey of behavioral finance, *Handbook of the Economics of Finance* 1, 1053-1128.
- Barras, L., Scaillet, O., and Wermers, R. (2010): False discoveries in mutual fund performance: Measuring luck in estimated alphas, *The Journal of Finance* 65, 179-216.
- Ben-Rephael, A., Kandel, S., and Wohl, A. (2012): Measuring investor sentiment with mutual fund flows, *Journal of Financial Economics* 104, 363-382.
- Berk, J. B., & Green, R. C. (2004). Mutual fund flows and performance in rational markets. *Journal of Political Economy*, 112(6), 1269-1295.
- Berk, J. B., and van Binsbergen, J. H. (2015): Measuring skill in the mutual fund industry, *Journal of Financial Economics* 118, 1-20.
- Białkowski, J., Etebari, A., and Wisniewski, T. P. (2012): Fast profits: Investor sentiment and stock returns during Ramadan, *Journal of Banking & Finance* 36, 835-845.
- Black, F. (1986): Noise, *The Journal of Finance* 41, 528-543.
- Brands, S., Brown, S. J., and Gallagher, D. R. (2005): Portfolio concentration and investment manager performance, *International Review of Finance* 5, 149-174.
- Campbell, J. Y., and Vuolteenaho, T. (2004): Inflation illusion and stock prices, *National Bureau of Economic Research* No. w10263.
- Carhart, M. M. (1997): On persistence in mutual fund performance, *The Journal of Finance* 52, 57-82.
- Chen, Y., Han, B.; and Pan, J. (2016): Sentiment Risk, Sentiment Timing, and Hedge Fund Returns, *Sentiment Timing, and Hedge Fund Returns (January 12, 2016)*.
- Christopherson, J. A., Ferson, W. E., and Glassman, D. A. (1998): Conditioning manager alphas on economic information: Another look at the persistence of performance, *The Review of Financial Studies* 11, 111-142.
- Cohen, L., Frazzini, A., and Malloy, C. (2007): The small world of investing: Board connections and mutual fund returns, *National Bureau of Economic Research Cambridge, Mass., USA*.

- Cremers, K. M., and Petajisto, A. (2009): How active is your fund manager? A new measure that predicts performance, *Review of Financial Studies* 22, 3329-3365.
- Cremers, M., Ferreira, M. A., Matos, P. P., and Starks, L. T. (2016): Indexing and active fund management: International evidence, *Journal of Financial Economics* 120, 539-560.
- Cullen, G., Gasbarro, D., Le, K. S., and Monroe, G. S. (2013): Does Selectivity in Mutual Fund Trades Exploit Sentiment Timing, unpublished working paper, Murdoch University, University of New South Wales.
- Da, Z., Engelberg J., and Gao P. (2015): The sum of all FEARS investor sentiment and asset prices, *Review of Financial Studies* 28, 1-32.
- Daniel, K., Grinblatt, M., Titman, S., and Wermers, R. (1997): Measuring mutual fund performance with characteristic- based benchmarks, *The Journal of Finance* 52, 1035-1058.
- Daniel, K., Hirshleifer, D., and Subrahmanyam, A. (1998): Investor psychology and security market under- and overreactions, *the Journal of Finance* 53, 1839-1885.
- Dowling, M., and Lucey, B. M. (2005): Weather, biorhythms, beliefs and stock returns—some preliminary Irish evidence, *International Review of Financial Analysis* 14, 337-355.
- Edmans, A., Garcia, D., and Norli, Ø. (2007): Sports sentiment and stock returns, *The Journal of Finance* 62, 1967-1998.
- Elton, E. J., Gruber, M. J., and Blake, C. R. (2012): An examination of mutual fund timing ability using monthly holdings data, *Review of Finance* 16, 619-645.
- Fama, E. F., and French, K. R. (1993): Common risk factors in the returns on stocks and bonds, *Journal of Financial Economics* 33, 3-56.
- Fama, E. F., and French, K. R. (2017): International tests of a five-factor asset pricing model, *Journal of Financial Economics*, 123, 441-463.
- Glode, V. (2011): Why mutual funds “underperform”, *Journal of Financial Economics* 99, 546-559.
- Grinblatt, M., and Keloharju, M. (2001): How distance, language, and culture influence stockholdings and trades, *The Journal of Finance* 56, 1053-1073.
- Grinblatt, M., Titman, S., and Wermers, R. (1995): Momentum investment strategies, portfolio performance, and herding: A study of mutual fund behavior, *The American Economic Review* 1088-1105.
- Hirshleifer, D., and Shumway, T. (2003): Good day sunshine: Stock returns and the weather, *The Journal of Finance* 58, 1009-1032.
- Jiang, G. J., Yao, T., and Yu, T. (2007): Do mutual funds time the market? Evidence from portfolio holdings, *Journal of Financial Economics* 86, 724-758.
- Jordan, B. D., and Riley, T. B. (2015): Volatility and mutual fund manager skill, *Journal of Financial Economics* 118, 289-298.
- Kacperczyk, M., Nieuwerburgh, S. V., and Veldkamp, L. (2014): Time- Varying Fund Manager Skill, *The Journal of Finance* 69, 1455-1484.
- Kacperczyk, M., and Seru, A. (2007): Fund manager use of public information: New evidence on managerial skills, *The Journal of Finance* 62, 485-528.
- Kacperczyk, M., Sialm, C., and Zheng, L. (2005): On the industry concentration of actively managed equity mutual funds, *The Journal of Finance* 60, 1983-2011.



- Kacperczyk, M., Nieuwerburgh, S. V.; and Veldkamp, L. (2009): Rational attention allocation over the business cycle, *National Bureau of Economic Research* No. w15450
- Kacperczyk, M., Nieuwerburgh, S. V., and Veldkamp, L. (2016): A rational theory of mutual funds' attention allocation, *Econometrica* 84, 571-626.
- Kaplanski, G., and Levy, H. (2010): Sentiment and stock prices: The case of aviation disasters, *Journal of Financial Economics* 95,174-201.
- Kosowski, R. (2011): Do mutual funds perform when it matters most to investors? US mutual fund performance and risk in recessions and expansions, *The Quarterly Journal of Finance* 1, 607-664.
- Lamont, O. A., and Thaler, R. H. (2003): Anomalies: The law of one price in financial markets, *The Journal of Economic Perspectives* 17, 191-202.
- López-Salido, D., Stein, J. C., and Zakrajšek, E. (2016): Credit-market sentiment and the business cycle, *National Bureau of Economic Research* No. w21879
- Massa, M., and Yadav, V. (2015): Investor Sentiment and Mutual Fund Strategies, *Journal of Financial and Quantitative Analysis* 50, 699-727.
- Miller, E. M. (1977): Risk, Uncertainty, and Divergence of Opinion, *Journal of Finance* 32, 1151–1168.
- Moreira, A., and Muir, T. (2016): Volatility managed portfolios, *National Bureau of Economic Research* No. w22208.
- Moskowitz, T. J. (2000). Discussion. *The Journal of Finance*, 55(4), 1695-1703.
- Novy-Marx, R. (2014): Understanding defensive equity, *National Bureau of Economic Research* No. w20591.
- Shleifer, A., and Vishny, R. W. (1997): The limits of arbitrage, *The Journal of Finance* 52, 35-55.
- Stambaugh, R. F., Yu, J., and Yuan, Y. (2012): The short of it: Investor sentiment and anomalies, *Journal of Financial Economics* 104, 288-302.
- Von Reibnitz, A. H. (2015): When Opportunity Knocks: Cross-Sectional Return Dispersion and Active Fund Performance, *Paper presented at the 26th Australasian Finance and Banking Conference*.
- Wermers, R. (2000): Mutual fund performance: An empirical decomposition into stock- picking talent, style, transactions costs, and expenses, *The Journal of Finance* 55, 1655-1703.

**Table I**

## Summary Statistics of Actively Managed Equity Mutual Funds' Characteristics

	<b>Mean</b>	<b>Median</b>	<b>Minimum</b>	<b>Maximum</b>
<b>Turnover (%)</b>	85.64	56.00	0.00	3,452.00
<b>Age (years)</b>	17.44	17.00	3.00	47.00
<b>Expense Ratio (%)</b>	1.28	1.21	0.00	9.16
<b>TNA (millions)</b>	1,267.96	234.49	8.26	202,305.77
<b>R<sup>2</sup><sub>t-1</sub></b>	0.883	0.922	0.219	0.991

*Notes:* This table shows descriptive statistics of individual fund estimates of  $R^2_{t-1}$  and control variables.  $R^2_{t-1}$  is calculated by regressing each fund's excess return (fund monthly raw return minus one-month T-bill rate of that month) on the multifactor model of Fama-French (1993) and Carhart (1997) (FFC model) over a time window of 24 months. Our sample contains 2190 actively-managed U.S. equity mutual funds over the period from January 1990 to December 2014, with 273,557 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.

