Summer 2017

Three Essays on Mutual Funds, Fund Management Skills, and Investor Sentiment

Feng Dong
Old Dominion University

THREE ESSAYS ON MUTUAL FUNDS, FUND

MANAGEMENT SKILLS, AND INVESTOR SENTIMENT

by

Feng Dong
B.A. May 2011, Oklahoma City University
M.A. June 2012, The Ohio State University

A Dissertation Submitted to the Faculty of Old Dominion University in Partial Fulfillment of the Requirements for the Degree of

DOCTOR OF PHILOSOPHY

BUSINESS ADMINISTRATION – FINANCE

OLD DOMINION UNIVERSITY
August 2017

Approved by:

John A. Doukas (Director)

Mohammad Najand (Member)

David Selover (Member)

ABSTRACT

THREE ESSAYS ON MUTUAL FUNDS, FUND MANAGEMENT SKILLS, AND INVESTOR SENTIMENT

Feng Dong
Old Dominion University, 2017
Director: Dr. John A. Doukas

The mutual fund research focus has switched from whether average active fund managers have fund management skill to whether a subset of active fund managers have skills that produce investor benefits. In this dissertation we participate into the study stream by investigating the relation between managerial skills possessed by mutual fund managers and fund performance.

Essay 1 focuses on whether investor sentiment affects the performance of skilled mutual fund managers. Stocks during periods of high investor sentiment are more likely to have noise, while during low investor sentiment periods stocks are more likely to trade close to their fundamental values. This implies that skilled fund managers are more likely to benefit fund investors the most during periods of high sentiment when asset prices are noisier and information is costlier. We empirically examine and confirm this intuition. Our results persist after distinguishing between management “skill” and “luck”.

Essay 2 addresses the question that whether skilled fund managers’ value added stock picking ability is associated with investing in firms run by skilled CEOs. We find that the performance of high managerial ability stocks has a strong explanation power on the performance of mutual funds with skilled managers. Our results suggest that fund managers’ ability to find and invest in firms with skilled CEOs is an essential element of their stock picking ability, and it can enhance the fund future performance significantly.

Essay 3 questions whether skill exists among European mutual fund industry, and if so, what factors can influence the validity and profitability of the skill. This research presents evidence that managerial skill exists in the European mutual fund industry. Furthermore, the relation remains positive and significant after controlling for investor sentiment and market dispersion. Additionally, we find a strong mediating effect of country characteristics on the relation between fund selectivity and fund performance.

Overall, this dissertation investigates the efficiency of fund manager's skills under different market states, finds the essential elements of fund manager's stock picking skills, and explores the research to other countries. Given the vital role of mutual fund industry to the financial markets, the findings of this dissertation show important values for further academic research and industry implications.

I dedicate my dissertation work to my family and many of my friends, especially to my loving wife, Qian Ma, who has supported me through the whole process. I also dedicate this dissertation to the help of many faculty and staff in Strome College of business, especially Andrew Cohen and Katrina Davenport. I will always appreciate all my classmates, Bader Almuhtadi, Son Dang, and Trung Nguyen, for being with me throughout the entire doctorate program. I also dedicate this work and give special thanks to my dog, Heimi, for cheering me up whenever I feel exhausted.

ACKNOWLEDGMENTS

I would like to express my deepest gratitude to my dissertation chair, Dr. John Doukas, for all his excellent guidance, caring, and patience, and I would never have been able to finish my dissertation without his support. I would also like to thank Dr. Mohammad Najand and Dr. David Selover for their valuable feedback and tremendous encouragement.

TABLE OF CONTENTS

Page

LIST OF TABLES

LIST OF FIGURES

INTRODUCTION

Mutual funds have become an increasingly important investment instrument and attract a large amount of capital, from individual investors to the financial markets. By the end of 2014, the total value of the assets managed by mutual funds was more than 31 trillion US dollars, which reflected a 20% growth rate from 2007. The mutual fund industry has been studies by finance and economics scholars for a long time and the research focus has switched from whether average active fund managers have fund management skill to whether a subset of active fund managers have skills that produce investor benefits. In this dissertation we participate into the study stream by investigating the relation between managerial skills possessed by mutual fund managers and fund performance.

Essay 1 focuses on whether investor sentiment affects the performance of skilled mutual fund managers. The price of stocks may differ from their fundamental value due to random noise. In this case, stocks during periods of high investor sentiment are more likely to have noise, while during low investor sentiment periods stocks are more likely to trade close to their fundamental values, i.e., have less noise. This implies that skilled fund managers with high insight and analytical ability are more likely to benefit fund investors the most during periods of high sentiment when asset prices are noisier and information is costlier. We empirically examine and confirm this intuition. Our results persist after distinguishing between management “skill” and “luck”.

Essay 2 addresses the question that whether skilled fund managers’ value added stock picking ability is associated with investing in firms run by skilled CEOs, using the latter as the identification strategy. We find that the performance of stocks from firms with skilled CEOs has a strong explanation power on the performance of actively-managed mutual funds with skilled fund managers. More importantly, this positive relationship only exists in mutual funds with high skill managers. Our results suggest that fund managers’ ability to find and invest in firms with skilled CEOs is an essential element of their stock picking ability, and it can enhance the fund future performance significantly.

In Essay 3 we explore the question and whether skill exists among European mutual fund industry, and if so, whether the validity and profitability of fund managerial skills are affected by investor sentiment, market dispersion, and country characteristics. Using a sample of 2,947 actively managed, domestic equity mutual funds from 11 European countries, this research presents evidence that the positive relation between fund selectivity and fund performance exists in the European mutual fund industry. Furthermore, the relation remains positive and significant after controlling for investor sentiment and market dispersion. In addition, we investigate the mediating effect of country characteristics on the relation between fund selectivity and fund performance, and find that managers’ selectivity ability is more valuable for funds in countries with high economic development, strong legal strength, small but highly liquid equity markets, and young mutual fund industries.

CHAPTER 1

INVESTOR SENTIMENT AND MUTUAL FUND PERFORMANCE

ABSTRACT

Do fund managers' stock trades add value during periods of heightened investor sentiment, a natural setting to detect skill, when asset prices are noisier, short-selling is limited and information is costlier? Our results reveal that fund managers with the highest (lowest) skill create (experience) $7.71 ($5.64) million of added value (loss) during high sentiment periods, but only $3.74 million for the entire sample period while they incur a value loss of $0.18 ($30.32) million in low sentiment periods. We also find that skilled fund managers' investments are associated with undervalued stocks. Our results persist after distinguishing between management "skill" and "luck".

