2019

When Fund Management Skill is More Valuable?

Feng Dong

John A. Doukas
Old Dominion University, jdoukas@odu.edu

Original Publication Citation

Dong, F., & Doukas, J. A. (2019). When fund management skill is more valuable? *European Financial Management*, 1-76. doi:10.1111/eufm.12234

When Fund Management Skill is More Valuable?

Feng Dong* and John A. Doukas**

ABSTRACT

Does fund management skill allow managers to identify mispriced securities more accurately and thereby make better portfolio choices resulting in superior fund performance when noise trading—a natural setting to detect skill — is more prevalent? We find skilled-fund managers with superior past performance to generate persistent excess risk-adjusted returns and experience significant capital inflows, especially in high sentiment times, high stock dispersion and economic expansion states when price signals are noisier. 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; mispricing, fund manager skill

*Dong, fdong@siena.edu, Siena College, School of Business, 216 Colbeth Hall, Loudonville, NY 12211, USA.

**Doukas, jdoukas@odu.edu, Old Dominion University Graduate School of Business, Constant Hall, Suite 2080 Norfolk, VA 23529-0222, USA, and Judge Business School, University of Cambridge.

We thank two anonymous referees, European Financial Management Association (EFMA) 2018 conference participants and Russ Wermers for valuable comments and the Conference Board for kindly providing us with the sentiment data. We also are grateful to Jeffrey Wurgler and Malcolm Baker for making their sentiment index publicly available. We also thank Stambaugh, Yu, and Yuan (2012) for providing their stock mispricing data.

"…noise creates the opportunity to trade profitably, but at the same time makes it difficult to trade profitably." - Fisher Black, 1986

1. Introduction

Apparently increasing evidence has accumulated regarding the extent to which financial markets are informationally inefficient as a result of investor cognitive biases

This article has been accepted for publication and undergone full peer review but has not been through the copyediting, typesetting, pagination and proofreading process, which may lead to differences between this version and the Version of Record. Please cite this article as doi: 10.1111/eufm.12234.

related to the noisiness of information (Tversky and Kahneman 1974; Hilbert 2012). Undoubtedly, noise trading activity is mostly prevalent when markets are crowded by sentiment driven noise traders and it has been held responsible for much of the market uncertainty during the last two decades. However, its impact on the performance of actively managed mutual fund remains unknown.[1] Shedding light on this issue is very important given that the bulk of investment activity has been delegated to professional fund managers. Hence, in this study we examine the extent to which market sentiment, as the most prominent state of market noise relative to others (i.e., high market dispersion states; economic expansions; stock mispricing, using a set of 11 market anomalies to identify overpriced stocks (Stambaugh et al., 2012) and market volatility), affects the performance of mutual fund managers and, especially, that of skilled fund managers? As Black (1986) argues, noise traders and professional investors with low levels of skill cannot discern valuable information from market noise and may treat market noise as useful information and trade based on it. We address this question by investigating whether market sentiment influences fund alphas, as noted by Miller (1997), which, in turn, based on the insight of Black (1986), makes it less (more) difficult for high (low) skill fund managers to carry out profitable trades. Specifically, we examine the capacity of U.S. domestic equity fund managers in adding value during periods of high sentiment, used as an "acid" test of management skill, when it is more difficult to identify profitable stocks. Unlike previous studies, we assess the added value of fund skill in high sentiment

[1] 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.

periods conditional on funds' past performance, capital inflows, high market dispersion, economic expansions, equity mispricing, based on a set of 11 market anomalies to identify overpriced stocks (Stambaugh et al., 2012), and market volatility conditions that make it more (less) likely for high (low) skill fund managers to improve and sustain fund performance.

While a large body of the literature arrives at the conclusion that actively managed funds, on average, underperform passively managed funds, recent papers find that funds with certain characteristics can outperform the market benchmark.[2] However, previous studies do not examine whether fund managers create added value when markets are crammed by high levels of noise as a result of investor sentiment, which is widely recognized as a market state of high noise trading activity. 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.[3] Whereas these studies show that fund alpha in various industry sectors is related to real economic forces, they do not shed light on the important question whether fund alpha is linked to fund managers' skill, particularly, in high investor sentiment states of the equity market when high (low) skill fund managers are expected to execute more (less) profitable trades. Unlike the previous

[2] For example, Kacperczyk, Sialm, and Zheng (2005), Cremers and Petajisto (2009), and Cremers, Ferreira, Matos, and Starks (2016) document that industry concentrated portfolio holdings or a large deviation of holdings away from a benchmark can outperform such a benchmark, net of expenses.

[3] 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.

literature, this paper aims to quantify whether fund management skill delivers high alpha during high sentiment times, when more managerial talent and resources (i.e. costs of gathering and processing private information is higher) are required to separate real information and market noise. That is, when the signal-to-noise ratio is lower. While a higher level of investor sentiment presents a more difficult environment for all active managers to pick valuable stocks and sectors, it should be less daunting to skilled fund managers who possess the ability (better informed traders) to discern noise from real information.

As explained by Black (1986), noise trader participation in the market, triggered by investor optimism, can move asset prices away from fundamental values. In fact, since investor sentiment has been shown to influence noise trader investment behavior and, in turn, asset prices (Miler, 1977; 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 the market benchmark and their low skilled counterparts by being able to better discern information from noise when the market is crowded by noise traders. Additionally, since noise trader activity is asymmetric across optimistic and pessimistic sentiment periods unsophisticated investors are more likely to enter the stock market during high sentiment times (Grinblatt and Keloharju, 2001; Lamont and Thaler, 2003). Moreover, based on the insights of Stambaugh, Yu, and Yuan (2012) and Antoniou, Doukas, and Subrahmanyam (2013), noise traders are more likely to drive prices away from intrinsic values by being reluctant to realize losses (sell losers) during periods of optimism to avoid regret and cognitive dissonance. Therefore, to the extent that skilled fund managers trade more on (private) information about the true value of financial assets under management, in contrast to the market benchmark and their low skill counterparts, they are expected to deliver more value during high sentiment periods. In sum, the important question whether fund managers' performance is affected by noise trading activity, prominent in high investor sentiment times, a natural setting to detect if fund managers possess skill, warrants investigation. To shed light on this issue we posit that the variation of skill across fund managers is a key determinant of fund performance (alpha).

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, preceding an increase (decrease) in investor sentiment (Cullen, Gasbarro, Le, and Monroe, 2013), in this study we treat sentiment as a market condition, not as a risk factor that skilled managers actively time investor sentiment by modifying fund strategies based on their sentiment prediction.[4] While our evidence is consistent with the previous literature showing that skilled fund managers outperform their low skill peers across time (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 due to short selling limitations (Shleifer and Vishny, 1997) and costlier value-relevant information that permit asset

[4] 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.

prices to drift away from intrinsic values. 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, we treat investor sentiment as a noisy market condition which allows us to determine whether skilled fund managers are able to outperform the market benchmark and their counterpart (average and low-skilled) managers. Our evidence, consistent with this conjecture, shows that skilled fund managers with superior past performance in high sentiment (noisy) periods consistently outperform the market benchmark and generate significantly and economically higher alpha than the average-skill and low-skill fund managers.

Furthermore, since previous studies document that mutual fund investors tend to chase funds with superior past performance (Chevalier and Ellison, 1997; Sirri and Tufano, 1998), in this study we examine and find that funds with expert performance realize higher risk-adjusted returns than funds with average past returns. Consistent with our main findings, this investigation demonstrates that high-skill management funds exhibit superior past performance and experience significant capital inflows, especially during high sentiment periods.

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, which does not require the use of fund portfolio holdings (i.e., Daniel, Grinblatt, Titman, and Wermers, 1997), and examine the relation between fund selectivity and performance across different states of investor sentiment.[5] 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)). Our evidence, based on both measures, consistently shows that high market sentiment harms fund performance, but managers with above-average stock-picking skill manage to protect fund performance from the adverse effects of high investor sentiment. 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.

Another interesting question, which has received little attention in the literature (e.g. Baks, Metrick, and Wachter, 2001), is what percentage of the skilled active fund managers is consistently associated with higher excess risk-adjusted returns under different states of investor sentiment. The answer to this question is very important because more and more capital is flowing from individual investors to professional investment managers. Conducting a lucky bias analysis, as in Barras, Scaillet, and Wermers (2010), which 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 considerably after controlling for lucky

[5] 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.

bias, while the portion of skilled fund managers who deliver significant alphas is much higher in high than low sentiment periods. This finding demonstrates the scarcity of skill fund management and the increasing share of index funds over recent times (Stambaugh, 2014).