**Table II**Portfolio Fund Alpha, Based on Sorting on Lagged  $R^2$  and Alpha

<i>Panel A: Portfolio fund alpha for the entire sample period</i>						
<b>Alpha<sub>t-1</sub></b>	<b>Fund selectivity (1-R<sup>2</sup><sub>t-1</sub>)</b>					
	<b>Low</b>	<b>4</b>	<b>3</b>	<b>2</b>	<b>High</b>	<b>All</b>
<b>Low</b>	-1.75*** (0.001)	-2.04*** (0.003)	-1.84** (0.015)	-1.97** (0.026)	-2.06 (0.117)	-1.93*** (0.002)
<b>2</b>	-1.43*** (0.001)	-0.99** (0.049)	-0.90 (0.154)	-0.34 (0.653)	0.34 (0.712)	-0.67 (0.196)
<b>3</b>	-0.94** (0.024)	-0.67 (0.143)	-1.17** (0.044)	-0.51 (0.450)	0.56 (0.501)	-0.55 (0.219)
<b>4</b>	-1.18** (0.011)	-1.16 (0.106)	0.11 (0.840)	-0.20 (0.792)	0.99 (0.277)	-0.28 (0.535)
<b>High</b>	-1.41* (0.051)	-0.81 (0.355)	-0.08 (0.912)	2.14** (0.025)	3.05** (0.023)	0.58 (0.381)
<b>All</b>	-1.34*** (0.001)	-1.14** (0.012)	-0.78 (0.110)	-0.19 (0.754)	0.58 (0.426)	-0.57 (0.166)
<i>Panel B: Portfolio fund alpha during high market sentiment</i>						
<b>Alpha<sub>t-1</sub></b>	<b>Low</b>	<b>4</b>	<b>3</b>	<b>2</b>	<b>High</b>	<b>All</b>
<b>Low</b>	-2.38*** (0.002)	-3.71*** (0.001)	-2.97** (0.017)	-2.68* (0.054)	-1.45 (0.412)	-2.65*** (0.006)
<b>2</b>	-2.34*** (0.001)	-1.38* (0.097)	-2.11** (0.026)	-1.02 (0.378)	0.02 (0.990)	-1.36* (0.095)
<b>3</b>	-1.36** (0.021)	-1.40** (0.050)	-2.19** (0.018)	-0.69* (0.508)	0.03 (0.982)	-1.12* (0.095)
<b>4</b>	-0.95 (0.187)	-1.19 (0.150)	-0.73 (0.381)	-0.01 (0.996)	0.36 (0.792)	-0.50 (0.488)
<b>High</b>	-1.92 (0.133)	-1.39 (0.379)	-0.50 (0.696)	2.70* (0.073)	4.82** (0.020)	0.75 (0.499)
<b>All</b>	-1.79*** (0.003)	-1.82** (0.014)	-1.70** (0.033)	-0.35 (0.721)	0.74 (0.508)	-0.98 (0.147)
<i>Panel C: Portfolio fund alpha during low market sentiment</i>						
<b>Alpha<sub>t-1</sub></b>	<b>Low</b>	<b>4</b>	<b>3</b>	<b>2</b>	<b>High</b>	<b>All</b>
<b>Low</b>	-1.14** (0.035)	-0.33 (0.668)	-0.90 (0.272)	-1.38 (0.156)	-2.35 (0.236)	-1.21 (0.117)
<b>2</b>	-0.61 (0.186)	-0.68 (0.161)	-0.45 (0.450)	-0.36 (0.670)	0.44 (0.711)	-0.34 (0.540)
<b>3</b>	-0.54 (0.280)	-0.31 (0.549)	-0.84 (0.136)	-0.81 (0.255)	0.58 (0.595)	-0.38 (0.413)
<b>4</b>	-1.34** (0.019)	-1.34 (0.253)	0.27 (0.687)	-1.22 (0.117)	1.40 (0.245)	-0.44 (0.410)
<b>High</b>	-0.68 (0.328)	0.30 (0.694)	0.16 (0.859)	0.89 (0.439)	0.63 (0.702)	0.26 (0.730)
<b>All</b>	-0.86** (0.026)	-0.47 (0.321)	-0.34 (0.457)	-0.58 (0.331)	0.17 (0.851)	-0.42 (0.341)

*Notes:* This table presents the portfolio fund alpha, annualized, using monthly returns, from January 1990 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 lagged  $R^2$  and then by fund  $\alpha_{t-1}$ . Both are obtained from the 24-month estimation period (t-24 to t-1) by regressing each fund's monthly excess returns (over the T-bill rate) on the factors from FFC model. Then, for the following month (t), we calculate the average monthly excess returns for each fund portfolio. This process is repeated by moving the estimation and test period one month at a time. Last, we regress the test period average portfolio returns on the FFC model. For each portfolio cell, we present portfolio alpha, which is the intercept from the above regression, and the P-value. \*\*\*, \*\*, \* denotes significance at the 1%, 5% or 10% level.

**Table III**

Portfolio BvanB Fund Alpha, Based on Sorting on BvanB Fund Skill and Lagged BvanB Fund Alpha

<i>Panel A: Portfolio BvanB fund alpha for the entire sample period</i>						
<b>BvanB Alpha<sub>t-1</sub></b>	<b>BvanB fund skill</b>					<b>All</b>
	<b>Low</b>	<b>4</b>	<b>3</b>	<b>2</b>	<b>High</b>	
<b>Low</b>	-18.06* (0.074)	-3.25 (0.115)	-1.44 (0.353)	-0.22 (0.850)	0.77 (0.609)	-4.44 (0.124)
<b>4</b>	-8.61 (0.103)	-3.25* (0.065)	-1.30 (0.324)	-0.42 (0.740)	1.03 (0.563)	-2.51 (0.194)
<b>3</b>	-4.84 (0.140)	-2.30 (0.138)	-0.87 (0.470)	0.31 (0.796)	1.22 (0.498)	-1.29 (0.393)
<b>2</b>	-4.52 (0.120)	-2.02 (0.168)	-0.64 (0.575)	0.14 (0.911)	2.14 (0.308)	-0.98 (0.500)
<b>High</b>	-4.80** (0.048)	-1.75 (0.182)	-0.20 (0.864)	0.64 (0.649)	3.74 (0.337)	-0.48 (0.769)
<b>All</b>	-8.82* (0.078)	-2.51 (0.115)	-0.89 (0.472)	0.09 (0.943)	1.78 (0.413)	-1.94 (0.280)
<i>Panel B: Portfolio BvanB fund alpha during high market sentiment</i>						
<b>BvanB Alpha<sub>t-1</sub></b>	<b>Low</b>	<b>4</b>	<b>3</b>	<b>2</b>	<b>High</b>	<b>All</b>
<b>Low</b>	-5.64 (0.732)	2.98 (0.356)	3.12 (0.217)	3.55* (0.054)	3.44 (0.167)	1.49 (0.755)
<b>4</b>	8.97 (0.249)	1.80 (0.516)	2.60 (0.207)	2.99 (0.141)	4.51 (0.138)	4.17 (0.166)
<b>3</b>	4.67 (0.344)	2.04 (0.416)	2.85 (0.138)	3.78* (0.055)	3.64 (0.234)	3.39 (0.169)
<b>2</b>	3.39 (0.441)	2.23 (0.339)	2.78 (0.140)	3.24 (0.114)	5.25 (0.128)	3.38 (0.157)
<b>High</b>	1.65 (0.656)	1.90 (0.370)	3.03 (0.122)	3.86 (0.101)	7.71 (0.219)	3.63 (0.183)
<b>All</b>	3.21 (0.682)	2.19 (0.387)	2.88 (0.154)	3.48* (0.082)	4.91 (0.172)	3.21 (0.276)
<i>Panel C: Portfolio BvanB fund alpha during low market sentiment</i>						
<b>BvanB Alpha<sub>t-1</sub></b>	<b>Low</b>	<b>4</b>	<b>3</b>	<b>2</b>	<b>High</b>	<b>All</b>
<b>Low</b>	-30.32** (0.011)	-9.39*** (0.001)	-5.95*** (0.001)	-3.95*** (0.006)	-1.85 (0.284)	-10.29*** (0.002)
<b>4</b>	-25.96*** (0.001)	-8.22*** ( $<.001$ )	-5.14*** (0.001)	-3.77*** (0.010)	-2.40 (0.198)	-9.10*** ( $<.001$ )
<b>3</b>	-14.22*** (0.001)	-6.58*** (0.001)	-4.54*** (0.001)	-3.11** (0.018)	-1.15 (0.557)	-5.92*** (0.001)
<b>2</b>	-12.33*** (0.001)	-6.20*** (0.001)	-4.02*** (0.002)	-2.92** (0.032)	-0.93 (0.700)	-5.28*** (0.001)
<b>High</b>	-11.17*** (0.001)	-5.35*** (0.001)	-3.38*** (0.007)	-2.54* (0.091)	-0.18 (0.969)	-4.53*** (0.009)
<b>All</b>	-20.68*** (0.001)	-7.15*** (0.001)	-4.61*** (0.001)	-3.26** (0.018)	-1.30 (0.599)	-7.02*** (0.001)

*Notes:* This table 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 (Equation 3) and then by BvanB fund alpha<sub>t-1</sub>, and both are described in detail in section 3.2.2. 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.

**Table IV**

Portfolio Fund Alpha, Based on Sorting on Lagged  $R^2$  and Fund Alpha, in High and Low Market Dispersion Periods

<i>Panel A: During high market dispersion</i>						
$\text{Alpha}_{t-1}$	Fund selectivity ( $1-R^2_{t-1}$ )					
	Low	4	3	2	High	All
<b>Low</b>	-2.31*** (0.002)	-3.59*** (0.002)	-1.87 (0.163)	-1.92 (0.201)	-1.39 (0.534)	-2.22** (0.040)
<b>2</b>	-2.00*** (0.004)	-1.39* (0.096)	-1.38 (0.196)	-0.16 (0.902)	1.46 (0.341)	-0.69 (0.432)
<b>3</b>	-1.53** (0.026)	-1.31* (0.083)	-2.04** (0.037)	-0.83 (0.459)	-0.20 (0.889)	-1.18 (0.113)
<b>4</b>	-2.39*** (0.002)	-1.39 (0.121)	-0.21 (0.822)	0.01 (0.995)	1.02 (0.497)	-0.59 (0.442)
<b>High</b>	-1.98 (0.118)	-2.37 (0.139)	0.07 (0.962)	3.57** (0.031)	4.55** (0.035)	0.77 (0.509)
<b>All</b>	-2.05*** (0.001)	-2.02*** (0.009)	-1.09 (0.196)	0.11 (0.913)	1.09 (0.382)	-0.79 (0.272)