INTRODUCTION

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

Does investor sentiment affect the performance of skilled mutual fund managers? While investor sentiment has been held largely responsible for the dramatic rises and falls in financial asset prices during the last two decades, its impact on actively managed mutual funds' performance remains unknown. We address this question by examining whether variations in fund profitability can be explained by variations in investor sentiment, since sentiment affects the amount of noise trading as noted by Miller (1997), which, in turn, makes it difficult to carry out profitable trades, as discussed in Black (1986). Since fund managers trade on stocks, their capacity to add value is examined during periods of heightened optimistic investor sentiment, as an "acid" test of skill, when markets are noisier and it is more difficult to identify profitable stocks.

A large body of the literature, motivated by the question of whether fund managers create value, arrives at the conclusion that actively managed funds underperform passively managed funds. Using fund holdings' deviation from the benchmark portfolio to measure active management, the more recent literature shows that active management has a positive relationship with fund performance (Brands, Brown, and Gallagher, 2005; Kacperczyk, Sialm, and Zheng, 2005; Cremers and Petajisto, 2009; and Cremers, Ferreira, Matos, and Starks, 2015). This superior fund management performance is often attributed to management skills possessed by active fund managers such as stock-picking and market-timing talents.

On the other hand, while previous work has assumed that management skill is fixed, only a few studies have touched upon the question of whether active fund managers' skill varies with time. However, as with skills of other people, fund managers' management skill is developed with experience and the efficiency of the skill to generate profits for their clients should be highly affected by the state of financial markets and economic conditions, which are changing with time. In addition, studies addressing the question of whether a fund manager's skill varies with time continue to assume that market participants are rational, an assumption that has been challenged by many behavioral finance studies in recent years (DeBondt and Thaler, 1985; Shiller and Pound, 1989; Barber and Odean, 2001; and Barberis and Thaler, 2003). Furthermore, as explained by Black (1986), noise traders' participation in the market, which can be triggered by optimistic or pessimistic beliefs, will force asset prices to deviate from their fundamental values making it difficult to produce risk adjusted excess-returns. Additionally, noise traders' participation varies with time and could be related to the state of investor sentiment. Since investor sentiment has been shown to influence noise trader's investment behavior and by way of asset prices (Hirshleifer and Shumway, 2003; Dowling and Lucey, 2005; Edmans, Garcia, and Norli, 2007; Kaplanski and Levy, 2010; and Bialkowski, Etebari, and Wisniewski, 2012), fund performance could be also affected by the state of investor sentiment. In addition, there are reasons to believe that noise trader's activity is not symmetric across optimistic and pessimistic sentiment periods, but will be more prevalent during optimistic ones. For instance, Grinblatt and Keloharju (2001) and Lamont and Thaler (2003) report that unsophisticated investors are more likely to enter the stock market during prosperous and investor exuberant periods. Therefore, the above arguments could have implications about the performance of fund managers across time. Specifically, if skilled fund managers trade more on (private) information about the true value of financial assets under management, in contrast to their low skill counterparts, they are expected to deliver more value during high sentiment periods when financial asset prices are noisier than in low sentiment periods when financial markets are not crowded by unsophisticated (noisy) investors. In sum, previous findings raise the important question of whether fund managers' performance is affected by investor sentiment, a natural setting to detect if fund managers possess skill, when noise trading activity is prevalent. Surprisingly, this question has not yet been the focus of empirical investigation, and the aim of our analysis in this study is to address this issue using two different measures of fund skill and performance, controlling for the influence of economic business cycles and fund flows.

In contrast to the previous literature that examines whether fund managers try to exploit investor sentiment by deploying sentiment-based (timing) strategies in order to attract capital flows (Massa and Yadav, 2015) or whether funds tilt their portfolios toward better performing stocks when they buy (sell) stocks that are highly sensitive to market sentiment, measured by sentiment betas, preceding an increase (decrease) in investor sentiment (Cullen, Gasbarro, Le, and Monroe, 2013), we treat sentiment as a market condition, not as a risk factor where skilled managers actively time investor sentiment by modifying fund strategies based on their sentiment prediction.[1] While our evidence is consistent with the previous literature showing that skilled fund managers outperform their low skill peers, we mainly focus on whether fund managers' stock-selectivity skill is more profitable during high than low sentiment periods when noise trading is more prevalent and impactful on asset prices, due to short selling limitations (Shleifer and Vishny, 1997), in an attempt to determine the power of fund management skill. The practical implication of this analysis, is to aid investors to make more efficient fund investment decisions, especially when markets are populated by noise traders. 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 their average and low-skilled counterparts. When we treat sentiment as risk factor, we find that sentiment-based (timing) strategies are associated only with low skilled fund managers realizing significant risk-adjusted fund losses.

Another interesting question, which has received a little attention in the literature (e.g. Baks, Metrick, and Wachter, 2001) is what percentage of the active fund managers' skill is consistently associated with higher excess risk-adjusted returns in different states of investor sentiment. The answer to this question, which is addressed in this study, is very important

[1] 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.

because more and more capital is flowing from individual investors to professional investment managers.

To examine these two questions, we employ two different management skill and fund performance measures over the 1990–2014 period. We first use the Amihud and Goyenko (2013) selectivity skill, which does not require the fund portfolio holdings (i.e., as the one by Daniel et al., 1998), and condition the tests of the relationship between fund selectivity and performance on different states of investor sentiment. The results of these tests consistent with our hypothesis demonstrate that fund managers with superior skills generate significantly high risk-adjusted returns during high sentiment periods. While high investor sentiment tends to harm the average mutual fund performance, low skilled fund managers incur substantial losses.

Second, following Berk and van Binsbergen (2015), we reexamine the validity of our original results by using their measures of 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)) and management skill (i.e., skill ratio) and find consistently that investor 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 and even create value in high sentiment periods if they are endowed with superior management skill. Specifically, fund managers with the highest skill create \$7.71 million of added value during high sentiment periods which exceeds the average realized fund gains (\$3.74 million), while they incur a small value loss of \$0.18 million in low sentiment periods.[2] However, fund managers with the lowest skill experience a values loss of \$5.64 million during high sentiment periods which is far lower

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

than the average realized fund gains ($3.74 million), while they incur a substantial value loss of $30.32 million in low sentiment periods.

We also examine whether the superior performance of skilled fund managers in high sentiment periods comes through investing in undervalued stocks. Cross-sectional analysis on the relation between fund performance and stock mispricing, using a set of 11 market anomalies to identify overpriced stocks (Stambaugh, Yu, and Yuan, 2012), reveals a negative relation between fund performance and skilled fund management indicating that skilled fund managers' investments are associated with undervalued stocks.