Furthermore, we check the sensitivity of our results by carrying out a battery of robustness tests. We use stock mispricing as an alternative setting of noise trading activity, and consistently show that skilled fund managers create value by their ability to identify noise information and carry out profitable trades. In addition, we find that skilled fund managers do not appear to time investor sentiment. Finally, employing alternative measures of market sentiment,[6] we obtain qualitatively similar results to our main findings. Jointly, the evidence points that skilled managers generate high alphas in high sentiment periods and stock mispricing states suggests that they create value for fund investors when markets are populated by noisy investors (signals) and experience significant capital inflows by seizing investor attention.

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 robustness tests. Section 6 concludes.

[6] 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).

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; Cremers et al., 2016; and Dong and Doukas, 2019).

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, and the different abilities of institutional investors to gather and analyze information about the same firm can cause heterogenous opinions, which lead to different trading activities (Knyazeva, Knyazeva, and Kostovetsky, 2018). 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 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 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 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 travel 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 talent during high sentiment periods when market signals are noisy. That is, our objective is to examine whether the value created by fund managers is associated with their selectivity talent, especially in high sentiment times when markets are jammed by noise trading.

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. 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.[7] 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, expanse 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

[7] We use 24-month estimation window following Amihud and Goyenko (2013). In addition, as argued in Amihud and Goyenko (2013), making sure that the funds in the sample have been in the market for at least two years, can help to limit the effect of luck, since most unskilled but lucky fund managers cannot survive the market for a long run. The results are consistent when we use 12-month estimation window, but less significant.

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 the Internet Appendix 1.

Table 1 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.[8, 9] This shows 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 1 here]

[8] 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.

[9] Following Armihud and Goyenko (2013), the statistics reported in Table 1 are estimated before we delete outlier observations.

The main sentiment measures used in this paper is the Baker and Wurgler (2006) sentiment index (BW)[10] and the University of Michigan sentiment index (UM)[11]. Even though both optimistic and pessimistic beliefs, induced by high and low market sentiment, respectively, can affect asset prices, noise trading activity 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 activity. The BW index has been used widely in the finance literature and is constructed using five 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

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

[11] The UM sentiment data can be found on University of Michigan Surveys of Consumers website http://www.sca.isr.umich.edu/.

index. Furthermore, our findings are also 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 employ the fund management selectivity measure of Amihud and Goyenko (2013), introduced in the active fund management literature, as a predictor of fund performance (alpha). Amihud and Goyenko (2013) have empirically shown their fund management selectivity measure to have significant explanatory power in predicting fund alpha, after controlling for other fund level characteristics. The Amihud and Goyenko (2013) fund selectivity measure 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.[12]

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

[12] When we repeat the analysis using net alpha by subtracting expense ratio from gross alpha, we find similar results further validating the view that fund management skill is more valuable to investors when market sentiment is high.

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 Value-added fund management skill and alpha measures

As our second and more direct fund management skill measure, as claimed by Berk and van Binsbergen (2015), we use their value-added measure. Specifically, the Berk and van Binsbergen (2015) measure of fund management skill is obtained by estimating the value that a mutual fund extracts from capital markets. Berk and van Binsbergen (2015) document that investors recognize this skill and reward it by investing more capital with better funds. Their method allows to 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 a direct and 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, which they argue is the best alternative investment opportunity to investors.[13,14] 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 (11 Vanguard index funds) 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.[15] The benchmark is estimated by using 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^{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^{th} index fund of the whole period.

[13] The list of the 11 Vanguard index funds and their inception dates are shown in the Internet Appendix 2.

[14] To further validate the argument that skilled fund managers deliver higher performance for fund investors during high sentiment periods, we estimate the alphas of all 11 Vanguard index funds for all/high sentiment/low sentiment periods using FF3 model. The result, reported in the Internet Appendix 2, indicate that the effect of market sentiment to passive index funds is negligible and insignificant.

[15] 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.

Next, as shown below in Equation (2), we regress the excess returns of each fund *f* (i.e., the difference between the real fund returns over the corresponding risk-free rates in the same month), on the 11 Vanguard index fund orthogonal bases, using 24-month rolling window regression and moving forward 1 month each time, to estimate the correlation coefficients (β^{j}_{t-1}) between each orthogonal base (*j*) and fund return before the test month (*t*).

$$Excess\ Return_{f,t-1} = \sum_{j=1}^{11} \beta_{t-1}^{j} R_{t-1}^{j} + \alpha_{f,t-1} \quad (2)$$

Then, as displayed in Equation (3), we use the estimated correlation coefficients, calculated during the 24-month time window (*t*-24 to *t*-1) before the test month (*t*), and the real numbers of all 11 orthogonal bases in test month (*t*) to estimate the expected excess return of fund *f* in month (*t*). The fund expected excess 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.

$$Expected\ Excess\ Return_{f,t} = \sum_{j=1}^{11} \beta_{t-1}^{j} R_{t}^{j} + \alpha_{f,t} \quad (3)$$

Following Berk and van Binsbergen (2015), the fund performance measure we use, as shown in Equation (4), is the abnormal capital inflow a fund experiences in the test month (denoted as the value-added alpha), which is calculated as the fund's gross abnormal return (real excess return over its expected excess return) multiplied by the TNA of the fund at the beginning of the current month. The added-value fund excess performance is estimated as follows:

$$Value - added\ Alpha_{f,t} = \left(Real\ Excess\ Return_{f,t} - Expected\ Excess\ Return_{f,t}\right) * TNA_{f,t} \quad (4)$$

To gauge fund management skill, we use the skill ratio measure introduced by Berk and van Binsbergen (2015), referred to as the value-added fund skill. As shown in Equation (5), the value-added fund management skill for each fund in each month is the product of a fund's abnormal returns (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.[16] The fund management skill is calculated as follows:

$$Value - added\ Fund\ Skill_{f,t} = \frac{alpha_{f,t-1} * TNA_{f,t-2}}{SE_{f,t-1}} \quad (5)$$

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 is the inflation-adjusted of total net assets of the fund.

It is worth to emphasize here that the value-added fund management skill of Berk and van Binsbergen (2015) is not just a normalized version of the value-added alpha. The value-added fund management skill is the abnormal capital inflow one month before the test month (t-1) adjusted by the standard error of the fund alpha within the 24-month estimation window, while the value-added alpha captures the abnormal capital inflow (fund's gain) during the test month (t). The fund performance and fund management skill measures used in this study, are in line with the Berk and van Binsbergen (2015).

[16] Berk and van Binsbergen (2015), specifically claim that "Value added, the product of assets under management (AUM) and gross alpha, always measures skill".

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. The stock return dispersion in month t (MD_t) is calculated as follows:

$$MD_t = \sqrt{\frac{1}{n-1}\sum_{i=1}^{n}(R_{i,t} - R_{m,t})^2} \quad (6)$$

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.

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.[17] The CFNAI is a coincident indicator of national economic activity comprising 85 existing macroeconomic time series.

[17] 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.

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 γ, the lucky (unlucky) funds within the skilled funds category and unskilled funds category are the same, and are calculated as:

$$F_{\gamma}=\pi_0 * \gamma/2 \quad (7)$$

where π_0 is the true proposition of the zero-alpha fund category, and γ is the significance level we choose. Then, the true proportions of skilled funds, T_{γ}^{+}, and unskilled funds, T_{γ}^{-}, adjusted by the presence of lucky funds, F_{γ}, are measured as:

$$T_{\gamma}^{+} = S_{\gamma}^{+} - F_{\gamma} = S_{\gamma}^{+} - \pi_0 * \gamma/2 \quad (8)$$

$$T_{\gamma}^{-} = S_{\gamma}^{-} - F_{\gamma} = S_{\gamma}^{-} - \pi_0 * \gamma/2 \quad (9)$$

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 proposition of the zero-alpha fund category in each month is estimated as:

$$\pi_{0,t} = \frac{W_{\lambda^*,t}}{M_t} * \frac{1}{1-\lambda^*} \quad (10)$$

where λ^* is a sufficiently high P-value threshold (we use $\lambda^* = 0.6$, as suggested in Barras et al., 2010). W_{λ^*} equals the number of funds with a P-value exceeding λ^* 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 performance ($alpha_{t-1}$), 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 then 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 2. Next, we examine whether fund selectivity skill varies with time and specifically whether high fund-management 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 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 2 the annualized alpha and P-value for each portfolio for high (Panel B) and low (Panel C) sentiment periods.