<i>Panel B: During low market dispersion</i>						
$\text{Alpha}_{t-1}$	Fund selectivity ( $1-R^2_{t-1}$ )					
	Low	4	3	2	High	All
<b>Low</b>	-1.39*** (0.008)	-0.68 (0.289)	-1.60*** (0.006)	-2.10*** (0.010)	-2.92** (0.034)	-1.74*** (0.002)
<b>2</b>	-0.98** (0.015)	-0.67 (0.130)	-0.52 (0.307)	-0.35 (0.615)	-0.84 (0.368)	-0.68* (0.095)
<b>3</b>	-0.48 (0.210)	-0.14 (0.750)	-0.18 (0.730)	-0.20 (0.744)	1.47* (0.058)	0.10 (0.784)
<b>4</b>	0.13 (0.794)	-0.82 (0.475)	0.57 (0.303)	-0.16 (0.814)	1.13 (0.201)	0.17 (0.694)
<b>High</b>	-0.68 (0.304)	1.05 (0.119)	0.09 (0.884)	1.31 (0.136)	2.04 (0.187)	0.77 (0.191)
<b>All</b>	-0.68* (0.058)	-0.25 (0.547)	-0.33 (0.413)	-0.31 (0.518)	0.18 (0.786)	-0.28 (0.399)

*Notes:* The table presents the portfolio alpha, annualized, using monthly returns, in high and low market dispersion periods. If market dispersion index for the test month (t) is higher (lower) than the median number of all monthly market dispersion index numbers, we define this month as high (low) market dispersion month. Portfolios are formed by sorting all funds in each month into quintiles by lagged  $R^2$  and then by fund  $\text{alpha}_{t-1}$ . Both are obtained from the 24-month estimation period (t-24 to t-1) by regressing each fund's monthly excess returns (over the T-bill rate) on the factors from FFC model. Then, for the following month (t), we calculate the average monthly excess returns for each fund portfolio. The process repeats by moving the estimation and test period one month at a time. Last, we regress the test period average portfolio returns on the FFC model. For each portfolio cell we present portfolio alpha, which is the intercept from the above regression, and the P-value. The sample period of the test months is from February 1990 to December 2014 (299 months). Panel A shows the results of high market dispersion group and Panel B shows the results of low market dispersion group. For each portfolio, we present the portfolio alpha, annualized, using monthly returns and the P-value. \*\*\*, \*\*, \* denotes significance at the 1%, 5% or 10% level.

**Table V**

Portfolio Fund Alpha, Based on Sorting on Lagged  $R^2$  and Fund Alpha, in Economic Expansions and Economic Recessions

<i>Panel A: Economic expansions</i>						
<b>Alpha<sub>t-1</sub></b>	<b>Fund selectivity (1-R<sup>2</sup><sub>t-1</sub>)</b>					
	<b>Low</b>	<b>4</b>	<b>3</b>	<b>2</b>	<b>High</b>	<b>All</b>
<b>Low</b>	-1.52** (0.028)	-3.27*** (0.001)	-2.55** (0.029)	-4.09*** (0.003)	-3.12* (0.084)	-2.92*** (0.002)
<b>2</b>	-1.75*** (0.006)	-0.67 (0.381)	-2.65*** (0.003)	-1.00 (0.298)	-0.97 (0.401)	-1.41** (0.043)
<b>3</b>	-1.07* (0.075)	-0.95 (0.122)	-1.25 (0.142)	-1.14 (0.203)	-0.02 (0.983)	-0.89 (0.122)
<b>4</b>	-0.46 (0.459)	-1.83 (0.146)	-0.17 (0.810)	-0.57 (0.609)	1.48 (0.176)	-0.31 (0.610)
<b>High</b>	-0.75 (0.422)	-0.13 (0.892)	0.95 (0.268)	3.69*** (0.006)	4.11** (0.024)	1.58** (0.041)
<b>All</b>	-1.12** (0.032)	-1.38** (0.028)	-1.14* (0.086)	-0.65 (0.439)	0.27 (0.760)	-0.81 (0.152)
<i>Panel B: Economic recessions</i>						
<b>Alpha<sub>t-1</sub></b>	<b>Low</b>	<b>4</b>	<b>3</b>	<b>2</b>	<b>High</b>	<b>All</b>
<b>Low</b>	-1.89*** (0.003)	-1.04 (0.224)	-0.68 (0.464)	-0.30 (0.778)	-0.62 (0.738)	-0.90 (0.252)
<b>2</b>	-1.06** (0.042)	-1.19* (0.072)	0.73 (0.394)	0.65 (0.554)	1.99 (0.161)	0.22 (0.767)
<b>3</b>	-0.84 (0.127)	-0.06 (0.916)	-0.66 (0.393)	0.20 (0.835)	1.37 (0.325)	0.01 (0.987)
<b>4</b>	-1.87*** (0.006)	-0.38 (0.610)	0.63 (0.462)	0.45 (0.661)	0.99 (0.497)	-0.02 (0.972)
<b>High</b>	-1.79* (0.075)	-1.34 (0.313)	-0.62 (0.606)	1.61 (0.220)	3.54* (0.055)	0.27 (0.786)
<b>All</b>	-1.49*** (0.003)	-0.80 (0.175)	-0.12 (0.866)	0.51 (0.549)	1.48 (0.193)	-0.08 (0.891)

*Notes:* The table presents the portfolio alpha, annualized, using monthly returns, in economic expansions and economic recessions. If the Fed National Activity Index 3-month average (CFNAI MA3) for the test month (t) is higher (lower) than the median number of all monthly CFNAI MA3 index numbers, we define this month as economic expansion (recession) month. Portfolios are formed by sorting all funds in each month into quintiles by lagged  $R^2$  and then by fund alpha. Both are obtained from the 24-month estimation period (t-24 to t-1) by regressing each fund's monthly excess returns (over the T-bill rate) on the factors from FFC model. Then, for the following month (t), we calculate the average monthly excess returns for each fund portfolio. The process repeats by moving the estimation and test period one month at a time. Last, we regress the test period average portfolio returns on the FFC model. For each portfolio cell, we present portfolio alpha<sub>t-1</sub>, which is the intercept from the above regression, and the P-value. The sample period of the test months is from January 1990 to December 2014 (300 months). Panel A shows the results in economic expansions and Panel B shows the results in economic recessions. For each portfolio, we present the portfolio alpha, annualized, using monthly returns and the P-value. \*\*\*, \*\*, \* denotes significance at the 1%, 5% or 10% level.

**Table VI**

Regressions of Returns of Fund Portfolios on CAPM, FF3, and FFC Models

	CAPM			3 Factor Model			4 Factor Model		
	High Skill	Low Skill	High - Low	High Skill	Low Skill	High - Low	High Skill	Low Skill	High - Low
<b>Intercept</b>	0.14* (0.082)	-0.12*** (<.001)	0.13*** (<.001)	0.06 (0.304)	-0.13*** (<.001)	0.09*** (0.004)	0.05 (0.433)	-0.11*** (<.001)	0.08** (0.031)
<b>RM-Rf</b>	0.89*** (<.001)	1.02*** (<.001)	-0.06*** (<.001)	0.88*** (<.001)	1.02*** (<.001)	-0.07*** (<.001)	0.88*** (<.001)	1.01*** (<.001)	-0.06*** (<.001)
<b>SMB</b>				0.27*** (<.001)	0.05*** (<.001)	0.11*** (<.001)	0.27*** (<.001)	0.05*** (<.001)	0.11*** (<.001)
<b>HML</b>				0.19*** (<.001)	0.02** (0.052)	0.09*** (<.001)	0.20*** (<.001)	0.02 (0.164)	0.09*** (<.001)
<b>MOM</b>							0.02 (0.170)	-0.02*** (<.001)	0.02*** (0.001)
<b>Adj. R<sup>2</sup></b>	0.89	0.99	0.14	0.94	0.99	0.41	0.94	0.99	0.42

*Notes:* This table reports the regression results for monthly returns on portfolios with high or low skilled funds from January 1990 through December 2014 (300 months) based on CAPM model, FF3 model, and FFC model. The high (low) skilled fund portfolio is an equal weighted portfolio of active US equity funds with the highest (lowest) 20% selectivity ( $1-R^2_{t-1}$ ), where  $R^2_{t-1}$  is obtained from the 24-month estimation period (t-24 to t-1) by regressing each fund's monthly excess returns (over the T-bill rate) on the factors from FFC model. The process repeats by moving the estimation and test period one month at a time. The independent variables contain market excess return (RM-Rf), return difference of small and big size stocks (SMB), return difference of high and low book-to-market ratio stocks (HML), and return difference of past winner and loser stocks (MOM). The regression results of a hypothetical strategy of buying high skilled fund portfolio and selling low skilled fund portfolio are also reported in this table. The sample period of the test months is from January 1990 to December 2014 (300 months). The P-value and adjusted R<sup>2</sup> for each regression are also presented. \*\*\*, \*\*, \* denotes significance at the 1%, 5% or 10% level.