We then follow Barras, Scaillet, and Wermers (2010) and conduct a lucky bias analysis that allows us to determine if significant fund performance (*alpha*s) is due to luck alone, and not management skill, for the whole sample during high and low sentiment periods. The results show that, even though the percentage of skilled fund managers decreases considerably after controlling for lucky bias, a portion (around 2%, i.e., under the 5% significant level) of fund managers do possess skill capable of delivering significant *alpha*s during high sentiment periods. Our findings also hold when we control for the effects of net capital flows and volatility anomaly. In addition, when using the FEARS index (Da, Engelberg, and Gao, 2015) and the credit market sentiment index, as an alternative sentiment measures, these new results are qualitatively similar with our main findings. Jointly, the evidence that skilled managers generate high *alpha*s in high sentiment periods suggests that they can create value for fund investors when markets are populated by noisy investors (signals).

The rest of the paper is organized as follows. Section II describes the related literature and hypothesis development. Section III gives the data and empirical methodology. Section IV shows the results, along with a discussion of the results. Section V presents the robustness check. Section VI concludes.

RELATED LITERATURE AND HYPOTHESIS DEVELOPMENT

Malkiel (1995) found that equity mutual funds have underperformed the benchmark portfolio using both gross fund returns and net fund returns, and he suggests that investors should choose low-expense index funds rather than active funds. Gruber (1996) shows that compared with different indices, the average active mutual fund has a negative performance. In addition, Daniel, Grinblatt, Titman, and Wermers (1997), who employed a characteristics-based benchmark, claim that the average active fund can beat the benchmark, but by a very small amount. However, other studies document that even though active funds on average cannot beat the market benchmark, some of the active fund managers do have skills and achieve a superior performance (Brands et al., 2005; Kacperczyk et al., 2005; Cremers and Petajisto, 2009; and Cremers et al., 2015).

Empirical studies show that skilled managers do add value for their clients by selecting valuable stocks (Gruber, 1996; Carhart, 1997; Daniel et al., 1997; and Zheng, 1999), and that leads to the conclusion that fund managers' skill in identifying high-performance stocks is coming from their superior insight and analytical ability. Kacperczyk, Van Nieuwerburgh, and Veldkamp (2011) show that the skill comes from the managers' ability to anticipate micro- and macro-fundamentals. In addition, the previous literature shows that a fund attains superior performance if its manager focuses on the assets that s/he has specialized knowledge of. For example, Kacperczyk et al. (2005) found that funds focusing on some specific industries have better performance than the ones holding more diversified portfolios. Cohen, Frazzini, and Malloy (2007) showed that if fund managers and corporate board members have a close connection via shared education networks, fund managers prefer to place larger bets on those firms that such corporate board members serve and find that those funds perform significantly better on these holdings relative to their non-connected holdings. Kacperczyk and Seru (2007) reported that changing portfolio allocation based on public information decreases fund performance, which supports the argument that fund manager skill is coming from private information rather than public information.

While the most of this literature has focused on the stock-picking ability of fund managers, the findings on managers' market-timing ability are ambiguous. Jiang, Yao, and Yu (2007) employed a single-index model using measures of market timing based on mutual fund holdings, and they found that, on average, active fund managers have a positive market-timing ability. 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. Reibnitz (2013), for example, shows that the market environment impacts on the effectiveness of active strategies, and highly skilled managers can produce superior returns in times of high cross-sectional dispersion in stock returns. Some studies have focused on the relationship between fund performance and the business cycle and report that active funds, on average, have a better performance in recessions than in expansions (Kacperczyk, Van Nieuwerburgh, and Veldkamp 2014, 2016).

Unlike previous studies, we argue that the activities of investors are not consistently rational and, thus, fund profitability can be affected by investor sentiment. 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 capital asset pricing model (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 skilled fund managers to realize significant high *alphas*. Taken together, these arguments lead us to expect that fund managers with high selectivity skill will outperform their low selectivity skill counterparts in high and low sentiment periods.

Second, fund performance can be influenced by investor sentiment 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 outperforming (underperforming) the market benchmark in the near future. Antoniou, Doukas, and Subrahmanyam (2013) find a strong connection between sentiment and momentum. They argue that during high sentiment periods, information signals that oppose the direction of sentiment travels slowly due to investors' cognitive dissonance, and they show that the momentum strategy works only during optimistic (high sentiment) periods. In addition, due to short-sale constraints, mutual fund managers are more likely to bet on positive information. While stocks tend to be overvalued due to the momentum effect during high sentiment periods, stock prices will drift away from their intrinsic values and sophisticated fund managers should generate superior returns by taking advantage of this drift from true value during high sentiment times. That is, active fund managers with superior insight and analytical skill are expected not only to protect a fund's performance from this price to value drift, but also produce a higher fund *alpha* in high investor sentiment periods when noise investor participation in the market is high. On the other hand, their inability to generate high *alpha*s during low sentiment periods when asset prices are less noisy and near fundamental values may suggest that their superior insight and analytical skill is most relevant during high sentiment and noisy periods. Unlike previous studies, the novelty of this investigation is to shed light on whether fund managers' performance varies across different states of investor sentiment and particularly whether fund investors benefit the most from their selectivity skill especially during high sentiment periods when market signals are noisy.

DATA AND EMPIRICAL METHODOLOGY

Data and Sample Selection

Unlike most previous studies, which use the CRSP Survivor-Bias-Free Mutual Fund Database, we use the Bloomberg Fund Dataset, which is originally built for institutional investors in 1993 and is widely used in the finance industry nowadays. The dataset receives pricing and performance information from the fund management companies, administrators, and trustees directly, in the form of a feed or, more commonly, via automated email distribution channels with the entities. The exchange traded information comes directly from the exchange on which the mutual fund is listed. In addition, if one data point cannot pass the volatility threshold, which varies for each mutual fund based upon its past accepted volatility and the market in which the entity trades or prices, the data point will be rejected. These features, make Bloomberg fund data reliable for academic studies and not suffering from the standard sample bias. Our data sample period covers 24 years from January 1990 to December 2014. We use 24-month time windows to estimate selectivity and past fund *alpha*s, so the data were collected from December 1987. We collected monthly raw returns for each fund if the fund had full return data for the 24-month estimation period. We also collected fund-level control variables that may be associated with the fund's performance: turnover, which is the minimum of aggregated sales or aggregated purchases of securities divided by the total net assets of the fund, age, 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 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 Reibnitz (2013), 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 Reibnitz, 2013) is presented in Appendix I.

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.[3] 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.

TABLE 1.1

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. 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
R^2_{t-1}	0.883	0.922	0.219	0.991

The main sentiment measures used in this paper is the Baker and Wurgler (2006) sentiment index (BW)[4] and the University of Michigan sentiment index (UM)[5]. The BW index has been used widely in the finance literature and is constructed using six proxies of investors' propensity to invest in stocks: trading volume (total NYSE turnover); the premium for dividend paying stocks; the closed-end fund discount; the number and first-day returns of IPOs; and the equity share in new issues. The BW index data are collected 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

[3] 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.