[Insert Table 2 here]

Consistent with the findings of Amihud and Goyenko (2013), the results in Panel A of Table 2 show that greater fund selectivity, measured by (1-R^2_{t-1}), and superior past performance, measured by alpha$_{t-1}$, 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-$R^2_{t\text{-}1}$) portfolio to the low selectivity (low 1-$R^2_{t\text{-}1}$) portfolio. This pattern also indicates that funds in the highest selectivity (lowest R^2) portfolios are not outliers and that they are not driven by outlier funds with extreme low R^2. The highest annualized alpha is 3.05% (P = 0.023) for the fund portfolio with the highest selectivity and the best past performance. Since the 25 (5x5) portfolios, sorted by fund selectivity and past performance, are equally weighted, each portfolio contains 4% of total active managed mutual funds in our sample. Thus, the significant positive alphas from those two portfolios formed by funds with the best past performance and highest or second highest fund selectivity indicate that, 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 mutual fund investors. In sum, the results in Panel A of Table 2 reveal that funds' risk-adjusted excess return is higher for funds with greater fund selectivity skill (1-$R^2_{t\text{-}1}$), which is highly consistent with the patterns in Amihud and Goyenko (2013). Besides, the results highlight the essential role of past performance in identifying skilled mutual fund managers. For instance, all funds in the top selectivity quintile, without controlling for fund past performance, exhibit an average insignificant fund alpha of 0.58% (P=0.426), while all funds in the top past performance quintile, without controlling for fund selectivity, report a similar insignificant fund alpha of 0.58% (P=0.381). However, funds with the highest selectivity and best past performance yield a significant fund alpha (3.05%, P=0.023). Therefore, in this paper we define skilled-managed funds as the ones run by managers possessing high selectivity or value-added skill that have exhibited superior past performance.

We also calculate the performance difference between the high selectivity fund portfolio and the low selectivity fund portfolio by estimating a hypothetical portfolio of a long position in the high selectivity fund portfolio and a short position in the low selectivity fund portfolio for every lagged alpha quintile. These results, presented in the rightmost column of Table 2 under "High-Low," indicate that the return from this strategy is positive in all alpha quintiles except the lowest alpha quintile, which is negative but statistically insignificant. For the whole sample, the high selectivity fund portfolio outperforms the low selectivity fund portfolio by 1.92% (P = 0.019). For the highest and second-highest alpha quintiles, the hypothetical portfolios yield an annualized alpha of 4.46% (P = 0.003) and 1.17% (P = 0.037), respectively. In sum, the results in Panel A of Table 2 reveal that funds' risk-adjusted excess return is higher for funds with greater fund selectivity skill ($1\text{-}R^2_{t\text{-}1}$), which is highly consistent with the patterns in Amihud and Goyenko (2013).

As predicted, the results in Panels B and C of Table 2 demonstrate that high selectivity fund managers with superior past performance consistently outperform their low selectivity counterparts. In accord with our conjecture, this performance difference is significantly pronounced during high sentiment (noisy) periods. Specifically, when the level of investor sentiment 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. 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

2.53% (P = 0.046) extra risk-adjusted return than the market. However, the results in Panel C indicate that during low sentiment periods none of the fund portfolios beat the market benchmark significantly. Interestingly, funds with the lowest skill experience the lowest -1.14% (P = 0.035) excess returns than the market benchmark while none of the funds with the highest management skill realize significant losses suggesting that in times of low sentiment their performance is at par with the market. In addition, the hypothetical strategy fails to significantly outperform the market on average. 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 (i.e. low mispricing) due to the absence of noise traders.[18] Additionally, the hypothetical portfolios of long positions in the high past performance funds and short position in the low past performance funds show consistent positive alphas, indicating that funds with high past performance outperform funds with low past performance during both high and low sentiment states. However, this result is mainly driven by the superior performance of high skilled funds. A similar pattern does not hold for funds with low management skill. Jointly, these results suggest that fund selectivity skill is far more valuable to mutual fund

[18] 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 economically and statistically more significant, shown in the Internet Appendix 3.

investors in high sentiment times when price signals are noisy due to the greater presence of investor hype in the market.[19]

Since large company stocks are favored by institutional investors, we use high and low stock market capitalization as a proxy of a stock's institutional ownership and expect noise trading activity to be more prevalent in stocks with lower institutional ownership especially during high sentiment times. Based on this argument, we perform additional tests to examine i) whether small-cap companies' average performance is more negatively influenced by high market sentiment than large-cap companies and ii) whether small-cap focused funds (i.e., funds constrained by objective to invest in small capitalization stocks), compared with large-cap focused funds, lose more value for fund investors during high sentiment periods, when noise traders are more active and strongly affect the stock prices of small-cap companies. The results, reported in the Internet Appendix 4, are highly consistent with our hypothesis.

4.2 Fund portfolio performance and stock market dispersion

To examine whether fund management skill improves fund portfolio performance under equity market dispersion, 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 3 for the high (Panel A) and low (Panel B) market-dispersion periods indicate that

[19] Following Berk and van Binsbergen (2015), Dong and Doukas (2018) using the value-added fund skill measure they provide additional evidence in support of our fund-selectivity results.

fund managers with high selectivity skill 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 are also capable to 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 3 here]

4.3 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 4, reveal that more funds with high selectivity skill realize more 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). These findings suggest that the ability of skilled fund managers to deliver high alpha during recessions imply that fund investors are better off when they invest with high selectivity funds during adverse economic conditions. These results are consistent with the previous literature (Kacperczyk et al., 2009) reporting that skilled active funds provide an insurance mechanism against recessions.

[Insert Table 4 here]

Jointly, these results—while in line with previous studies—also demonstrate that skilled fund managers realize 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 Table 6, 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.

4.4 Fund management selectivity performance regression results

So far, we have analyzed the positive relation between active fund performance, selectivity, and sentiment. To ensure that our evidence, which shows that high selectivity funds do outperform low selectivity funds, is not sensitive to the choice of the factor model we also consider the use of different factor models. To do so, we first form two fund portfolios based on selectivity as in Amihud and Goyenko (2013). 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 5, 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 5 here]

Unsurprisingly, the low-selectivity fund portfolio delivers significant negative fund alphas in all three models. On the other hand, the high-selectivity 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 Table 2. 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 3.12% ($P < 0.001$), 2.16% ($P = 0.004$), and 1.92% ($P = 0.031$) annualized alphas in each of the three models, respectively.[20] 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 indicating that their superior performance is not driven by chasing momentum driven mispriced (overvalued) stocks in high sentiment times. The insignificant

[20] The annualized alpha is calculated as the monthly alpha (regression intercept) times 12 (i.e. 0.26*12=3.12%.; 0.18*12=2.16; 0.16*12=1.92)

coefficient between skilled fund 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,[21] while we also control for the market dispersion and business cycle effects.[22] To test whether the profitability of fund management skill (selectivity) is higher during high sentiment periods, we estimate the following model:

$$Alpha_{f,t} = \alpha_f + \beta_1 Selectivity_{f,t} + \beta_2 Sentiment_t + \beta_3 Alpha_{f,t-1} + \beta_4 Selectivity_{f,t} * Sentiment_t + \beta_5 Selectivity_{f,t} * Sentiment_t * Alpha_{f,t-1} + \sum Controls_{f,t} + \varepsilon_{f,t} \quad (11)$$

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

[21] 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.

[22] 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.

24-month estimation period. $Alpha_{t-1}$ is the intercept from the FFC model using a 24-month estimation period. Control variables in the regression include 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. Based on the central prediction of our hypothesis that active funds with superior past performance run by managers with high selectivity skills, they 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 $\beta_1 > 0$, $\beta_2 < 0$, $\beta_3 > 0$, $\beta_4 > 0$, and $\beta_5 > 0$.