**Table VII**

The Effect of Fund Selectivity and Investor Sentiment on Fund Performance

<i>Panel A: Using selectivity to measure skill</i>										
	<b>Fund Alpha (FFC model)</b>									
<b>Intercept</b>	-0.83*** (<.001)	-0.55*** (<.001)	-0.67*** (<.001)	-0.37*** (0.009)	-0.80*** (<.001)	-0.47*** (0.001)	-0.80*** (<.001)	-0.47*** (0.001)	-1.11*** (<.001)	-0.77*** (<.001)
<b>Selectivity</b>	0.67*** (<.001)	0.41*** (<.001)			0.71*** (<.001)	0.48*** (<.001)	0.68*** (<.001)	0.45*** (<.001)	0.71*** (<.001)	0.47*** (<.001)
<b>Sentiment</b>			-0.02** (0.014)	-0.09*** (<.001)	-0.05*** (<.001)	-0.11*** (<.001)	-0.08*** (<.001)	-0.13*** (<.001)	-0.14*** (<.001)	-0.19*** (<.001)
<b>Selectivity*Sentiment</b>							0.21*** (0.009)	0.17** (0.032)	0.23*** (0.005)	0.21*** (0.009)
<b>Market Dispersion</b>									0.03*** (<.001)	0.03*** (<.001)
<b>Business Cycle</b>									0.02 (0.122)	0.05*** (<.001)
<b>Alpha<sub>t-1</sub></b>		0.30*** (<.001)		0.33*** (<.001)		0.32*** (<.001)		0.32*** (<.001)		0.32*** (<.001)
<b>Turnover</b>	-3.90E-04*** (<.001)	-2.70E-04*** (<.001)	-3.40E-04*** (<.001)	-2.20E-04*** (0.001)	-3.90E-04*** (<.001)	-2.60E-04*** (<.001)	-3.80E-04*** (<.001)	-2.50E-04*** (<.001)	-3.80E-04*** (<.001)	-2.50E-04*** (<.001)
<b>Expense Ratio</b>	-4.80E-04 (0.633)	-7.10E-04 (0.475)	-6.80E-05 (0.946)	-4.50E-04 (0.655)	-4.60E-04 (0.643)	-7.00E-04 (0.485)	-4.70E-04 (0.640)	-7.00E-04 (0.483)	-6.00E-04 (0.550)	-8.40E-04 (0.400)
<b>log(TNA)</b>	0.46*** (<.001)	0.30*** (<.001)	0.44*** (<.001)	0.26*** (0.002)	0.46*** (<.001)	0.28*** (0.001)	0.46*** (<.001)	0.28*** (0.001)	0.50*** (<.001)	0.31*** (<.001)
<b>[log(TNA)]<sup>2</sup></b>	-0.04*** (<.001)	-0.03** (0.024)	-0.04*** (0.002)	-0.02* (0.092)	-0.04*** (<.001)	-0.02** (0.039)	-0.04*** (<.001)	-0.02** (0.038)	-0.05*** (<.001)	-0.03** (0.016)
<b>Log(age)</b>	-0.11*** (<.001)	-0.07*** (<.001)	-0.13*** (<.001)	-0.10*** (<.001)	-0.12*** (<.001)	-0.09*** (<.001)	-0.13*** (<.001)	-0.09*** (<.001)	-0.11*** (<.001)	-0.08*** (<.001)
<b>Adj. R<sup>2</sup></b>	0.002	0.008	0.001	0.008	0.003	0.008	0.003	0.008	0.003	0.009



Panel B: Using logistic transformed selectivity to measure skill

	Fund Alpha (FFC model)									
<b>Intercept</b>	-0.58***	-0.39***	-0.67***	-0.37***	-0.53***	-0.28***	-0.53***	-0.29**	-0.84***	-0.58***
	(<.001)	(0.005)	(<.001)	(0.009)	(<.001)	(0.047)	(<.001)	(0.043)	(<.001)	(<.001)
<b>TSelectivity</b>	0.08***	0.05***			0.08***	0.06***	0.08***	0.06***	0.09***	0.06***
	(<.001)	(<.001)			(<.001)	(<.001)	(<.001)	(<.001)	(<.001)	(<.001)
<b>Sentiment</b>			-0.02**	-0.09***	-0.06***	-0.11***	0.02	-0.07***	-0.04*	-0.11***
			(0.014)	(<.001)	(<.001)	(<.001)	(0.511)	(0.003)	(0.088)	(<.001)
<b>TSelectivity*Sentiment</b>							0.03***	0.02*	0.04***	0.02**
							(0.001)	(0.065)	(<.001)	(0.016)
<b>Market Dispersion</b>									0.03***	0.03***
									(<.001)	(<.001)
<b>Business Cycle</b>									0.02	0.05***
									(0.127)	(<.001)
<b>Alpha<sub>t-1</sub></b>		0.30***		0.33***		0.32***		0.32***		0.32***
		(<.001)		(<.001)		(<.001)		(<.001)		(<.001)
<b>Turnover</b>	-3.90E-04***	-2.70E-04***	-3.40E-04***	-2.20E-04***	-3.90E-04***	-2.60E-04***	-3.80E-04***	-2.60E-04***	-3.80E-04***	-2.50E-04***
	(<.001)	(<.001)	(<.001)	(0.001)	(<.001)	(<.001)	(<.001)	(<.001)	(<.001)	(<.001)
<b>Expense Ratio</b>	-4.70E-04	-7.10E-04	-6.80E-05	-4.50E-04	-4.60E-04	-7.10E-04	-4.90E-04	-7.20E-04	-6.30E-04	-8.70E-04
	(0.639)	(0.479)	(0.946)	(0.655)	(0.643)	(0.479)	(0.623)	(0.470)	(0.529)	(0.384)
<b>log(TNA)</b>	0.46***	0.30***	0.44***	0.26***	0.46***	0.28***	0.46***	0.28***	0.50***	0.31***
	(<.001)	(<.001)	(<.001)	(0.002)	(<.001)	(0.001)	(<.001)	(0.001)	(<.001)	(<.001)
<b>[log(TNA)]<sup>2</sup></b>	-0.04***	-0.03**	-0.04***	-0.02*	-0.04***	-0.02**	-0.04***	-0.02**	-0.05***	-0.03**
	(<.001)	(0.023)	(0.002)	(0.092)	(<.001)	(0.036)	(<.001)	(0.035)	(<.001)	(0.015)
<b>Log(age)</b>	-0.11***	-0.07***	-0.13***	-0.10***	-0.12***	-0.09***	-0.12***	-0.09***	-0.11***	-0.07***
	(<.001)	(<.001)	(<.001)	(<.001)	(<.001)	(<.001)	(<.001)	(<.001)	(<.001)	(<.001)
<b>Adj. R<sup>2</sup></b>	0.002	0.008	0.001	0.008	0.002	0.008	0.003	0.008	0.003	0.009

Notes: This table reports the results of regressing fund alpha on manager's selectivity and investor sentiment controlling for other fund characteristics. The dependent variable is fund alpha, which is 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 FFC model factor loadings from the 24-month estimation period (t-24 to t-1) by the FFC model 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 selectivity (1-R<sup>2</sup><sub>t-1</sub>), market sentiment (BW sentiment index, available at Jeffrey Wurgler's website) and selectivity\*sentiment, which is the product of selectivity and market sentiment. Fund-level control variables contain expense ratio, log value of fund age, fund turnover, log value of total net assets (TNA), and squared log value of TNA. Following Amihud and Goyenko (2013), we show the results with and without alpha<sub>t-1</sub> as control variables, where Alpha<sub>t-1</sub> is the intercept from the 24-month estimation period (t-24 to t-1). Sample period covers from January 1990 through December 2014. In Panel B, we also report the results using transformed selectivity (TSelectivity), as we shown that R<sup>2</sup> is highly negative skewed. The P-value and adjusted R<sup>2</sup> for each regression are also presented. \*\*\*, \*\*, \* denotes significance at the 1%, 5% or 10% level.

**Table VIII**

The Effect of Fund Skill Ratio and Investor Sentiment on Fund Performance

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

*Notes:* This table 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<sup>2</sup> for each regression are also presented. \*\*\*, \*\*, \* denotes significance at the 1%, 5% or 10% level.

**Table IX**

Skill versus Luck on the Fund Performance Using Fund Alpha to Measure Performance

<i>Panel A: Proportion of Unskilled and Skilled Funds</i>									
	<b>Zero Alpha</b>	<b>Unskilled</b>	<b>Skilled</b>						
<b>Proportion</b>	84.29%	11.30%	4.41%						
<b>Ave. # of funds</b>	893	164	89						
	<b>Left Tail</b>				<b>Right Tail</b>				
<b>Significant level</b>	0.05	0.10	0.15	0.20	0.20	0.15	0.10	0.05	<b>Sig. level</b>
<b>Signif. %</b>	4.55%	7.17%	9.23%	11.30%	4.41%	3.47%	2.53%	1.49%	<b>Signif. %</b>
<b># of funds</b>	66	104	134	164	89	70	51	30	<b># of funds</b>
<b>unlucky %</b>	1.24%	2.55%	3.72%	6.10%	3.26%	2.43%	1.64%	0.79%	<b>lucky %</b>
<b># of funds</b>	18	37	54	89	66	49	33	16	<b># of funds</b>
<b>unskilled %</b>	3.31%	4.62%	5.51%	6.40%	1.63%	1.04%	0.89%	0.69%	<b>skilled %</b>
<b># of funds</b>	48	67	80	91	24	21	18	14	<b># of funds</b>
<b>Alpha (% /month)</b>	-0.277	-0.321	-0.340	-0.354	0.826	0.884	0.961	1.081	<b>Alpha (% /month)</b>
<b>Alpha Stdv.</b>	1.979	1.985	1.995	2.007	3.434	3.537	3.670	3.530	<b>Alpha Stdv.</b>

<i>Panel B: Proportion of Unskilled and Skilled Funds in High Market Sentiment</i>									
	<b>Zero Alpha</b>	<b>Unskilled</b>	<b>Skilled</b>						
<b>Proportion</b>	84.29%	10.06%	5.10%						
<b>Ave. # of funds</b>	876	142	102						
	<b>Left Tail</b>				<b>Right Tail</b>				
<b>Sig. level</b>	0.05	0.10	0.15	0.20	0.20	0.15	0.10	0.05	<b>Sig. level</b>
<b>Signif. %</b>	3.90%	6.23%	8.22%	10.06%	5.10%	4.10%	3.05%	1.85%	<b>Signif. %</b>
<b># of funds</b>	55	88	116	142	102	82	61	37	<b># of funds</b>
<b>unlucky %</b>	1.20%	2.48%	3.68%	4.89%	3.35%	2.55%	1.70%	0.85%	<b>lucky %</b>
<b># of funds</b>	17	35	52	69	67	51	34	17	<b># of funds</b>
<b>unskilled %</b>	2.69%	3.75%	4.53%	4.37%	1.57%	1.55%	1.35%	1.00%	<b>skilled %</b>
<b># of funds</b>	38	53	64	73	35	31	27	20	<b># of funds</b>
<b>Alpha (% /month)</b>	-0.764	-0.743	-0.707	-0.686	0.832	0.899	0.996	1.143	<b>Alpha (% /month)</b>
<b>Alpha Stdv.</b>	2.038	2.042	2.055	2.078	3.780	3.934	4.115	3.924	<b>Alpha Stdv.</b>