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

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

defined as a high (low) investor sentiment month. The UM index is another sentiment index measured outside of the financial market and used widely in finance studies. The results are consistent with those using BW sentiment index. Furthermore, our findings are also supported by using two alternative sentiment measures: credit market sentiment index and the Financial and Economic Attitudes Revealed by Search (FEARS) index, as reported in the robustness tests.

Empirical Methodology

Fund Management Selectivity and Alpha Measures

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

$$Selectivity = 1 - R^2 = \frac{RMSE^2}{Total\,Variance} = \frac{RMSE^2}{Systematic\ Risk^2 + RMSE^2} \tag{1}$$

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 Eq. (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 (Daniel et al. 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 (2002) 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.

BvanB Fund Management Added Value and BvanB Alpha Measures

As our second fund management skill measure, we use the method of Berk and van Binsbergen (2015), who deduce fund management skill based on the extra value added to the fund (i.e., the mean of the product of the gross abnormal return and fund size at the beginning of the period) divided by its standard error, measured over the period December 2002 to December 2014. As discussed in Berk and Green (2002), even the gross *alpha* is not a suitable performance measure. Mutual funds share the same investment mechanism, and a value measure, rather than a return measure, is more appropriate approach to measure fund performance. To measure fund performance, the gross abnormal return has to be 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.[6] 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 available to investors at that time. The benchmark should have two characteristics: the return of the benchmark should be known to investors and the benchmark can be traded. Unfortunately, the benchmarks used in factor models do not meet these criteria. Therefore, Berk and van Binsbergen (2015) suggest to use the set of passively managed index funds offered by Vanguard as the alternative investment opportunity set, and they define the fund benchmark as the closet portfolio formed by those index funds.

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

Next, as shown in Eq. (2), we regress the excess returns of each fund *f* on the 11 Vanguard index fund orthogonal bases for the whole sample period from December 2002 to December 2014, using 24-month rolling window regression and moving forward 1 month each time.

---

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

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

The performance measure we use is the abnormal capital inflow a fund experiences in the test month (denoted BvanB *alpha*), which is calculated as the fund's gross abnormal return (real raw return over its expected return) multiplied by the TNA of the fund at the beginning of the current month. The fund expected return is the product of multiplying the coefficients between each Vanguard index fund orthogonal basis and fund excess return from the 24-month preceding estimation period by the real numbers of each Vanguard index fund orthogonal basis in the current month.

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

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

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 (Reibnitz, 2013; and Kacperczyk et al., 2014, 2016). Active opportunity in the market, captured by cross-sectional dispersion in stock returns, as argued by Reibnitz (2013), could influence fund performance by the variation in the arrival of firm-specific information. During a high market-dispersion period, the market price is affected more by firm-specific information than market conditions. If 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 Reibnitz (2013), we calculate market dispersion for each month. This is estimated as the average diversion between the equally weighted average return on S&P 500 constituents in each month and the return of each S&P 500 constituent in the same month. The stock return dispersion in month t (MD_t) is calculated as follows:

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

where n is the number of S&P 500 constituents in month t, $R_{i,t}$ is the return of each constituent i in this month, and $R_{m,t}$ is the equally weighted average return of all S&P 500 constituents in month t. We collected the list of S&P 500 constituents and their monthly returns from Bloomberg database. Bloomberg reports these historical data since February 1990, so our dataset for market dispersion ranges from February 1990 to December 2014.

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. (2014) 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 (Wermers, 2000; Glode, 2011; Kosowski, 2011; and Reibnitz, 2013). Thus, one can argue that the effect of investor sentiment on mutual fund performance is caused by the correlation between the cyclical variation in sentiment and economic cycles. For that reason, we use the Chicago Fed National Activity Index 3 month average (CFNAI MA3), following Kacperczyk et al. (2014), to capture the effects of the business cycle on fund performance.[7] The CFNAI is a coincident indicator of national economic activity comprising 85 existing macroeconomic time series.

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:

$$F_{\gamma}=\pi_0 * \gamma/2 \tag{5}$$

[7] 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.

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:

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

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

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

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

where λ^* is a sufficiently high P-value threshold (we use λ^* = 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.

EMPIRICAL RESULTS

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-$R^2_{t\text{-}1}$) and sort all the funds into five quintiles based on their selectivity ranking. Within each quintile, we sort funds into five portfolios based on their prior one month's *alpha* ($alpha_{t\text{-}1}$), which is the intercept of the rolling regressions. This procedure produces 25 (5x5) portfolios with different selectivity and fund *alpha*s, 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-$R^2_{t\text{-}1}$) and past performance ($alpha_{t\text{-}1}$), 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 mainly whether high selectivity is associated with higher (lower) fund performance during high (low) states of sentiment. We address this question by examining whether variations in fund performance can be explained by variations in sentiment in line with the underlying hypothesis of this paper predicting that fund managers endowed with high selectivity skill should be associated with higher risk-adjusted excess returns during high investor sentiment periods. We used the BW sentiment index to measure the investor sentiment and separate our sample into high/low sentiment subgroups based on the investor sentiment, and each subgroup contains 150 months' observations. Then we repeat the previous analysis for high and low sentiment periods by sorting funds in each month by fund selectivity and past performance and present in Table 2 the annualized *alpha* and P-value for each portfolio for high (Panel B) and low (Panel C) sentiment periods.

TABLE 1.2

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

This table presents the portfolio fund *alpha*, annualized, using monthly returns, from January1990 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	4	3	2	High	All	High-Low
Low	-1.75***	-2.04***	-1.84**	-1.97**	-2.06	-1.93***	-0.20
	(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	0.87**
	(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	0.65
	(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	1.05**
	(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	2.24***
	(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	0.92**
	(0.001)	(0.012)	(0.110)	(0.754)	(0.426)	(0.166)	(0.019)
High-Low	0.19	0.62	0.91*	2.03***	2.57**	1.27**	
	(0.606)	(0.191)	(0.061)	(0.001)	(0.004)	(0.004)	

Panel B: Portfolio fund alpha during high market sentiment

$Alpha_{t-1}$	Low	4	3	2	High	All	High-Low
Low	-2.38***	-3.71***	-2.97**	-2.68*	-1.45	-2.65***	0.47
	(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*	1.18*
	(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*	0.61
	(0.021)	(0.050)	(0.018)	(0.508)	(0.982)	(0.095)	(0.340)
4	-0.95	-1.19	-0.73	-0.01	0.36	-0.50	0.64
	(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	3.39***
	(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	1.25**
	(0.003)	(0.014)	(0.033)	(0.721)	(0.508)	(0.147)	(0.046)
High-Low	0.17	1.03	1.23	2.48***	3.03**	1.59**	
	(0.787)	(0.209)	(0.117)	(0.009)	(0.015)	(0.017)	