[Insert Table 6 here]

Consistent with the results presented earlier and the above prediction, the results in Panel A of Table 6 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 significant (0.172, $P = 0.032$) 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. The coefficient of the interactive variable, $Selectivity*Sentiment*Alpha_{t-1}$, is positive and significant in regressions [5] and [6], indicating that funds with skilled managers and high past performance deliver greater alpha in high market sentiment states.[23]

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 (12), instead of the original selectivity measure.

$$TSelectivity = \log\left(\frac{Selectivity}{1-Selectivity}\right) \quad (12)$$

The new results, reported in Panel B of Table 6, 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 and the coefficient of the interaction variable, *TSelectivity*Sentiment*, and fund performance is still positive and statistically significant (0.019, P=0.065). As before, the coefficients of the interactive variable $TSelectivity*Sentiment*Alpha_{t-1}$ are consistently positive and statistically significant. Jointly, the results in Table 6 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

[23] Our regression specifications are consistent with Amihud and Goyenko (2013). We also estimate regressions with fix effects and cluster-robust standard errors, and find similar results.

by $1-R^2_{t-1}$, and show superior past performance, especially during high sentiment periods.[24,25]

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 by low skill fund managers.

4.5 Lucky bias analysis

4.5.1 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 performed the Barras et al. (2010) a lucky bias analysis for the entire sample by replicating the analysis for both high and low sentiment periods. As shown in Panel A of Table 7, using fund risk-adjusted excess return (fund alpha) as a performance measure,

[24] 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 the Internet Appendix 5, are consistent with our previously reported findings. We also estimate regressions with fix effects and cluster-robust standard errors and find similar results.

[25] Using the value-added fund skill (ratio) and performance (alpha) measures, Dong and Doukas (2018) offer additional support to this result by showing that, on average, sentiment harms the overall fund performance, but this does not hold for skilled fund managers.

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 indicating that some of the mutual fund managers do possess management skill, but the proportion is very low.

[Insert Table 7 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. The portion of truly skilled mutual fund managers increases to 1.57% when we move the significance level from 5% to 20%. 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 result indicates that during high than low sentiment periods, when the market is noisy, and information is costly, skilled fund managers consistently outperform the market benchmark.

4.5.2 Value-added fund performance lucky bias results

When we replicate the lucky bias analysis using the value-added 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 7. Specifically, as shown in Table 8 Panel A, on average, 7.52% of funds outperform the market benchmark at the

20% 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 8 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 1.63%, using selectivity ($1-R^2$) measure, and 5.40%, using value-added skill measure, which both are below the 20% 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.[26]

4.6 Stock mispricing and mutual fund performance

Next, one can argue that the superior performance of high selectivity fund managers during high sentiment periods is driven by investing in “bubble-prone” stocks (i.e., overpriced stocks). The opposite view, however, holds that high selectivity fund managers are not expected to improve fund performance by opportunistically investing in overpriced stocks during high sentiment times. To address this issue, we 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 (bubble-prone) stocks. That is, 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).[27,28] 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

---

[26] These results are available upon request.

[27] 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.

[28] The data are available through Yu Yuan’s website http://www.saif.sjtu.edu.cn/facultylist/yyuan/.

highest mispricing values are identified as overpriced by the market due to high market sentiment, they should be less attractive to skilled fund managers. Thus, we expect to observe a less significant or insignificant relationship between skilled fund managers' performance and highly mispriced (overpriced) stocks, while our hypothesis predicts a significant negative correlation between the performance of funds managed by less skilled managers and overpriced stocks. Then, we calculate the value weighted average of stock mispricing (*VW_MISP*) for all stocks within each fund.[29] To check the sensitivity of our results, we replace the value weighted average mispricing with the equal weighted average of stock mispricing (*EW_MISP*) for all stocks within each fund. Next, 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 9 here]

Table 9 presents the regression coefficients 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 ($Alpha_{t-1}$), 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, indicating that overvalued stocks are more attractive to unskilled fund managers. For example, when sorting funds based on

[29] Fund holdings information is manually collected through Bloomberg Portfolio Analysis Database.

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 the value-added 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, rather than overvalued ("bubble-prone") ones.

4.7 Fund capital inflows and fund performance analysis

The portfolio sorting and multivariate analysis, thus far, show 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 mutual funds. 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 these issues by investigating whether the funds with skilled managers and superior past performance attract more capital inflows and 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:

$$Net\ capital\ flow_{f,t} = TNA_{f,t} - (1 + R_{f,t}) * TNA_{f,t-1} \quad (13)$$

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 (Fow_{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 (10).

[Insert Table 10 here]

Consistent with our prediction, the results in Table 10 column [1] show a negative and significant relation between the previous month capital inflows ($Flow_{t-1}$) and fund *alpha*, which suggests that extra capital inflows create more pressure on fund managers to invest resulting in lower fund *alpha*. The insignificant impact of the interaction variables *Flow*Sentiment* in t-1 and t-2 (P = 0.990 and P = 0.596, respectively) on fund alpha, as shown in column [2], indicate that the negative relation between the previous months' capital inflows and fund performance is not sentiment-related. The coefficients of the interaction *Flow*Selectivity* in t-1 and t-2, as reported in column [3], are positive and significant (P = 0.000), suggesting that managers with high selectivity skill deliver higher alpha than their unskilled fund counterparts implying that they direct the extra capital inflows in better investment opportunities. The result in column [4] further confirms that past performance matters fund alpha. Last, the positive and significant coefficients of the interaction variables, $Flow_{t-1}*Selectivity*Alpha_{t-1}$ and $Flow_{t-2}*Selectivity*Alpha_{t-1}$ yield direct support that fund investors are better off by investing in funds with superior managerial skill and with high past performance. Overall, these results demonstrate that managers with high selectivity skill generate higher alpha by investing increased capital inflows, as a result of their past performance, to superior investment opportunities.

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 capital 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 investor 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:

$$R_{p,t} - R_{f,t} = \alpha + \beta_1(RM - Rf)_t + \beta_2 SMB_t + \beta_3 HML_t + \beta_4 MOM_t + \beta_5 Sentiment_t \quad (14)$$

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. β_5 is the sentiment beta estimated by running regression (14) with a 24-month moving window. Then, we run the following cross-sectional regression of portfolio return (15) (and portfolio alpha obtained from FFC model (16)) on the sentiment beta, with or without fund-level control variables:

$$R_{p,t} - R_{f,t} = \gamma + \omega Sentiment\ Beta_{t-1} + \varphi \sum Controls_t + \epsilon_{p,t} \quad (15)$$

$$alpha_{p,t} = \gamma + \omega Sentiment\ Beta_{t-1} + \varphi \sum Controls_t + \epsilon_{p,t} \quad (16)$$

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

[Insert Table 11 here]

Table 11 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 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 test the sensitivity of our results by controlling for the effect of the volatility anomaly.[30]

In accord with section 4.1, we sort all the funds in each month into 25 (5x5) portfolios with a different selectivity ($1\text{-}R^2_{t\text{-}1}$) 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

[30] 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.

obtain the abnormal risk-adjusted excess return, i.e., portfolio fund alpha. Table 12 presents the annualized fund alpha and P-value for each portfolio in high (Panel A) and low (Panel B) sentiment periods, respectively.

[Insert Table 12 here]

These results continue to show that skilled fund managers' performance is superior during high investor sentiment periods indicating that they are not sensitive to the 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}) 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. 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).[31] Taken together, these results provide supplemental evidence in support of our baseline hypothesis that skilled managers produce higher fund alphas during high sentiment periods, and this relationship is not biased by the volatility anomaly.

[31] The same analysis is re-examined using the UM index and the results are consistent with the results using the BW index.

5.3 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 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 specifically examine whether skilled mutual fund managers deliver greater value (alpha) during high sentiment states, 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.

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 and persistent fund performance during high investor sentiment periods. Assessing the performance of fund managers in stock mispricing states, as an alternative set of noise trading activity, 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. Additionally, the findings of this study offer new evidence that mutual fund investors are significantly better off by allocating capital to funds characterized by superior managerial high and superior past performance.

We also perform a lucky bias analysis and find that more fund managers with superior management skills can generate persistent excess risk-adjusted returns during high sentiment periods, which further supports the argument that fund skill is more profitable and valuable for fund investors in the presence of greater noise in the market.

Our findings are robust to sentiment beta effect, stock market dispersion, macroeconomic environment, alternative sentiment measures, and the effect of the volatility anomaly. Overall, our findings conclusively show that skilled fund managers create more value and exhibit persistent performance during high than low sentiment periods, when noise trading activity 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*.