<i>Panel C: Proportion of Unskilled and Skilled Funds in Low Market Sentiment</i>									
	<b>Zero Alpha</b>	<b>Unskilled</b>	<b>Skilled</b>						
<b>Proportion</b>	83.78%	12.52%	3.70%						
<b>Ave. # of funds</b>	910	185	75						
	<b>Left Tail</b>				<b>Right Tail</b>				
<b>Sig. level</b>	0.05	0.10	0.150	0.2	0.20	0.15	0.10	0.05	<b>Sig. level</b>
<b>Signif. %</b>	5.28%	8.12%	10.35%	12.52%	3.70%	2.86%	2.02%	1.13%	<b>Signif. %</b>
<b># of funds</b>	78	120	153	185	75	58	41	23	<b># of funds</b>
<b>unlucky %</b>	1.35%	2.64%	3.93%	6.10%	3.06%	2.32%	1.53%	0.74%	<b>lucky %</b>
<b># of funds</b>	20	39	58	77	62	47	31	15	<b># of funds</b>
<b>unskilled %</b>	3.93%	5.48%	6.43%	6.03%	0.73%	0.54%	0.49%	0.39%	<b>skilled %</b>
<b># of funds</b>	58	81	95	108	13	11	10	8	<b># of funds</b>
<b>Alpha (% /month)</b>	-0.197	-0.224	-0.236	-0.245	0.814	0.854	0.884	0.939	<b>Alpha (% /month)</b>
<b>Alpha Stdv.</b>	1.958	1.959	1.965	1.971	2.579	2.490	2.418	2.380	<b>Alpha Stdv.</b>

*Notes:* Fund performance is measured using fund alpha based on FFC model. Panel A shows the estimated proportions of zero-alpha, unskilled, and skilled funds in the funds population with the monthly average fund number in each category based on Barras, Scaillet, and Wermers (2010)’s methodology of false discoveries. It also exhibits the proportion of funds in the right and left tails using four significant levels (0.05, 0.10, 0.15, and 0.20). The significant proportion in left tail is divided into unlucky and unskilled categories, and the significant proportion in right tail is divided into lucky and skilled categories. Average fund alpha and fund alpha standard division are also reported. Panel B and C show the results of false discoveries analysis during high and low sentiment periods. The BW sentiment index is used to capture market sentiment and is 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.

**Table X**

Skill versus Luck on the Fund Performance Using BvanB Fund Alpha to Measure Performance

<i>Panel A: Proportion of Unskilled and Skilled Funds</i>									
	<b>Zero Alpha</b>	<b>Unskilled</b>	<b>Skilled</b>						
<b>Proportion</b>	82.20%	10.27%	7.52%						
<b>Ave. # of funds</b>	1261	158	115						
	<b>Left Tail</b>				<b>Right Tail</b>				
<b>Sig. level</b>	0.05	0.10	0.15	0.20	0.20	0.15	0.10	0.05	<b>Sig. level</b>
<b>Signif. %</b>	5.08%	7.42%	9.06%	10.27%	7.52%	6.68%	5.58%	3.73%	<b>Signif. %</b>
<b># of funds</b>	78	114	139	158	115	102	86	57	<b># of funds</b>
<b>unlucky %</b>	3.00%	3.05%	3.09%	3.13%	2.13%	2.24%	2.40%	2.25%	<b>lucky %</b>
<b># of funds</b>	46	47	47	48	33	34	37	35	<b># of funds</b>
<b>unskilled %</b>	2.08%	4.37%	5.96%	7.14%	5.40%	4.44%	3.18%	1.48%	<b>skilled %</b>
<b># of funds</b>	32	67	91	110	83	68	49	23	<b># of funds</b>
<b>BvanB Alpha (\$/month)</b>	-3.991	-4.079	-3.674	-3.692	3.434	3.636	3.643	3.683	<b>BvanB Alpha (\$/month)</b>
<b>BvanB Alpha Stdv.</b>	3.049	3.465	2.652	3.122	2.626	2.765	2.508	2.428	<b>BvanB Alpha Stdv.</b>
<i>Panel B: Proportion of Unskilled and Skilled Funds in High Market Sentiment</i>									
	<b>Zero Alpha</b>	<b>Unskilled</b>	<b>Skilled</b>						
<b>Proportion</b>	77.47%	11.13%	11.40%						
<b>Ave. # of funds</b>	1219	175	179						
	<b>Left Tail</b>				<b>Right Tail</b>				
<b>Sig. level</b>	0.05	0.10	0.15	0.20	0.20	0.15	0.10	0.05	<b>Sig. level</b>
<b>Signif. %</b>	5.54%	8.01%	9.80%	11.13%	11.40%	10.09%	8.47%	5.78%	<b>Signif. %</b>
<b># of funds</b>	87	126	154	175	179	159	133	91	<b># of funds</b>
<b>unlucky %</b>	3.02%	3.00%	3.02%	3.07%	2.80%	2.90%	3.05%	3.06%	<b>lucky %</b>
<b># of funds</b>	47	47	48	48	44	46	48	48	<b># of funds</b>
<b>unskilled %</b>	2.53%	5.01%	6.78%	8.06%	8.60%	7.19%	5.41%	2.71%	<b>skilled %</b>
<b># of funds</b>	40	79	107	127	135	113	85	43	<b># of funds</b>
<b>BvanB Alpha (\$/month)</b>	-3.932	-3.874	-3.566	-3.903	3.598	3.847	3.986	4.172	<b>BvanB Alpha (\$/month)</b>
<b>BvanB Alpha Stdv.</b>	2.916	2.650	2.323	3.612	2.203	2.58	2.37	2.291	<b>BvanB Alpha Stdv.</b>
<i>Panel C: Proportion of Unskilled and Skilled Funds in Low Market Sentiment</i>									
	<b>Zero Alpha</b>	<b>Unskilled</b>	<b>Skilled</b>						
<b>Proportion</b>	86.87%	9.42%	3.71%						
<b>Ave. # of funds</b>	1298	141	55						
	<b>Left Tail</b>				<b>Right Tail</b>				
<b>Sig. level</b>	0.05	0.10	0.15	0.20	0.20	0.15	0.10	0.05	<b>Sig. level</b>
<b>Signif. %</b>	4.63%	6.83%	8.32%	9.42%	3.71%	3.31%	2.74%	1.72%	<b>Signif. %</b>
<b># of funds</b>	69	102	124	141	55	49	41	26	<b># of funds</b>
<b>unlucky %</b>	2.98%	3.09%	3.17%	3.19%	1.47%	1.59%	1.75%	1.45%	<b>lucky %</b>
<b># of funds</b>	45	46	47	48	22	24	26	22	<b># of funds</b>
<b>unskilled %</b>	1.64%	3.74%	5.16%	6.23%	2.24%	1.72%	0.98%	0.27%	<b>skilled %</b>
<b># of funds</b>	25	56	77	93	33	26	15	4	<b># of funds</b>
<b>BvanB Alpha (\$/month)</b>	-4.052	-4.284	-3.782	-3.484	3.273	3.421	3.279	3.088	<b>BvanB Alpha (\$/month)</b>
<b>BvanB Alpha Stdv.</b>	3.199	4.132	2.957	2.558	2.992	2.944	2.614	2.478	<b>BvanB Alpha Stdv.</b>

Notes: Fund performance is measured using BvanB fund alpha based on 11 Vanguard Index Fund orthogonal bases. Panel A shows the estimated proportions of zero-alpha, unskilled, and skilled funds in the funds population with the monthly average fund number in each category based on Barras, Scaillet, and Wermers (2010)'s methodology of false discoveries. It also exhibits the proportion of funds in the right and left tails using four significant levels (0.05, 0.10, 0.15, and 0.20). The significant proportion in left tail is divided into unlucky and unskilled categories, and the significant proportion in right tail is divided into lucky and skilled categories. Average BvanB fund alpha and BvanB fund alpha standard division are also reported. Panel B and C show the results of false discoveries analysis during high and low sentiment periods. The sentiment index data are 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.

**Table XI**

## Stock Mispricing and Mutual Fund Performance

	Fund Alpha (FFC model)					
	All	Lowest Selectivity Skill	4	3	2	Highest Selectivity Skill
<b>VW_MISP</b>	-0.085***	-0.111***	-0.101***	-0.105***	-0.072***	-0.069***
<i>P-Value</i>	(<.0001)	(<.0001)	(<.0001)	(0.000)	(0.008)	(0.007)
<i>Controls</i>	Yes	Yes	Yes	Yes	Yes	Yes
<i>Adj. R<sup>2</sup></i>	0.085	0.135	0.124	0.145	0.139	0.089
<b>EW_MISP</b>	-0.101***	-0.111***	-0.102***	-0.121***	-0.097***	-0.101***
<i>P-Value</i>	(<.0001)	(<.0001)	(<.0001)	(<.0001)	(0.000)	(<.0001)
<i>Controls</i>	Yes	Yes	Yes	Yes	Yes	Yes
<i>Adj. R<sup>2</sup></i>	0.108	0.134	0.118	0.155	0.165	0.135
	BvanB Fund Alpha					
	All	Lowest BvanB Skill	2	3	4	Highest BvanB Skill
<b>VW_MISP</b>	-3.470***	-7.799**	-1.671	-0.604**	0.061	-2.455
<i>P value</i>	(0.005)	(0.037)	(0.132)	(0.034)	(0.973)	(0.583)
<i>Controls</i>	Yes	Yes	Yes	Yes	Yes	Yes
<i>Adj. R<sup>2</sup></i>	0.090	0.095	0.181	0.181	0.038	0.030
<b>EW_MISP</b>	-3.098**	-8.018**	-2.013*	-0.461	0.709	-0.353
<i>P value</i>	(0.012)	(0.037)	(0.083)	(0.104)	(0.702)	(0.933)
<i>Controls</i>	Yes	Yes	Yes	Yes	Yes	Yes
<i>Adj. R<sup>2</sup></i>	0.089	0.095	0.184	0.172	0.020	0.028

*Notes:* This table presents the coefficient between fund performance and fund mispricing level, along with the corresponding P-value and regression adjusted R<sup>2</sup>, by regressing fund performance on fund level mispricing for each management skill quintile while controlling for past fund performance (Alpha<sub>t-1</sub>), expense ratio, log value of fund age, fund turnover, log value of total net assets (TNA), and squared log value of TNA. Fund performance is estimated using both Fund Alpha and BvanB Fund Alpha measures. Fund level mispricing is measured using two ways: (i) VW\_MISP is the market value weighted average of stock mispricing for all stocks within each fund and (ii) EW\_MISP is the equal weighted average of stock mispricing for all stocks within each fund. Stock mispricing value is introduced by Stambaugh et al. (2012) and the data are available through Yu Yuan's website (<http://www.saif.sjtu.edu.cn/facultylist/yyuan/>). Furthermore, the sample is split into quintiles based on their selectivity or BvanB skill, which are estimated using 24-month regression from October 2011 to September 2013. Fund holdings information are manually collected through Bloomberg Portfolio Analysis Database, and the data are collected for the last quarter of 2013. \*\*\*, \*\*, \* denotes significance at the 1%, 5% or 10% level.