Panel C: Portfolio fund alpha during low market sentiment

$Alpha_{t-1}$	Low	4	3	2	High	All	High-Low
Low	-1.14**	-0.33	-0.90	-1.38	-2.35	-1.21	-0.68
	(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	0.47
	(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	0.44
	(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	1.32*
	(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	0.65
	(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	0.45
	(0.026)	(0.321)	(0.457)	(0.331)	(0.851)	(0.341)	(0.312)
High-Low	0.41	0.54	0.70	1.39*	1.68	0.94*	
	(0.312)	(0.232)	(0.208)	(0.055)	(0.196)	(0.070)	

Consistent with the findings of Amihud and Goyenko (2013), the results in Panel A of Table 2 show that greater fund selectivity, as measured by (1-$R^2_{t\text{-}1}$), 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. The highest annualized *alpha* is 3.05% (P = 0.023) for the fund portfolio with the highest selectivity and the best past performance. On average, around 8% of mutual funds outperform the benchmark significantly every month, which confirms that a relatively small fraction of some active funds does have selectivity skill that creates value for fund investors.

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 and significant in all *alpha* quintiles except for the low *alpha* quintile. For the whole sample, the high selectivity fund portfolio outperforms the low selectivity fund portfolio by 0.92% (P = 0.019). For the highest and second-highest *alpha* quintiles, the hypothetical portfolio yields an annualized *alpha* of 2.24% (P = 0.003) and 1.05% (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-$R^2_{t\text{-}1}$), 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 outperform the market benchmark and their low selectivity counterparts only during high sentiment periods. When investor sentiment level is high, as shown in Panel B, the highest past *alpha* quintile managers with the highest skill and second-highest skill produce

4.82% (P = 0.020) and 2.70% (P = 0.073) higher excess returns than the market benchmark, respectively. In sum, about 8% of active funds outperform the market benchmark during high sentiment periods. The hypothetical strategy of a long position in the high selectivity fund portfolio and a short position in the low selectivity fund portfolio, rightmost "High-Low," yields 1.25% (P = 0.046) extra return than the market. However, the results in Panel C indicate that during low sentiment periods none of the fund portfolios can beat the market benchmark significantly. 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* only during high sentiment periods. Funds with higher selectivity skill deliver higher risk-adjusted returns in high sentiment periods. During low sentiment periods, they fail to outperform the market when asset prices are commonly believed to trade near their intrinsic values due to the absence of noise traders.[8] Jointly, these results suggest that fund selectivity skill is far more valuable to fund investors when there is high sentiment and price signals are noisy due to the greater presence of investor hype in the market.

BvanB Fund Management Added Value Performance Results

In this section, we report results based on the Berk and van Binsbergen (2015) fund selectivity measure, i.e., BvanB fund skill. As noted earlier, this fund skill measure allows us to deduce the fund selectivity based on the extra value added to the fund (i.e., the mean of the product of the gross abnormal return and fund size at the beginning of the period divided by its

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

standard error) measured over the 24-month estimation period. The advantage of this metric it that it permits to gauge the success of a fund manager based on the added value of an investment opportunity (i.e., the net present value (NPV) of an investment) rather than the return a fund earns (i.e., the internal rate of return (IRR)), as bigger funds could generate more value even if they have lower *alpha*s. To form the portfolios, we first rank all funds within each month based on their prior month's BvanB fund skill, as described in Eq. (3), and sort them into five quintiles. Within each quintile, we sort funds into five portfolios based on their previous performance, i.e., the BvanB fund $alpha_{t\text{-}1}$. The BvanB fund $alpha_{t\text{-}1}$ of each fund in each month is the product of fund $alpha_{t\text{-}1}$ and fund inflation-adjusted TNA at the beginning of the last month in the 24-month estimation period, while fund $alpha_{t\text{-}1}$ is obtained by regressing each fund's monthly excess returns on the 11 Vanguard index funds orthogonal bases. Then, for the following month, we calculate the average monthly excess return for each portfolio, and we regress the test period average portfolio returns on the alternative investment opportunity market benchmark. For each portfolio, we present the portfolio BvanB fund *alpha*, which is the product of the intercept from the above regression and the average inflation-adjusted TNA of all funds within the portfolio at the beginning of the current month, and present these results in Table 3.[9] This procedure produces 25 (5x5) portfolios with a different BvanB fund skill and BvanB fund $alpha_{t\text{-}1}$, and each portfolio contains 4% of the total mutual funds within the same month.

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

TABLE 1.3
Portfolio BvanB Fund *Alpha*, Based on Sorting on BvanB Fund Skill and Lagged BvanB Fund *Alpha*

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

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

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

Panel B: Portfolio BvanB fund alpha during high market sentiment

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

Panel C: Portfolio BvanB fund alpha during low market sentiment

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

Consistent with our previous findings (Table 2), the results in Table 3 reveal that funds with superior management skills, as measured by BvanB fund skill, have better performance. The results of Panel A in the row "All" show that fund portfolio performance (BvanB fund *alpha*) decreases as we move from the high BvanB fund skill portfolio to the low BvanB fund skill portfolio, i.e., greater fund skill produces higher BvanB fund *alpha*s. The highest annualized BvanB fund alpha is 3.74 (P = 0.337) for the fund portfolio with the highest BvanB fund skill and the best past performance. While highly skilled fund managers with high past performance, Q5, do not outperform the benchmark significantly every month, the low-skilled ones realize significant losses of -4.80 (P = 0.048). The reason is that highly skilled managers, due to their high past performance, experience high capital inflow and—under the pressure to invest the extra capital received from investors—they are forced to make suboptimal investment decisions due to limited optimal investment opportunities in the market. This, in return, lowers the profitability of their skills.

The results for the hypothetical portfolio of a long position in a high BvanB fund skill portfolio and a short position in a low BvanB fund skill portfolio for each lagged *alpha* quintile, presented in the rightmost column of Panel A under "High-Low," indicate that the return from this strategy is positive and significant in all *alpha* quintiles. For example, the high BvanB skill fund portfolio outperforms the low BvanB skill fund portfolio by 5.30 (P = 0.044). For the highest and second-highest BvanB *alpha* quintiles, the hypothetical portfolio yields an annualized *alpha* of 4.27 (P = 0.061) and 3.33 (P = 0.053), respectively. On average, the high BvanB fund skill portfolio adds 5.30 million dollars more capital than the low BvanB fund skill portfolio every month (P = 0.044). Overall, these results confirm that funds with the best past performance are associated with the most highly skilled managers.