Antoniou, C., Doukas, J. A., and Subrahmanyam, A. (2013): Cognitive dissonance, sentiment, and momentum, *Journal of Financial and Quantitative Analysis* 48, 245-275.

Antoniou, 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.

Barber, B., and Odean, T. (2008): All That Glitters: The Effect of Attention and News on the Buying Behavior of Individual and Institutional Investors, *Review of Financial Studies* 21, 785-818

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)*.

Chevalier, J., and Ellison, G. (1997). Risk taking by mutual funds as a response to incentives. *Journal of Political Economy*, 105(6), 1167-1200.

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.

Dong, F., and Doukas, J. A. (2018). Fund Management Skill and Noise Trading. *The Journal of Portfolio Management*, 44(5), 113-124.

Dong, F., & Doukas, J. A. (2019). The payback of mutual fund selectivity in European markets. *European Financial Management*, 25(1), 160-180.

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.

Hilbert, M. (2012): Toward a synthesis of cognitive biases: How noisy information processing can bias human decision making. *Psychological Bulletin 138*, 211-237

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.

Knyazeva, A., Knyazeva, D., & Kostovetsky, L. (2018). Investor heterogeneity and trading. *European Financial Management*, 24(4), 680-718.

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.

Sirri, E. R., and Tufano, P. (1998). Costly search and mutual fund flows. *The Journal of Finance*, (53), 1589-1622.

Stambaugh, R. F. (2014): Presidential address: Investment noise and trends, *The Journal of Finance*, 69, 1415-1453.

Stambaugh, R. F., Yu, J., and Yuan, Y. (2012): The short of it: Investor sentiment and anomalies, *Journal of Financial Economics* 104, 288-302.

Tversky, A., Kahneman, D. (1974): Judgment under Uncertainty: Heuristics and Biases. *Science* 185, 1124-1131

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 1. Summary Statistics of Actively Managed Equity Mutual Funds' Characteristics

This table shows descriptive statistics of individual fund estimates of R^2_{t-1} and control variables before the removal of outlier observations as in Armihud and Goyenko (2013) for comparison purposes. R^2_{t-1} is calculated by regressing each fund's excess return (fund monthly raw return minuses 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.

	Mean	**Median**	**Minimum**	**Maximum**
Turnover (%)	85.64	56.00	0.00	3,452.00
Age (years)	17.44	17.00	3.00	47.00
Expense Ratio (%)	1.28	1.21	0.00	9.16
TNA (millions)	1,267.96	234.49	8.26	202,305.77
$\mathbf{R^2_{t-1}}$	0.883	0.922	0.219	0.991

Table 2. Portfolio Fund Alpha, Based on Sorting on Selectivity and $Alpha_{t-1}$, in High and Low Sentiment Periods

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.

Panel A: Portfolio fund alpha for the entire sample period

	Fund selectivity ($1-R^2_{t-1}$)						
$Alpha_{t-1}$	**Low**	**2**	**3**	**4**	**High**	**All**	**High-Low**
Low	-1.75***	-2.04***	-1.84**	-1.97**	-2.06	-1.93***	-0.31
	(0.001)	(0.003)	(0.015)	(0.026)	(0.117)	(0.002)	(0.765)
2	-1.43***	-0.99**	-0.90	-0.34	0.34	-0.67	1.77**
	(0.001)	(0.049)	(0.154)	(0.653)	(0.712)	(0.196)	(0.047)
3	-0.94**	-0.67	-1.17**	-0.51	0.56	-0.55	1.50
	(0.024)	(0.143)	(0.044)	(0.450)	(0.501)	(0.219)	(0.145)
4	-1.18**	-1.16	0.11	-0.20	0.99	-0.28	2.17**
	(0.011)	(0.106)	(0.840)	(0.792)	(0.277)	(0.535)	(0.037)
High	-1.41*	-0.81	-0.08	2.14**	3.05**	0.58	4.46***
	(0.051)	(0.355)	(0.912)	(0.025)	(0.023)	(0.381)	(0.003)
All	-1.34***	-1.14**	-0.78	-0.19	0.58	-0.57	1.92**
	(0.001)	(0.012)	(0.110)	(0.754)	(0.426)	(0.166)	(0.019)
High-Low	0.34	1.23	1.76*	4.11***	5.11**	2.51**	
	(0.606)	(0.191)	(0.061)	(0.001)	(0.004)	(0.004)	

Panel B: Portfolio fund alpha during high market sentiment

	Fund selectivity ($1-R^2_{t-1}$)						
$Alpha_{t-1}$	**Low**	**2**	**3**	**4**	**High**	**All**	**High-Low**
Low	-2.38***	-3.71***	-2.97**	-2.68*	-1.45	-2.65***	0.93

	(0.002)	(0.001)	(0.017)	(0.054)	(0.412)	(0.006)	(0.614)
2	-2.34***	-1.38*	-2.11**	-1.02	0.02	-1.36*	2.36*
	(0.001)	(0.097)	(0.026)	(0.378)	(0.990)	(0.095)	(0.068)
3	-1.36**	-1.40**	-2.19**	-0.69*	0.03	-1.12*	1.39
	(0.021)	(0.050)	(0.018)	(0.508)	(0.982)	(0.095)	(0.34)
4	-0.95	-1.19	-0.73	-0.01	0.36	-0.50	1.31
	(0.187)	(0.150)	(0.381)	(0.996)	(0.792)	(0.488)	(0.396)
High	-1.92	-1.39	-0.50	2.70*	4.82**	0.75	6.74***
	(0.133)	(0.379)	(0.696)	(0.073)	(0.020)	(0.499)	(0.006)
All	-1.79***	-1.82**	-1.70**	-0.35	0.74	-0.98	2.53**
	(0.003)	(0.014)	(0.033)	(0.721)	(0.508)	(0.147)	(0.046)
High-Low	0.46	2.32	2.47	5.38***	6.27**	3.40**	
	(0.787)	(0.209)	(0.117)	(0.009)	(0.015)	(0.017)	

Panel C: Portfolio fund alpha during low market sentiment

	Fund selectivity ($1-R^2_{t-1}$)						
$Alpha_{t-1}$	**Low**	**2**	**3**	**4**	**High**	**All**	**High-Low**
Low	-1.14**	-0.33	-0.90	-1.38	-2.35	-1.21	-1.21
	(0.035)	(0.668)	(0.272)	(0.156)	(0.236)	(0.117)	(0.470)
2	-0.61	-0.68	-0.45	-0.36	0.44	-0.34	1.05
	(0.186)	(0.161)	(0.450)	(0.670)	(0.711)	(0.540)	(0.386)
3	-0.54	-0.31	-0.84	-0.81	0.58	-0.38	1.12
	(0.280)	(0.549)	(0.136)	(0.255)	(0.595)	(0.413)	(0.449)
4	-1.34**	-1.34	0.27	-1.22	1.40	-0.44	2.74*
	(0.019)	(0.253)	(0.687)	(0.117)	(0.245)	(0.410)	(0.051)
High	-0.68	0.30	0.16	0.89	0.63	0.26	1.31
	(0.328)	(0.694)	(0.859)	(0.439)	(0.702)	(0.730)	(0.458)
All	-0.86**	-0.47	-0.34	-0.58	0.17	-0.42	1.03
	(0.026)	(0.321)	(0.457)	(0.331)	(0.851)	(0.341)	(0.312)
High-Low	0.46	0.63	1.06	2.27*	2.98	1.47*	
	(0.312)	(0.232)	(0.208)	(0.055)	(0.196)	(0.070)	

Table 3. Portfolio Fund Alpha, Based on Sorting on Selectivity and $Alpha_{t-1}$, in High and Low Market Dispersion Periods

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 $alpha_{t-1}$. 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. 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.