**Table XII**

Fama-MacBeth Regressions of Fund Returns and Alpha on Sentiment Beta

	Excess Return				Alpha			
	Low Skill		High Skill		Low Skill		High Skill	
<b>Intercept</b>	0.51*	-10.35	0.74***	-0.44	-0.16***	-1.22	0.04	-1.28
	(0.065)	(0.467)	(<.001)	(0.949)	(<.001)	(0.457)	(0.49)	(0.408)
<b>Sentiment Beta</b>	-0.06	-0.23	0.10	0.15	0.26***	0.26***	0.00	0.01
	(0.935)	(0.725)	(0.71)	(0.618)	(<.001)	(<.001)	(0.95)	(0.836)
<b>Expense ratio (%)</b>		0.11		0.25		0.04		0.19*
		(0.992)		(0.577)		(0.977)		(0.064)
<b>Log(Age)</b>		-0.19		0.08		0.02		-0.06
		(0.181)		(0.764)		(0.328)		(0.368)
<b>Turnover (%)</b>		-0.13***		-0.01		0.00		0.00
		(0.012)		(0.525)		(0.776)		(0.980)
<b>Log(TNA)</b>		6.79**		0.22		0.30		0.49
		(0.013)		(0.943)		(0.340)		(0.444)

*Notes:* This table reports results from Fama-MacBeth regressions of high skilled and low skilled fund portfolios' excess returns, as well as alphas, on funds' sentiment beta with controls of fund characteristics. In each month and for each portfolio with 24 monthly returns, sentiment beta is estimated by regressing the fund's excess returns on the BW sentiment index along with controls from FFC factor model. Then, we perform cross-sectional regressions of fund excess return (or alpha) on sentiment beta with controls for fund characteristics. Fund-level control variables contain expense ratio, log value of fund age, fund turnover, and log value of TNA. Sample period covers from January 1990 through December 2014. \*\*\*, \*\*, \* denotes significance at the 1%, 5% or 10% level.

**Table XIII**

The Effect of Fund Flow and Investor Sentiment on Fund Performance

	<b>Fund Alpha</b>			
	(1)	(2)	(3)	(4)
<b>Intercept</b>	-1.07*** (<.001)	-0.97*** (<.001)	-1.25*** (<.001)	-1.04*** (<.001)
<b>Selectivity</b>			0.42*** (<.001)	0.36*** (<.001)
<b>Sentiment</b>		-0.09*** (<.001)		-0.12*** (<.001)
<b>Selectivity*Sentiment</b>				0.17** (0.040)
<b>Flow<sub>t-1</sub></b>	-6.40E-05** (0.040)	-3.71E-05 (0.270)	-6.71E-04*** (<.001)	-3.33E-05 (0.290)
<b>Flow<sub>t-2</sub></b>	2.95E-05 (0.350)	6.25E-05* (0.070)	-2.69E-04*** (<.001)	5.97E-05* (0.060)
<b>Flow<sub>t-1</sub>*Selectivity</b>			3.97E-03*** (<.001)	
<b>Flow<sub>t-2</sub>*Selectivity</b>			2.30E-03*** (<.001)	
<b>Flow<sub>t-1</sub>*Sentiment</b>		1.69E-06 (0.970)		
<b>Flow<sub>t-2</sub>*Sentiment</b>		-2.15E-05 (0.620)		
<b>Alpha<sub>t-1</sub></b>	0.32*** (<.001)	0.34*** (<.001)	0.33*** (<.001)	0.33*** (<.001)
<b>Turnover</b>	0.00*** (<.001)	0.00*** (<.001)	-4.84E-04*** (<.001)	-4.68E-04*** (<.001)
<b>Expense ratio</b>	-0.04*** (<.001)	-0.04*** (0.010)	-0.05*** (<.001)	-0.05*** (<.001)
<b>Log(TNA)</b>	0.63*** (<.001)	0.60*** (<.001)	0.71*** (<.001)	0.62*** (<.001)
<b>[Log(TNA)]<sup>2</sup></b>	-0.07*** (<.001)	-0.06*** (<.001)	-0.08*** (<.001)	-0.07*** (<.001)
<b>Log(age)</b>	-0.09*** (<.001)	-0.10*** (<.001)	-0.08*** (<.001)	-0.10*** (<.001)
<b>Adj. R<sup>2</sup></b>	0.009	0.009	0.012	0.010

Notes: This table reports the regression results of following model:

$$\begin{aligned}
 \text{Alpha}_{i,t} = & \alpha + \beta_1 \text{Selectivity}_{i,t} + \beta_2 \text{Sentiment}_t + \beta_3 \text{Selectivity}_{i,t} * \text{Sentiment}_t \\
 & + \beta_4 \text{Flow}_{i,t-1} + \beta_5 \text{Flow}_{i,t-2} + \beta_6 (\text{Flow}_{i,t-1} * \text{Selectivity}_{i,t}) + \beta_7 (\text{Flow}_{i,t-2} * \text{Selectivity}_{i,t}) \\
 & + \beta_8 (\text{Flow}_{i,t-1} * \text{Sentiment}_t) + \beta_9 (\text{Flow}_{i,t-2} * \text{Sentiment}_t) + \gamma \sum \text{Controls}_{i,t} + \varepsilon_t
 \end{aligned}$$

The dependent variable is fund alpha. The main independent variables are fund selectivity ( $1-R^2_{t-1}$ ), market sentiment (BW sentiment index, available at Jeffrey Wurgler's website), selectivity\*Sentiment, which is the product of selectivity and market sentiment,  $\text{flow}_{i,p+q}$ , which is the net capital flow of fund i in month t+q (q equals -2, -1); and the product of fund flow with sentiment and the product of fund flow with selectivity. Control variables contain  $\text{Alpha}_{t-1}$ , which is the intercept from the 24-month estimation period (t-24 to t-1), expense ratio, log value of fund age, fund turnover, log value of fund total net assets (TNA), and squared log value of fund TNA. Sample period covers from January 1990 through December 2014. The P-value and adjusted R<sup>2</sup> for each regression are also presented. \*\*\*, \*\*, \* denotes significance at the 1%, 5% or 10% level.