The results in Panels B and C of Table 3 demonstrate that highly skilled managers do better during high sentiment periods than in low sentiment periods. In high sentiment periods (Panel B), consistent with the previous evidence, the highest annualized BvanB fund *alpha* is \$7.71 million (P = 0.337) for the fund portfolio with the highest BvanB fund skill and the best past performance. Even though this number is not significant, it is much higher than the entire sample period, i.e., \$3.74 million (P = 0.337). This indicates that the performance of skilled fund managers is pronounced when financial markets are populated with noisy investors. This means that managers with the highest skill produce \$7.71 million added value during high sentiment periods, but only \$3.74 million for the entire period. That is, they can double a fund's added value in high sentiment periods even though they experience an increased inflow of capital because of their superior past performance. While highly skilled managers with high past performance, Q5, do not significantly outperform the benchmark every month, the low-skilled ones do not realize losses (P = 0.656) in high sentiment periods. This performance difference shows that highly skilled fund managers do considerably better in high sentiment periods (Panel B) than in the entire sample period (Panel A). The reason that highly skilled managers with high past performance do not realize statistically significant superior performance in high sentiment periods is because they experience high capital inflows and under the pressure to invest the extra capital received from investors it lowers the profitability of their skill due to limited optimal investment opportunities.

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

Fund Portfolio Performance and Stock Market Dispersion

As discussed in section III, equity market dispersion and the state of the economy can influence the performance of skilled fund managers. To examine their impact on fund portfolio performance, we first repeat our portfolio sorting analysis simply based on the market dispersion. Similar to our sentiment analysis, we divide our sample into high and low market-dispersion periods based on the median number of the market-dispersion index, calculated for January 1990 to December 2014. The reported results in Table 4 for the high (Panel A) and low (Panel B) market-dispersion periods indicate that skilled fund managers outperform their unskilled peers and the market benchmark, especially during high market-dispersion periods. This pattern, which is consistent with our high sentiment results, suggests that skilled fund managers can add value to fund investor portfolios when the market is subject to considerable uncertainty and more difficult than normal times for fund investors to interpret financial price signals.

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 5, reveal that more funds with high selectivity skill realize positive risk-adjusted excess returns in economic expansions, which is 1.58% (P = 0.041), than in economic recessions, which is 0.27% (P = 0.786). In addition, the performance dispersion between the highest selectivity fund and the lowest selectivity fund is more pronounced in economic recessions, i.e., 2.71% (P = 0.008), than in expansions, i.e., 2.41% (P = 0.021), which is consistent with the previous literature (Kacperczyk et al., 2011) that found that skilled active funds provide an insurance mechanism against recessions.

Jointly, these results—while in line with previous studies—also demonstrate that skilled fund managers have superior performance during states of high equity market dispersion and economic expansion. However, one can argue that it is essentially market dispersion or business cycle, rather than investor sentiment that determines the fund performance difference between the high and low sentiment states. In response to this argument, as shown later in Tables 7 and 8, we account for the stock market dispersion and business cycle effects in our analysis and find

TABLE 1.4

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

The table presents the portfolio *alpha*, annualized, using monthly returns, in high and low market sentiment 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. The process repeats by moving the estimation and test period one month at a time. Last, we regress the test period average portfolio returns on the FFC model. For each portfolio cell we present portfolio *alpha*, which is the intercept from the above regression, and the P-value. The sample period of the test months is from February 1990 to December 2014 (299 months). Panel A shows the results of high market dispersion group and Panel B shows the results of low market dispersion group. For each portfolio, we present the portfolio *alpha*, annualized, using monthly returns and the P-value. ***, **, * denotes significance at the 1%, 5% or 10% level.

Panel A: During high market dispersion

	Fund selectivity ($1-R^2_{t-1}$)						
***Alpha*$_{t-1}$**	**Low**	**4**	**3**	**2**	**High**	**All**	**High-Low**
Low	-2.31***	-3.59***	-1.87	-1.92	-1.39	-2.22**	0.38
	(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	1.73**
	(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	0.57
	(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	1.68**
	(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	3.28***
	(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	1.53**
	(0.001)	(0.009)	(0.196)	(0.913)	(0.382)	(0.272)	(0.020)
High-Low	0.06	0.57	0.88	2.61**	2.88*	1.41*	
	(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**	**4**	**3**	**2**	**High**	**All**	**High-Low**
Low	-1.39***	-0.68	-1.60***	-2.10***	-2.92**	-1.74***	-0.78
	(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*	0.03
	(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	0.88**
	(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	0.47
	(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	1.38
	(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	0.40
	(0.058)	(0.547)	(0.413)	(0.518)	(0.786)	(0.399)	(0.312)
High-Low	0.51	0.93**	1.02***	1.83***	2.62**	1.38***	
	(0.168)	(0.018)	(0.004)	(0.002)	(0.011)	(0.001)	

TABLE 1.5

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

The table presents the portfolio *alpha*, annualized, using monthly returns, in high and low market sentiment periods. If the Fed National Activity Index 3 month average (CFNAI MA3) for the test month (t) is higher (lower) than the median number of all monthly CFNAI MA3 index numbers, we define this month as economic expansion (recession) month. Portfolios are formed by sorting all funds in each month into quintiles by lagged R^2 and then by fund *alpha*. Both are obtained from the 24-month estimation period (t-24 to t-1) by regressing each fund's monthly excess returns (over the T-bill rate) on the factors from FFC model. Then, for the following month (t), we calculate the average monthly excess returns for each fund portfolio. The process repeats by moving the estimation and test period one month at a time. Last, we regress the test period average portfolio returns on the FFC model. For each portfolio cell, we present portfolio $alpha_{t-1}$, 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**	**4**	**3**	**2**	**High**	**All**	**High-Low**
Low	-1.52**	-3.27***	-2.55**	-4.09***	-3.12*	-2.92***	-0.88
	(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**	0.35
	(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	0.47
	(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	0.92
	(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**	2.41**
	(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	0.64
	(0.032)	(0.028)	(0.086)	(0.439)	(0.760)	(0.152)	(0.176)
High-Low	0.37	1.56**	1.82***	3.82***	3.60***	2.24***	
	(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**	**4**	**3**	**2**	**High**	**All**	**High-Low**
Low	-1.89***	-1.04	-0.68	-0.30	-0.62	-0.90	0.61
	(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	1.55**
	(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	0.95
	(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	1.44*
	(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	2.71***
	(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	1.46**
	(0.003)	(0.175)	(0.866)	(0.549)	(0.193)	(0.891)	(0.013)
High-Low	0.06	-0.17	-0.01	0.92	2.11*	0.58	
	(0.914)	(0.789)	(0.982)	(0.185)	(0.094)	(0.301)	

that funds with skilled managers continue to have a significantly better performance during high investor sentiment periods.