Panel A: During high market dispersion

	Fund selectivity ($1-R^2_{t-1}$)						
$Alpha_{t-1}$	**Low**	**2**	**3**	**4**	**High**	**All**	**High-Low**
Low	-2.31***	-3.59***	-1.87	-1.92	-1.39	-2.22**	0.92
	(0.002)	(0.002)	(0.163)	(0.201)	(0.534)	(0.040)	(0.729)
2	-2.00***	-1.39*	-1.38	-0.16	1.46	-0.69	3.46**
	(0.004)	(0.096)	(0.196)	(0.902)	(0.341)	(0.432)	(0.017)
3	-1.53**	-1.31*	-2.04**	-0.83	-0.20	-1.18	1.33
	(0.026)	(0.083)	(0.037)	(0.459)	(0.889)	(0.113)	(0.452)
4	-2.39***	-1.39	-0.21	0.01	1.02	-0.59	3.41**
	(0.002)	(0.121)	(0.822)	(0.995)	(0.497)	(0.442)	(0.045)
High	-1.98	-2.37	0.07	3.57**	4.55**	0.77	6.53***
	(0.118)	(0.139)	(0.962)	(0.031)	(0.035)	(0.509)	(0.008)
All	-2.05***	-2.02***	-1.09	0.11	1.09	-0.79	3.14**
	(0.001)	(0.009)	(0.196)	(0.913)	(0.382)	(0.272)	(0.020)
High-Low	0.33	1.22	1.94	5.49**	5.94*	2.99*	
	(0.925)	(0.498)	(0.308)	(0.015)	(0.051)	(0.062)	

Panel B: During low market dispersion

Fund selectivity ($1-R^2_{t-1}$)

$Alpha_{t-1}$	Low	2	3	4	High	All	High-Low
Low	-1.39***	-0.68	-1.60***	-2.10***	-2.92**	-1.74***	-1.53
	(0.008)	(0.289)	(0.006)	(0.010)	(0.034)	(0.002)	(0.278)
2	-0.98**	-0.67	-0.52	-0.35	-0.84	-0.68*	0.14
	(0.015)	(0.130)	(0.307)	(0.615)	(0.368)	(0.095)	(0.947)
3	-0.48	-0.14	-0.18	-0.20	1.47*	0.10	1.95**
	(0.210)	(0.750)	(0.730)	(0.744)	(0.058)	(0.784)	(0.044)
4	0.13	-0.82	0.57	-0.16	1.13	0.17	1.00
	(0.794)	(0.475)	(0.303)	(0.814)	(0.201)	(0.694)	(0.350)
High	-0.68	1.05	0.09	1.31	2.04	0.77	2.72
	(0.304)	(0.119)	(0.884)	(0.136)	(0.187)	(0.191)	(0.107)
All	-0.68*	-0.25	-0.33	-0.31	0.18	-0.28	0.86
	(0.058)	(0.547)	(0.413)	(0.518)	(0.786)	(0.399)	(0.312)
High-Low	0.71	1.73**	1.69***	3.41***	4.96**	2.51***	
	(0.168)	(0.018)	(0.004)	(0.002)	(0.011)	(0.001)	

Table 4. Portfolio Fund Alpha, Based on Sorting on Selectivity and $Alpha_{t-1}$, in Economic Expansions and Economic Recessions

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. 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 $alpha_{t-1}$, 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.

Panel A: Economic expansions

	Fund selectivity ($1-R^2_{t-1}$)						
Alpha$_{t-1}$	**Low**	**2**	**3**	**4**	**High**	**All**	**High-Low**
Low	-1.52**	-3.27***	-2.55**	-4.09***	-3.12*	-2.92***	-1.60
	(0.028)	(0.001)	(0.029)	(0.003)	(0.084)	(0.002)	(0.327)
2	-1.75***	-0.67	-2.65***	-1.00	-0.97	-1.41**	0.78
	(0.006)	(0.381)	(0.003)	(0.298)	(0.401)	(0.043)	(0.532)
3	-1.07*	-0.95	-1.25	-1.14	-0.02	-0.89	1.05
	(0.075)	(0.122)	(0.142)	(0.203)	(0.983)	(0.122)	(0.334)
4	-0.46	-1.83	-0.17	-0.57	1.48	-0.31	1.94
	(0.459)	(0.146)	(0.810)	(0.609)	(0.176)	(0.610)	(0.123)
High	-0.75	-0.13	0.95	3.69***	4.11**	1.58**	4.86**
	(0.422)	(0.892)	(0.268)	(0.006)	(0.024)	(0.041)	(0.021)
All	-1.12**	-1.38**	-1.14*	-0.65	0.27	-0.81	1.39
	(0.032)	(0.028)	(0.086)	(0.439)	(0.760)	(0.152)	(0.176)
High-Low	0.77	3.14**	3.50***	7.78***	7.23***	4.50***	
	(0.478)	(0.012)	(0.003)	(<.001)	(0.003)	(<.001)	

Panel B: Economic recessions

	Fund selectivity ($1-R^2_{t-1}$)						
Alpha$_{t-1}$	**Low**	**2**	**3**	**4**	**High**	**All**	**High-Low**
Low	-1.89***	-1.04	-0.68	-0.30	-0.62	-0.90	1.27
	(0.003)	(0.224)	(0.464)	(0.778)	(0.738)	(0.252)	(0.512)
2	-1.06**	-1.19*	0.73	0.65	1.99	0.22	3.05**
	(0.042)	(0.072)	(0.394)	(0.554)	(0.161)	(0.767)	(0.019)
3	-0.84	-0.06	-0.66	0.20	1.37	0.01	2.21

	(0.127)	(0.916)	(0.393)	(0.835)	(0.325)	(0.987)	(0.195)
4	-1.87***	-0.38	0.63	0.45	0.99	-0.02	2.86*
	(0.006)	(0.610)	(0.462)	(0.661)	(0.497)	(0.972)	(0.077)
High	-1.79*	-1.34	-0.62	1.61	3.54*	0.27	5.33***
	(0.075)	(0.313)	(0.606)	(0.220)	(0.055)	(0.786)	(0.008)
All	-1.49***	-0.80	-0.12	0.51	1.48	-0.08	2.97**
	(0.003)	(0.175)	(0.866)	(0.549)	(0.193)	(0.891)	(0.013)
High-Low	0.10	-0.30	0.06	1.91	4.16*	1.17	
	(0.914)	(0.789)	(0.982)	(0.185)	(0.094)	(0.301)	

Table 5. Regressions of Returns of Fund Portfolios on CAPM, FF3, and FFC Models

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. This process is repeated 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^2 for each regression are also presented. ***, **, * denotes significance at the 1%, 5% or 10% level.

	CAPM			**3 Factor Model**			**4 Factor Model**		
	High Selectivity	**Low Selectivity**	**High - Low**	**High Selectivity**	**Low Selectivity**	**High - Low**	**High Selectivity**	**Low Selectivity**	**High - Low**
Intercept	0.14*	-0.12***	0.26***	0.06	-0.13***	0.18***	0.05	-0.11***	0.16**
	(0.082)	(<.001)	(<.001)	(0.304)	(<.001)	(0.004)	(0.433)	(<.001)	(0.031)
RM-Rf	0.89***	1.02***	-0.12***	0.88***	1.02***	-0.14***	0.88***	1.01***	-0.12***
	(<.001)	(<.001)	(<.001)	(<.001)	(<.001)	(<.001)	(<.001)	(<.001)	(<.001)
SMB				0.27***	0.05***	0.22***	0.27***	0.05***	0.22***
				(<.001)	(<.001)	(<.001)	(<.001)	(<.001)	(<.001)

HML				0.19***	0.02**	0.18***	0.20***	0.02	0.18***
				(<.001)	(0.052)	(<.001)	(<.001)	(0.164)	(<.001)
MOM							0.02	-0.02***	0.04***
							(0.170)	(<.001)	(0.001)
Adj. R^2	0.89	0.99	0.14	0.94	0.99	0.41	0.94	0.99	0.42

Table 6. The Effect of Fund Selectivity and Investor Sentiment on Fund Performance

Notes: This table reports the results of regressing fund alpha on manager's selectivity, investor sentiment, and fund alpha$_{t-1}$, 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. This process is repeated by moving the estimation and test period one month at a time. 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, fund alpha$_{t-1}$, and Selectivity*Sentiment*Alpha$_{t-1}$, which is the product of these three variables. 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$_{t-1}$ as control variables, where Alpha$_{t-1}$ 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^2 is highly negative skewed. The P-value and adjusted R^2 for each regression are also presented. ***, **, * denotes significance at the 1%, 5% or 10% level.