**Table XIV**

The Effect of Volatility Anomaly and Investor Sentiment on Fund Performance

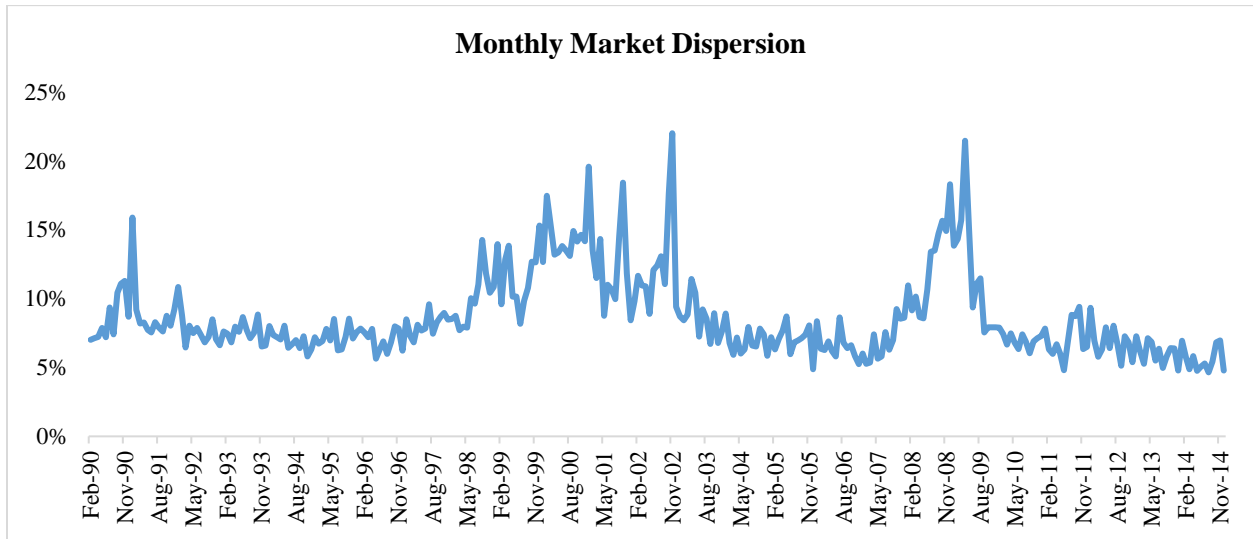
<i>Panel A: FF 5 factor plus momentum model in high market sentiment</i>						
<b>Alpha<sub>t-1</sub></b>	<b>Fund selectivity (1-R<sup>2</sup><sub>t-1</sub>)</b>					
	<b>Low</b>	<b>4</b>	<b>3</b>	<b>2</b>	<b>High</b>	<b>All</b>
<b>Low</b>	-2.28*** (0.005)	-3.59*** (0.002)	-3.50*** (0.008)	-3.94*** (0.005)	-1.66 (0.363)	-3.00*** (0.003)
<b>2</b>	-2.67*** ( $<.001$ )	-1.57* (0.073)	-3.41*** ( $<.001$ )	-2.31** (0.047)	-0.77 (0.593)	-2.14*** (0.010)
<b>3</b>	-1.59*** (0.009)	-1.77** (0.019)	-2.90*** (0.002)	-1.74* (0.099)	-0.73 (0.556)	-1.74** (0.012)
<b>4</b>	-0.84 (0.265)	-0.82 (0.340)	-0.61 (0.491)	-0.20 (0.870)	-0.06 (0.967)	-0.50 (0.506)
<b>High</b>	-0.41 (0.746)	0.59 (0.707)	1.70 (0.159)	4.54*** (0.003)	6.66*** (0.002)	2.63** (0.013)
<b>All</b>	-1.56** (0.013)	-1.44* (0.059)	-1.75** (0.038)	-0.75 (0.469)	0.68 (0.563)	-0.96 (0.178)
<i>Panel B: FF 5 factor plus momentum model in low market sentiment</i>						
<b>Alpha<sub>t-1</sub></b>	<b>Low</b>	<b>4</b>	<b>3</b>	<b>2</b>	<b>High</b>	<b>All</b>
<b>Low</b>	-1.24** (0.027)	-0.05 (0.953)	-0.85 (0.317)	-1.09 (0.274)	-2.26 (0.271)	-1.09 (0.173)
<b>2</b>	-0.56 (0.244)	-0.51 (0.311)	-0.04 (0.943)	-0.01 (0.990)	0.71 (0.566)	-0.09 (0.874)
<b>3</b>	-0.20 (0.697)	-0.24 (0.650)	-0.50 (0.386)	-0.30 (0.680)	0.96 (0.395)	-0.05 (0.916)
<b>4</b>	-1.05* (0.071)	-1.08 (0.374)	0.74 (0.257)	-0.63 (0.426)	2.30* (0.059)	0.06 (0.906)
<b>High</b>	-0.34 (0.629)	0.75 (0.341)	0.92 (0.277)	1.96* (0.081)	1.93 (0.247)	1.04 (0.142)
<b>All</b>	-0.68* (0.084)	-0.22 (0.648)	0.06 (0.891)	-0.02 (0.969)	0.75 (0.426)	-0.02 (0.961)

*Notes:* The table presents the portfolio alpha, annualized, using monthly returns, in high and low market sentiment periods. 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 lagged R<sup>2</sup> and then by fund alpha<sub>t-1</sub>. Both are obtained from the 24-month estimation period (t-24 to t-1) by regressing each fund's monthly excess returns (over the T-bill rate) on the factors from FFC model. Then, for the following month (t), we calculate the average monthly excess returns for each fund portfolio. The process repeats by moving the estimation and test period one month at a time. Last we regress the test period average portfolio returns on Fama-French 5 factor plus momentum model. For each portfolio cell, we present portfolio alpha, which is the intercept from the above regression, and the P-value. The sample period of the test months is from January 1990 to December 2014 (300 months). Panel A shows the results of high market sentiment group and Panel B shows the results of low market sentiment group. For each portfolio, we present the portfolio alpha, annualized, using monthly returns and the P-value. \*\*\*, \*\*, \* denotes significance at the 1%, 5% or 10% level.



**Figure I**

Time Series Plot of Monthly Market Dispersion



*Notes:* This figure shows the time series plot of monthly market dispersion from February 1990 to December 2014. The market dispersion is calculated using equally weighed monthly cross-return of S&P 500 index constituents.

## Appendix I

### Data Collection Process Comparison

	<b>Reibnitz (2013)</b>	<b>Amihud and Goyenko (2013)</b>	<b>This Paper</b>
<b>Sample Period</b>	42 years (1972-2013)	21 years (1990-2010)	25 years (1990-2014)
<b>Database</b>	CRSP Survivor-Bias-Free Mutual Fund Database	CRSP Survivor-Bias-Free Mutual Fund Database	Bloomberg Fund Database
<b>Estimation Period</b>	24-36 Months	24 Months	24 Months
<b>Criteria to choose US Equity Mutual funds</b>	<p>1. Using Wiesenberger objective codes, Strategic Insight Objective, Lipper Objective, and Lipper Asset and Classification Codes to eliminate balanced, bond, index, and international and sector funds.</p> <p>2. Removing funds whose names indicate that they are not active domestic equity funds, for example those with names that contain "Index," "S&amp;P 500," "Global," or "Fixed-Income."</p> <p>3. 70% of the fund portfolio in common stocks on average over the sample period.</p>	<p>1. Using Wiesenberger objective codes, Strategic Insight Objective, Lipper Objective, and Lipper Asset and Classification Codes to eliminate balanced, bond, index, and international and sector funds.</p> <p>2. Eliminating index funds by deleting those whose name includes the word "index" or the abbreviation "ind", "S&amp;P", "DOW", "Wilshire", and/or "Russell".</p> <p>3. Eliminating balanced funds, international funds (either by their stated style or by their name), sector funds, and funds that hold less than 70% in common stocks.</p>	<p>1. All status (dead and alive)</p> <p>2. Geographical focus: United States</p> <p>3. Asset class focus: Equity</p> <p>4. Country of Domicile: United States</p> <p>5. Inception Date: before 12/31/2012</p> <p>6. Fund Type: Open end mutual fund</p> <p>7. Description does not contain any of the partial words "index, ind, S&amp;P, DOW, Wilshire, Russell, global, fixed-income, international, sector, balanced".</p>
<b>TNA limitation</b>	Monthly TNA is more than 15 million in December 2013 dollars.	TNA is more than 15 million.	Monthly TNA is more than 15 million in December 2013 dollars.
<b>Outliers</b>	top and bottom 0.5% R <sup>2</sup> are limited	top and bottom 0.5% R <sup>2</sup> are limited	top and bottom 0.5% R <sup>2</sup> are limited
<b>Total Funds Number</b>	3,048	2,460	2,190
<b>Fund-month Observations</b>	343,349	237,290	273,557
	<b>R<sup>2</sup></b>		
<b>Mean</b>	0.913	0.910	0.883
<b>Median</b>	0.930	0.929	0.922
<b>Min</b>	0.181	0.529	0.219
<b>Max</b>	0.999	0.994	0.991

## Appendix II

### Vanguard Index funds

<b>Fund Name</b>	<b>Ticker</b>	<b>Inception Date</b>
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 table 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.

### Appendix III

Portfolio Fund *Alpha*, Based on Sorting on Lagged  $R^2$  and Fund *Alpha*, in High and Low Market Sentiment Periods Using UM Index

<i>Panel A: High market sentiment periods</i>						
Alpha <sub>t-1</sub>	Fund selectivity (1-R <sup>2</sup> <sub>t-1</sub> )					
	Low	4	3	2	High	All
<b>Low</b>	-2.05*** (0.010)	-4.14*** (<.001)	-2.54* (0.052)	-2.85* (0.053)	-2.69 (0.151)	-2.86*** (0.005)
<b>2</b>	-2.01*** (0.003)	-0.67 (0.436)	-1.38 (0.151)	-0.67 (0.564)	0.69 (0.585)	-0.81 (0.291)
<b>3</b>	-0.45 (0.478)	-1.29* (0.060)	-1.67* (0.058)	-0.60 (0.526)	0.93 (0.383)	-0.62 (0.307)
<b>4</b>	-0.06 (0.943)	-1.48 (0.280)	-0.31 (0.708)	0.46 (0.712)	3.35*** (0.008)	0.40 (0.583)
<b>High</b>	-1.24 (0.340)	-1.15 (0.476)	0.22 (0.866)	4.14*** (0.009)	5.80*** (0.004)	1.56 (0.162)
<b>All</b>	-1.16* (0.060)	-1.76** (0.025)	-1.15 (0.136)	0.07 (0.943)	1.58 (0.130)	-0.49 (0.451)

<i>Panel B: Low market sentiment periods</i>						
Alpha <sub>t-1</sub>	Fund selectivity (1-R <sup>2</sup> <sub>t-1</sub> )					
	Low	4	3	2	High	All
<b>Low</b>	-1.24** (0.023)	-0.53 (0.457)	-1.92** (0.015)	-2.12** (0.013)	-2.12 (0.262)	-1.58** (0.028)
<b>2</b>	-0.85* (0.055)	-1.46*** (0.004)	-1.28** (0.032)	-1.03 (0.219)	-0.77 (0.548)	-1.08* (0.070)
<b>3</b>	-1.16*** (0.009)	-0.25 (0.634)	-1.35** (0.035)	-1.12 (0.154)	-0.27 (0.825)	-0.82 (0.117)
<b>4</b>	-2.03*** (<.001)	-1.02* (0.081)	-0.25 (0.707)	-1.45* (0.062)	-1.20 (0.355)	-1.19** (0.025)
<b>High</b>	-1.14 (0.117)	-0.15 (0.860)	-0.77 (0.390)	0.07 (0.953)	0.23 (0.897)	-0.35 (0.650)
<b>All</b>	-1.29*** (0.001)	-0.68 (0.122)	-1.10** (0.030)	-1.13* (0.081)	-0.79 (0.436)	-1.00** (0.041)

*Notes:* The table presents the portfolio alpha, annualized, using monthly returns, in high and low market sentiment periods based on the University of Michigan consumer sentiment index (UM sentiment index). If the UM sentiment index for the test month (t) is higher (lower) than the median number of all monthly UM 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 lagged  $R^2$  and then by fund alpha. Both are obtained for the 24-month estimation period (t-24 to t-1) by regressing each fund's monthly excess returns (over the T-bill rate) on the factors from FFC model. Then, for the following month (t), we calculate the average monthly excess returns for each fund portfolio. The process repeats by moving the estimation and test period one month at a time. Last, we regress the test period average portfolio returns on the FFC model. For each portfolio cell, we present portfolio alpha, which is the intercept from the above regression, and the P-value. The sample period of the test months is from January 1990 to December 2014 (300 months). Panel A shows the results of high market sentiment group and Panel B shows the results of low market sentiment group. For each portfolio, we present the portfolio alpha, annualized, using monthly returns and the P-value. \*\*\*, \*\*, \* denotes significance at the 1%, 5% or 10% level.