Fund Management Selectivity Performance Regression Results

So far we have analyzed the linear relationship between active fund performance, selectivity, and sentiment, but we want to make sure that high selectivity funds do outperform low selectivity funds using different factor models. To do so, we first formed two fund portfolios based on selectivity. In each month from January 1990 to December 2014, we formed five equally weighted fund portfolios based on their selectivity, which is estimated using rolling regressions of the FFC model with the 24-month time windows. These portfolios are rebalanced every month. Within these five portfolios, we only focus on the highest selectivity fund portfolio and the lowest selectivity fund portfolio. Within each month, we calculate the equally weighted average return for both portfolios and this provides a time series of monthly performance estimates for each portfolio. We then calculate the risk-adjusted returns of high and low selectivity fund portfolios using the CAPM model, FF3 model, and FFC model. The results are shown in Table 6, 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".

TABLE 1.6
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. The process repeats by moving the estimation and test period one month at a time. The independent variables contain market excess return (RM-Rf), return difference of small and big size stocks (SMB), return difference of high and low book-to-market ratio stocks (HML), and return difference of past winner and loser stocks (MOM). The regression results of a hypothetical strategy of buying high skilled fund portfolio and selling low skilled fund portfolio are also reported in this table. The sample period of the test months is from January 1990 to December 2014 (300 months). The P-value and adjusted R^2 for each regression are also presented. ***, **, * denotes significance at the 1%, 5% or 10% level.

	CAPM			3 Factor Model			4 Factor Model		
	High Skill	**Low Skill**	**High - Low**	**High Skill**	**Low Skill**	**High - Low**	**High Skill**	**Low Skill**	**High - Low**
Intercept	0.14*	-0.12***	0.13***	0.06	-0.13***	0.09***	0.05	-0.11***	0.08**
	(0.082)	(<.001)	(<.001)	(0.304)	(<.001)	(0.004)	(0.433)	(<.001)	(0.031)
RM-Rf	0.89***	1.02***	-0.06***	0.88***	1.02***	-0.07***	0.88***	1.01***	-0.06***
	(<.001)	(<.001)	(<.001)	(<.001)	(<.001)	(<.001)	(<.001)	(<.001)	(<.001)
SMB				0.27***	0.05***	0.11***	0.27***	0.05***	0.11***
				(<.001)	(<.001)	(<.001)	(<.001)	(<.001)	(<.001)
HML				0.19***	0.02**	0.09***	0.20***	0.02	0.09***
				(<.001)	(0.052)	(<.001)	(<.001)	(0.164)	(<.001)
MOM							0.02	-0.02***	0.02***
							(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

Unsurprisingly, the low-skilled fund portfolio delivers significant negative fund *alpha*s in all three models. On the other hand, the highly skilled fund portfolio *alpha* is statistically insignificant in the FF3 and FFC models, which indicates that, on average, fund managers do not outperform these multifactor benchmarks. This is consistent with our earlier results demonstrating that only a small fraction of (skilled) fund managers (i.e., with the highest selectivity (Q5 quintile)), as shown in Tables 2 and 3. The high selectivity fund portfolio outperforms its low selectivity counterpart significantly in all three models. The hypothetical strategy of a long position in the high selectivity fund portfolio and a short position in the low selectivity delivers 1.56% ($P < 0.001$), 1.08% ($P = 0.004$), and 0.96% ($P = 0.031$) annualized *alpha*s in each of the three models, respectively.[10] After adjusting for other risk factors, the

[10] The annualized *alpha* is calculated as the monthly *alpha* (regression intercept) times 12.

spread in *alpha* between the high selectivity fund portfolio and the low selectivity fund portfolio decreases but continuous to remain significant. In addition, the significant negative relationship (-0.02, P < 0.001) between the return of the low selectivity portfolio and the momentum risk factor (MOM) indicates that low-skill managers require a lower return to invest in high-momentum-related stocks, suggesting that low-skilled managers behave like the average investor who chases momentum market anomalies by paying high prices. This confirms that they lack analytic and investment selection skills. However, this is not the case for the skilled fund managers. The insignificant coefficient between skilled fund 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,[11] while we also control for the market dispersion and business cycle effects.[12] To test whether the profitability of fund management skill (selectivity) is higher during high sentiment periods, we estimate the following model:

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

where $Alpha_{f,t}$ is calculated as the difference in the fund's excess return in each month (over the T-bill rate) and the expected excess return in the same month. The expected excess return for each fund in each month is calculated by multiplying the FFC model factor loadings from the 24-

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

[12] 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.

month preceding estimation period by the factors in the current month. The estimation and test periods are rolling one month at a time. Selectivity for each fund is calculated as 1-R^2_{t-1}, and R^2 is estimated using the FFC model with the 24-month estimation period. Control variables in the regression include $alpha_{t-1}$, expense ratio, log value of fund age, fund turnover, log of fund total net assets, and squared log value of the fund total net assets. $Alpha_{t-1}$ is the intercept from the FFC model using a 24-month estimation period, and as in Amihud and Goyenko (2013), we report results with and without $alpha_{t-1}$ as control variables. Based on the central prediction of our hypothesis that active funds run by managers with high selectivity skills are expected to produce a better performance during high investor sentiment periods, when market signals are likely to be more noisy, than in low sentiment periods, we hypothesize that $\beta_1 > 0$, $\beta_2 < 0$, and $\beta_3 > 0$.

Consistent with the univariate results presented earlier and the above prediction, the results in Table 7 Panel A show that selectivity in all regression specifications, in accordance with the evidence in Amihud and Goyenko (2013), is positive and significantly correlated with fund *alpha* ($P < 0.001$) while sentiment is negative and significantly related to fund *alpha* ($P < 0.001$), suggesting that, on average, fund performance is adversely affected when the market is plagued by noisy price signals as is most likely to be the case during high sentiment periods. However, the coefficient of the interaction variable between fund management selectivity and sentiment, *Selectivity*Sentiment*, is highly significant (0.23, $P = 0.005$ without $alpha_{t-1}$, and 0.21, $P = 0.009$ with $alpha_{t-1}$) and positively related to fund performance. Consistent with our hypothesis, this result demonstrates that during high sentiment periods, fund managers endowed with high selectivity deliver high *alpha*s. This implies that high selectivity managers possess the ability to identify and make superior investments to the benefit of fund investors during high sentiment periods when the market is populated by noisy investors.