Panel A: Using selectivity to measure skill

	Fund Alpha					
	[1]	[2]	[3]	[4]	[5]	[6]
Intercept	-0.534***	-0.373***	-0.456***	-0.458***	-0.468***	-0.768***
	(0.000)	(0.009)	(0.001)	(0.001)	(0.001)	(0.000)

Selectivity	0.413***		0.479***	0.454***	0.476***	0.500***
	(0.000)		(0.000)	(0.000)	(0.000)	(0.000)
Alpha$_{t-1}$	0.303***	0.333***	0.319***	0.319***	0.257***	0.259***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Sentiment		-0.092***	-0.105***	-0.130***	-0.122***	-0.176***
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Selectivity*Sentiment				0.172**		
				(0.032)		
Selectivity*Sentiment*Alpha$_{t-1}$					0.493***	0.486***
					(0.000)	(0.000)
Market Dispersion						0.027**
						(0.000)
Business Cycle						0.043***
						(0.000)
Turnover	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***
	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)
Expense Ratio	-0.010	0.000	-0.010	-0.010	-0.019	-0.020
	(0.430)	(0.983)	(0.426)	(0.435)	(0.145)	(0.124)
log(TNA)	0.296***	0.255***	0.279***	0.281***	0.293***	0.318***
	(0.000)	(0.002)	(0.001)	(0.001)	(0.000)	(0.000)
[log(TNA)]^2	-0.027**	-0.020*	-0.024**	-0.024**	-0.026**	-0.029**
	(0.023)	(0.091)	(0.037)	(0.036)	(0.028)	(0.012)
Log(age)	-0.072***	-0.097***	-0.092***	-0.093***	-0.096***	-0.080***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Adj. R^2	0.008	0.008	0.008	0.008	0.009	0.010

Panel B: Using logistic transformed selectivity to measure skill

	Fund Alpha					
	[1]	[2]	[3]	[4]	[5]	[6]
Intercept	-0.375***	-0.373***	-0.258*	-0.264*	-0.375***	-0.660***
	(0.009)	(0.009)	(0.071)	(0.066)	(0.009)	(0.000)
TSelectivity	0.047***		0.059***	0.058***	0.043***	0.047***
	(0.000)		(0.000)	(0.000)	(0.000)	(0.000)
Alpha$_{t-1}$	0.304***	0.333***	0.320***	0.320***	0.361***	0.361***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Sentiment		-0.092***	-0.112***	-0.072***	-0.044***	-0.100***
		(0.000)	(0.000)	(0.002)	(0.000)	(0.000)
TSelectivity*Sentiment				0.019*		
				(0.065)		
TSelectivity*Sentiment*Alpha$_{t-1}$					0.145***	0.146***
					(0.000)	(0.000)
Market Dispersion						0.026***
						(0.000)
Business Cycle						0.027***
						(0.010)
Turnover	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***
	(0.000)	(0.001)	(0.000)	(0.000)	(0.001)	(0.001)
Expense Ratio	-0.015	0.000	-0.017	-0.017	-0.001	-0.002
	(0.259)	(0.983)	(0.196)	(0.195)	(0.950)	(0.866)
log(TNA)	0.297***	0.255***	0.281***	0.283***	0.314***	0.345***

	(0.000)	(0.002)	(0.001)	(0.001)	(0.000)	(0.000)
[log(TNA)]^2	-0.027**	-0.020*	-0.025**	-0.025**	-0.028**	-0.032***
	(0.021)	(0.091)	(0.033)	(0.032)	(0.016)	(0.005)
Log(age)	-0.069***	-0.097***	-0.089***	-0.090***	-0.089***	-0.077***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Adj. R^2	0.008	0.008	0.008	0.008	0.011	0.012

Table 7. Skill versus Luck on the Fund Performance Using Fund Alpha to Measure Performance

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.

Panel A: Proportion of Unskilled and Skilled Funds

	Zero Alpha	**Unskilled**	**Skilled**
Proportion	84.29%	11.30%	4.41%
Ave. # of funds	893	164	89

	Left Tail				**Right Tail**				
Significant level	0.05	0.10	0.15	0.20	0.20	0.15	0.10	0.05	**Sig. level**
Signif. %	4.55%	7.17%	9.23%	11.30%	4.41%	3.47%	2.53%	1.49%	**Signif. %**

# of funds	66	104	134	164	89	70	51	30	**# of funds**
unlucky %	1.24%	2.55%	3.72%	6.10%	3.26%	2.43%	1.64%	0.79%	**lucky %**
# of funds	18	37	54	89	66	49	33	16	**# of funds**
unskilled %	3.31%	4.62%	5.51%	6.40%	1.63%	1.04%	0.89%	0.69%	**skilled %**
# of funds	48	67	80	91	24	21	18	14	**# of funds**
Alpha (% /month)	-0.277	-0.321	-0.340	-0.354	0.826	0.884	0.961	1.081	**Alpha (% /month)**
Alpha Stdv.	1.979	1.985	1.995	2.007	3.434	3.537	3.670	3.530	**Alpha Stdv.**

Panel B: Proportion of Unskilled and Skilled Funds in High Market Sentiment

	Zero Alpha	**Unskilled**	**Skilled**
Proportion	84.84%	10.06%	5.10%
Ave. # of funds	876	142	102

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

Panel C: Proportion of Unskilled and Skilled Funds in Low Market Sentiment

	Zero Alpha	**Unskilled**	**Skilled**

Proportion	83.78%	12.52%	3.70%
Ave. # of funds	910	185	75

	Left Tail				Right Tail				
Sig. level	0.05	0.10	0.15	0.20	0.20	0.15	0.10	0.05	**Sig. level**
Signif. %	5.28%	8.12%	10.35%	12.52%	3.70%	2.86%	2.02%	1.13%	**Signif. %**
# of funds	78	120	153	185	75	58	41	23	**# of funds**
unlucky %	1.35%	2.64%	3.93%	6.10%	3.06%	2.32%	1.53%	0.74%	**lucky %**
# of funds	20	39	58	77	62	47	31	15	**# of funds**
unskilled %	3.93%	5.48%	6.43%	6.03%	0.73%	0.54%	0.49%	0.39%	**skilled %**
# of funds	58	81	95	108	13	11	10	8	**# of funds**
Alpha (% /month)	-0.197	-0.224	-0.236	-0.245	0.814	0.854	0.884	0.939	**Alpha (% /month)**
Alpha Stdv.	1.958	1.959	1.965	1.971	2.579	2.490	2.418	2.380	**Alpha Stdv.**

Table 8. Skill versus Luck on the Fund Performance Using Value-added Fund Alpha to Measure Performance

Fund performance is measured using value-added 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 value-added fund alpha and value-added 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.

Panel A: Proportion of Unskilled and Skilled Funds

	Zero Alpha	Unskilled	Skilled
Proportion	82.20%	10.27%	7.52%
Ave. # of funds	1261	158	115

	Left Tail				Right Tail				
Sig. level	0.05	0.10	0.15	0.20	0.20	0.15	0.10	0.05	**Sig. level**
Signif. %	5.08%	7.42%	9.06%	10.27%	7.52%	6.68%	5.58%	3.73%	**Signif. %**
# of funds	78	114	139	158	115	102	86	57	**# of funds**
unlucky %	3.00%	3.05%	3.09%	3.13%	2.13%	2.24%	2.40%	2.25%	**lucky %**
# of funds	46	47	47	48	33	34	37	35	**# of funds**
unskilled %	2.08%	4.37%	5.96%	7.14%	5.40%	4.44%	3.18%	1.48%	**skilled %**
# of funds	32	67	91	110	83	68	49	23	**# of funds**
Value-added Alpha ($/month)	-3.991	-4.079	-3.674	-3.692	3.434	3.636	3.643	3.683	**Value-added Alpha ($/month)**
Value-added Alpha Stdv.	3.049	3.465	2.652	3.122	2.626	2.765	2.508	2.428	**Value-added Alpha Stdv.**

Panel B: Proportion of Unskilled and Skilled Funds in High Market Sentiment

	Zero Alpha	Unskilled	Skilled
Proportion	77.47%	11.13%	11.40%
Ave. # of funds	1219	175	179

	Left Tail				Right Tail				
Sig. level	0.05	0.10	0.15	0.20	0.20	0.15	0.10	0.05	**Sig. level**
Signif. %	5.54%	8.01%	9.80%	11.13%	11.40%	10.09%	8.47%	5.78%	**Signif. %**
# of funds	87	126	154	175	179	159	133	91	**# of funds**
unlucky %	3.02%	3.00%	3.02%	3.07%	2.80%	2.90%	3.05%	3.06%	**lucky %**