## Appendix IV

Portfolio BvanB Fund Alpha, Based on Sorting on BvanB Skill and Lagged Fund Alpha, in High and Low Market Sentiment Periods Using UM Index

<i>Panel A: Portfolio BvanB alpha based on alternative investment opportunity</i>						
<b>Alpha<sub>t-1</sub></b>	<b>BvanB fund skill</b>					<b>All</b>
	<b>Low</b>	<b>4</b>	<b>3</b>	<b>2</b>	<b>High</b>	
<b>Low</b>	-29.64*** ( $<.001$ )	-11.21*** ( $<.001$ )	-8.13*** ( $<.001$ )	-8.32*** ( $<.001$ )	-23.35*** ( $<.001$ )	-16.13*** ( $<.001$ )
<b>4</b>	-11.07*** (0.001)	-4.61*** (0.001)	-3.05*** (0.008)	-2.09 (0.092)	-3.86 (0.166)	-4.94*** (0.002)
<b>3</b>	-4.17 (0.137)	-1.87 (0.166)	-0.44 (0.689)	0.28 (0.817)	1.83 (0.511)	-0.87 (0.555)
<b>2</b>	0.01 (0.998)	0.84 (0.550)	1.79 (0.115)	2.95** (0.023)	8.76*** (0.001)	2.87* (0.064)
<b>High</b>	18.16*** ( $<.001$ )	6.79*** ( $<.001$ )	7.32*** ( $<.001$ )	9.02*** ( $<.001$ )	30.39*** ( $<.001$ )	14.34*** ( $<.001$ )
<b>All</b>	-7.58** (0.027)	-2.01 (0.159)	-0.50 (0.668)	0.37 (0.775)	2.76 (0.337)	-0.95 (0.548)

<i>Panel B: Portfolio BvanB alpha in high market sentiment</i>						
<b>Alpha<sub>t-1</sub></b>	<b>BvanB fund skill</b>					<b>All</b>
	<b>Low</b>	<b>4</b>	<b>3</b>	<b>2</b>	<b>High</b>	
<b>Low</b>	-23.81*** ( $<.001$ )	-7.87*** (0.001)	-5.51*** (0.007)	-5.93*** (0.010)	-23.37*** ( $<.001$ )	-13.30*** ( $<.001$ )
<b>4</b>	-4.55 (0.293)	-1.45 (0.511)	-0.49 (0.789)	0.55 (0.780)	-1.43 (0.755)	-1.47 (0.549)
<b>3</b>	3.80 (0.375)	1.82 (0.403)	2.65 (0.149)	3.27 (0.114)	7.18 (0.103)	3.74 (0.131)
<b>2</b>	9.43** (0.040)	5.24** (0.028)	5.48*** (0.005)	6.59*** (0.004)	12.96*** (0.003)	7.94*** (0.003)
<b>High</b>	30.95*** ( $<.001$ )	12.64*** ( $<.001$ )	12.61*** ( $<.001$ )	13.69*** ( $<.001$ )	35.95*** ( $<.001$ )	21.17*** ( $<.001$ )
<b>All</b>	1.59 (0.758)	2.07 (0.364)	2.95 (0.127)	3.64* (0.091)	6.26 (0.180)	3.62 (0.166)

<i>Panel C: Portfolio BvanB alpha in low market sentiment</i>						
<b>Alpha<sub>t-1</sub></b>	<b>BvanB fund skill</b>					<b>All</b>
	<b>Low</b>	<b>4</b>	<b>3</b>	<b>2</b>	<b>High</b>	
<b>Low</b>	-35.40*** ( $<.001$ )	-14.49*** ( $<.001$ )	-10.71*** ( $<.001$ )	-10.68*** ( $<.001$ )	-23.33*** ( $<.001$ )	-18.92*** ( $<.001$ )
<b>4</b>	-17.50*** ( $<.001$ )	-7.73*** ( $<.001$ )	-5.58*** ( $<.001$ )	-4.70*** (0.002)	-6.26* (0.051)	-8.35*** ( $<.001$ )
<b>3</b>	-12.02*** (0.001)	-5.51*** (0.001)	-3.49*** (0.003)	-2.66** (0.040)	-3.44 (0.315)	-5.43*** (0.001)
<b>2</b>	-9.28** (0.019)	-3.49** (0.018)	-1.86* (0.089)	-0.64 (0.603)	4.62 (0.138)	-2.13 (0.162)
<b>High</b>	5.56 (0.192)	1.03 (0.487)	2.09* (0.082)	4.41*** (0.003)	24.90*** ( $<.001$ )	7.60*** ( $<.001$ )
<b>All</b>	-16.63*** (0.001)	-6.04*** (0.001)	-3.91*** (0.003)	-2.85** (0.043)	-0.70 (0.836)	-5.45*** (0.002)

*Notes:* This table 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 University of Michigan consumer sentiment index (UM sentiment index). If the UM sentiment index for the test month (t) is higher (lower) than the median number of all monthly UM 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 (Equation 3) and then by BvanB fund alpha<sub>t-1</sub>, and both are described in detail in section 3.2.2. 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.

## Appendix V

The Effect of Fund Selectivity, Skill Ratio, and Investor Sentiment on Fund Performance, Controlling for Macroeconomic Conditions

	Fund alpha (FFC model)			Fund BvanB alpha	
<b>Intercept</b>	-0.794*** (<.0001)	-0.844*** (<.0001)	<b>Intercept</b>	-0.547*** (<.0001)	-0.428*** (0.002)
<b>Selectivity</b>	0.410*** (<.0001)	0.414*** (<.0001)	<b>BvanB Skill</b>	2.664*** (<.0001)	2.693*** (<.0001)
<b>Sentiment</b>	-0.242*** (<.0001)	-0.260*** (<.0001)	<b>Sentiment</b>	-0.361*** (<.0001)	-0.406*** (<.0001)
<b>Selectivity*Sentiment</b>	0.278*** (0.001)	0.286*** (0.000)	<b>BvanB Skill*Sentiment</b>	1.712*** (<.0001)	1.738*** (<.0001)
<b>Market Dispersion</b>		0.010*** (<.0001)	<b>Market Dispersion</b>		0.057*** (<.0001)
<b>Aggregate Dividend Yield</b>	-8.026*** (<.0001)	-6.060*** (0.001)	<b>Aggregate Dividend Yield</b>	9.760*** (0.000)	-1.919 (0.467)
<b>Default Spread</b>	0.275*** (<.0001)	0.218*** (<.0001)	<b>default Spread</b>	-0.023 (0.176)	-0.216*** (<.0001)
<b>Term Spread</b>	-0.015* (0.053)	-0.023*** (0.005)	<b>Term Spread</b>	0.158*** (<.0001)	0.088*** (<.0001)
<b>Three Month T-bill</b>	0.047*** (<.0001)	0.040*** (<.0001)	<b>Three Month T-bill</b>	0.106*** (<.0001)	0.064*** (<.0001)
<b>Alpha<sub>t-1</sub></b>	0.320*** (<.0001)	0.322*** (<.0001)	<b>BvanB Alpha<sub>t-1</sub></b>	0.204*** (<.0001)	0.202*** (<.0001)
<b>Turnover</b>	-0.071*** (<.0001)	-0.069*** (<.0001)	<b>Turnover</b>	-0.011 (0.193)	-0.008 (0.320)
<b>Expense Ratio</b>	0.000*** (0.000)	0.000*** (0.000)	<b>Expense Ratio</b>	0.000 (0.824)	0.000 (0.868)
<b>log(TNA)</b>	-0.001 (0.432)	-0.001 (0.414)	<b>log(TNA)</b>	0.033*** (0.001)	0.032*** (0.001)
<b>[log(TNA)]<sup>2</sup></b>	0.322*** (0.000)	0.326*** (0.000)	<b>[log(TNA)]<sup>2</sup></b>	-0.084 (0.258)	-0.042 (0.574)
<b>Log(age)</b>	-0.029** (0.012)	-0.030*** (0.010)	<b>Log(age)</b>	0.009 (0.389)	0.004 (0.733)
<b>Adj. R<sup>2</sup></b>	0.010	0.010	<b>Adj. R<sup>2</sup></b>	0.790	0.790

*Notes:* This table reports the results of regressing fund performance (fund alpha based on FFC model or fund BvanB alpha) on manager's skill (selectivity or BvanB skill ratio) and investor sentiment, controlling for other characteristics. The main independent variables are fund selectivity ( $1-R^2_{t-1}$ ), market sentiment (BW sentiment index, available at Jeffrey Wurgler's website) and selectivity\*sentiment, which is the product of selectivity and market sentiment. We use four macroeconomic variables to control for economic conditions: aggregate dividend yield, which is the total cash dividends on the value-weighted CRSP index over prior 12 months divided by the current level of the index; default spread, which is the difference between Moody's BAA-rated bonds yield and AAA-rated bonds yield; term spread, which is the difference between ten-year treasury bonds yield and three-month T-bills yield; and the yield on the three-month T-bill. Fund-level control variables contain expense ratio, log value of fund age, fund turnover, log value of total net assets (TNA), and squared log value of TNA. The P-value and adjusted R2 for each regression are also presented. \*\*\*, \*\*, \* denotes significance at the 1%, 5% or 10% level.