# of funds	47	47	48	48	44	46	48	48	**# of funds**
unskilled %	2.53%	5.01%	6.78%	8.06%	8.60%	7.19%	5.41%	2.71%	**skilled %**
# of funds	40	79	107	127	135	113	85	43	**# of funds**
Value-added Alpha ($/month)	-3.932	-3.874	-3.566	-3.903	3.598	3.847	3.986	4.172	**Value-added Alpha ($/month)**
Value-added Alpha Stdv.	2.916	2.650	2.323	3.612	2.203	2.58	2.37	2.291	**Value-added Alpha Stdv.**

Panel C: Proportion of Unskilled and Skilled Funds in Low Market Sentiment

	Zero Alpha	**Unskilled**	**Skilled**
Proportion	86.87%	9.42%	3.71%
Ave. # of funds	1298	141	55

	Left Tail				**Right Tail**				
Sig. level	0.05	0.10	0.15	0.20	0.20	0.15	0.10	0.05	**Sig. level**
Signif. %	4.63%	6.83%	8.32%	9.42%	3.71%	3.31%	2.74%	1.72%	**Signif. %**
# of funds	69	102	124	141	55	49	41	26	**# of funds**
unlucky %	2.98%	3.09%	3.17%	3.19%	1.47%	1.59%	1.75%	1.45%	**lucky %**
# of funds	45	46	47	48	22	24	26	22	**# of funds**
unskilled %	1.64%	3.74%	5.16%	6.23%	2.24%	1.72%	0.98%	0.27%	**skilled %**
# of funds	25	56	77	93	33	26	15	4	**# of funds**
Value-added Alpha ($/month)	-4.052	-4.284	-3.782	-3.484	3.273	3.421	3.279	3.088	**Value-added Alpha ($/month)**
Value-added Alpha Stdv.	3.199	4.132	2.957	2.558	2.992	2.944	2.614	2.478	**Value-added Alpha Stdv.**

Table 9. Stock Mispricing and Mutual Fund Performance

This table presents the coefficient between fund performance and fund mispricing level, along with the corresponding P-value and regression adjusted R^2, by regressing fund performance on fund level mispricing for each management skill quintile while controlling for past fund performance ($Alpha_{t-1}$), expense ratio, log value of fund age, fund turnover, log value of total net assets (TNA), and squared log value of TNA. Fund performance is estimated using both Fund Alpha and value-added 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 value-added 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.

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

Table 10. The Effect of Fund Capital Inflows and Investor Sentiment on Fund Performance

Notes: This table reports the results of regressing fund alpha on manager's selectivity, investor sentiment, fund $alpha_{t-1}$, and fund capital inflows in previous two months ($Flow_{t-1}$ and $Flow_{t-2}$), 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. This process is repeated by moving the estimation and test period one month at a time. The main independent variables are fund selectivity ($1-R^2_{t-1}$), market sentiment (BW sentiment index, available at Jeffrey Wurgler's website), fund $alpha_{t-1}$, previous fund flows, and their interactive variables. Control variables contain $Alpha_{t-1}$, 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^2 for each regression are also presented. ***, **, * denotes significance at the 1%, 5% or 10% level.

	Fund Alpha				
	[1]	[2]	[3]	[4]	[5]
Intercept	-1.126***	-1.017***	-1.307***	-1.097***	-1.127***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Selectivity			0.405***	0.376***	0.442***
			(0.000)	(0.000)	(0.000)
Sentiment		-0.088***		-0.098***	-0.099***
		(0.000)		(0.000)	(0.000)
$Alpha_{t-1}$	0.325***	0.340***	0.329***	0.329***	0.311***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$Flow_{t-1}$	-0.006**	-0.004	-0.067***	-0.004	0.001
	(0.040)	(0.275)	(0.000)	(0.264)	(0.642)
$Flow_{t-2}$	0.003	0.006*	-0.027***	0.006*	-0.003
	(0.350)	(0.065)	(0.000)	(0.068)	(0.324)

$Flow_{t-1}$*Selectivity			0.397***		
			(0.000)		
$Flow_{t-2}$*Selectivity			0.230***		
			(0.000)		
$Flow_{t-1}$*Sentiment		0.000			
		(0.990)			
$Flow_{t-2}$*Sentiment		-0.002			
		(0.596)			
$Flow_{t-1}$*Selectivity*$Alpha_{t-1}$					0.063***
					(0.000)
$Flow_{t-2}$*Selectivity*$Alpha_{t-1}$					0.075***
					(0.000)
Turnover	0.000***	0.000***	-0.001***	-0.001***	-0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Expense ratio	-0.004***	-0.004***	-0.004***	-0.004***	-0.004***
	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)
Log(TNA)	0.631***	0.597***	0.710***	0.617***	0.628***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$[Log(TNA)]^2$	-0.066***	-0.061***	-0.079***	-0.064***	-0.065***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Log(age)	-0.084***	-0.102***	-0.077***	-0.098***	-0.100***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Adj. R^2	0.009	0.009	0.012	0.010	0.016

Table 11. Fama-MacBeth Regressions of Fund Returns and Alpha on Sentiment Beta

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.

	Excess Return				Alpha			
	Low Skill		High Skill		Low Skill		High Skill	
Intercept	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)
Sentiment Beta	-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)
Expense ratio (%)		0.11		0.25		0.04		0.19*
		(0.992)		(0.577)		(0.977)		(0.064)
Log(Age)		-0.19		0.08		0.02		-0.06
		(0.181)		(0.764)		(0.328)		(0.368)
Turnover (%)		-0.13***		-0.01		0.00		0.00
		(0.012)		(0.525)		(0.776)		(0.980)
Log(TNA)		6.79**		0.22		0.30		0.49
		(0.013)		(0.943)		(0.340)		(0.444)

Table 12. The Effect of Volatility Anomaly and Investor Sentiment on Fund Performance

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^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. The 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 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.

Panel A: FF 5 factor plus momentum model in high market sentiment

	Fund selectivity ($1-R^2_{t-1}$)					
$Alpha_{t-1}$	**Low**	**2**	**3**	**4**	**High**	**All**
Low	-2.28***	-3.59***	-3.50***	-3.94***	-1.66	-3.00***
	(0.005)	(0.002)	(0.008)	(0.005)	(0.363)	(0.003)
2	-2.67***	-1.57*	-3.41***	-2.31**	-0.77	-2.14***
	(<.001)	(0.073)	(<.001)	(0.047)	(0.593)	(0.010)
3	-1.59***	-1.77**	-2.90***	-1.74*	-0.73	-1.74**
	(0.009)	(0.019)	(0.002)	(0.099)	(0.556)	(0.012)
4	-0.84	-0.82	-0.61	-0.20	-0.06	-0.50
	(0.265)	(0.340)	(0.491)	(0.870)	(0.967)	(0.506)
High	-0.41	0.59	1.70	4.54***	6.66***	2.63**
	(0.746)	(0.707)	(0.159)	(0.003)	(0.002)	(0.013)
All	-1.56**	-1.44*	-1.75**	-0.75	0.68	-0.96
	(0.013)	(0.059)	(0.038)	(0.469)	(0.563)	(0.178)

Panel B: FF 5 factor plus momentum model in low market sentiment

$Alpha_{t-1}$	**Low**	**2**	**3**	**4**	**High**	**All**
Low	-1.24**	-0.05	-0.85	-1.09	-2.26	-1.09
	(0.027)	(0.953)	(0.317)	(0.274)	(0.271)	(0.173)
2	-0.56	-0.51	-0.04	-0.01	0.71	-0.09
	(0.244)	(0.311)	(0.943)	(0.990)	(0.566)	(0.874)
3	-0.20	-0.24	-0.50	-0.30	0.96	-0.05
	(0.697)	(0.650)	(0.386)	(0.680)	(0.395)	(0.916)

4	-1.05*	-1.08	0.74	-0.63	2.30*	0.06
	(0.071)	(0.374)	(0.257)	(0.426)	(0.059)	(0.906)
High	-0.34	0.75	0.92	1.96*	1.93	1.04
	(0.629)	(0.341)	(0.277)	(0.081)	(0.247)	(0.142)
All	-0.68*	-0.22	0.06	-0.02	0.75	-0.02
	(0.084)	(0.648)	(0.891)	(0.969)	(0.426)	(0.961)