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

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

The new results, reported in Table 7 Panel B, have a similar pattern with those presented previously in Panel A. The logistic-transformed selectivity measure is positively correlated with fund *alpha* ($P < 0.001$). As in Panel A, *Sentiment* retains its negative relation with fund *alpha* (-0.04, $P = 0.088$ without $alpha_{t-1}$, and -0.11, $P < 0.001$ with $alpha_{t-1}$) and the coefficient of the new interaction variable, *TSelectivity*Sentiment*, and fund performance is still positive and statistically significant (0.04, $P < 0.001$ without $alpha_{t-1}$, and 0.02, $P = 0.016$ with $alpha_{t-1}$). Jointly, the results in Table 7 demonstrate a positive and significant relationship between fund performance and fund management skill in high sentiment periods. A funds' risk-adjusted excess return is higher for funds run by high selectivity managers, as measured by $1\text{-}R^2_{t-1}$, in high sentiment periods.

TABLE 1.7

The Effect of Fund Selectivity and Investor Sentiment on Fund Performance

This table reports the results of regressing fund *alpha* on manager's selectivity and investor sentiment controlling for other fund characteristics. The dependent variable is fund *alpha*, which is the difference between fund excess return (over T-bill rate) in month t and the expected excess return of the same month. The expected excess return for each fund in month t is calculated by multiplying the FFC model factor loadings from the 24 month estimation period (t-24 to t-1) by the FFC model factors in current month. The process repeats by moving the estimation and test period one month at a time. The main independent variables are fund selectivity ($1-R^2_{t-1}$), market sentiment (BW sentiment index, available at Jeffrey Wurgler's website) and selectivity*sentiment, which is the product of selectivity and market sentiment. 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* (FFC model)									
Intercept	-0.83***	-0.55***	-0.67***	-0.37***	-0.80***	-0.47***	-0.80***	-0.47***	-1.11***	-0.77***
	(<.001)	(<.001)	(<.001)	(0.009)	(<.001)	(0.001)	(<.001)	(0.001)	(<.001)	(<.001)
Selectivity	0.67***	0.41***			0.71***	0.48***	0.68***	0.45***	0.71***	0.47***
	(<.001)	(<.001)			(<.001)	(<.001)	(<.001)	(<.001)	(<.001)	(<.001)
Sentiment			-0.02**	-0.09***	-0.05***	-0.11***	-0.08***	-0.13***	-0.14***	-0.19***
			(0.014)	(<.001)	(<.001)	(<.001)	(<.001)	(<.001)	(<.001)	(<.001)
Selectivity*Sentiment							0.21***	0.17**	0.23***	0.21***
							(0.009)	(0.032)	(0.005)	(0.009)
Market Dispersion									0.03***	0.03***
									(<.001)	(<.001)
Business Cycle									0.02	0.05***
									(0.122)	(<.001)
***Alpha*$_{t-1}$**		0.30***		0.33***		0.32***		0.32***		0.32***
		(<.001)		(<.001)		(<.001)		(<.001)		(<.001)
Turnover	-3.90E-04***	-2.70E-04***	-3.40E-04***	-2.20E-04***	-3.90E-04***	-2.60E-04***	-3.80E-04***	-2.50E-04***	-3.80E-04***	-2.50E-04***
	(<.001)	(<.001)	(<.001)	(0.001)	(<.001)	(<.001)	(<.001)	(<.001)	(<.001)	(<.001)
Expense Ratio	-4.80E-04	-7.10E-04	-6.80E-05	-4.50E-04	-4.60E-04	-7.00E-04	-4.70E-04	-7.00E-04	-6.00E-04	-8.40E-04
	(0.633)	(0.475)	(0.946)	(0.655)	(0.643)	(0.485)	(0.640)	(0.483)	(0.550)	(0.400)
log(TNA)	0.46***	0.30***	0.44***	0.26***	0.46***	0.28***	0.46***	0.28***	0.50***	0.31***
	(<.001)	(<.001)	(<.001)	(0.002)	(<.001)	(0.001)	(<.001)	(0.001)	(<.001)	(<.001)
$[\log(TNA)]^2$	-0.04***	-0.03**	-0.04***	-0.02*	-0.04***	-0.02**	-0.04***	-0.02**	-0.05***	-0.03**
	(<.001)	(0.024)	(0.002)	(0.092)	(<.001)	(0.039)	(<.001)	(0.038)	(<.001)	(0.016)
Log(age)	-0.11***	-0.07***	-0.13***	-0.10***	-0.12***	-0.09***	-0.13***	-0.09***	-0.11***	-0.08***
	(<.001)	(<.001)	(<.001)	(<.001)	(<.001)	(<.001)	(<.001)	(<.001)	(<.001)	(<.001)
Adj. R^2	0.002	0.008	0.001	0.008	0.003	0.008	0.003	0.008	0.003	0.009

Panel B: Using logistic transformed selectivity to measure skill

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

BvanB Fund Management Added Value Regression Results

We re-examine the effect of fund management skill and its interaction with sentiment on fund performance using the BvanB fund skill (ratio) and performance (*alpha*) measures, as defined in section III.B.2, to estimate the following model:

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

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

Basically, the regression results in Table 8 show that BvanB fund skill significantly contributes to the fund performance, BvanB fund *alpha*, in all regressions. Consistent with the previous results, we find mostly a significant negative relationship between investor sentiment and fund performance, but a positive and significant association between the interaction variable, BvanB *skill*Sentiment*, and fund performance. This indicates that, on average, sentiment harms the overall fund performance, but this does not hold for skilled fund managers. In fact, skilled fund managers during high sentiment periods experience a significantly better performance than in low sentiment periods due to their ability to identify and make superior investments in high sentiment periods when the market is populated by noisy investors. The positive and significant relationship between fund past performance, BvanB $Alpha_{t-1}$, and fund performance, BvanB fund *alpha*, reveals a strong persistent performance of skilled managers. These results, as shown in the far-right regressions, remain robust after controlling for the state of the economy and stock market dispersion. 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.[13]

[13] Avramov and Wermers (2006) argue that some macroeconomic variables can effect fund managers skill and influence fund performance. To address this question, 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. The results are consistent with our findings and can be found in Appendix V.

TABLE 1.8

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

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

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

Stock Mispricing and Mutual Fund Performance

We next examine whether the superior performance of skilled fund managers in high sentiment periods, when the views of more optimistic (noisy) investors are more pronounced and short selling is limited, comes through investing in undervalued stocks. To address this issue, we perform a cross-sectional analysis on the relation between fund performance and stock mispricing, using a set of 11 market anomalies to identify overpriced stocks (Stambaugh et al., 2012), and expect a negative relation to emerge for skilled fund managers.[14,15] 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. Then, we calculate the value weighted average of stock mispricing (*VW_MISP*) for all stocks within each fund.[16] 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. Then, we break our sample into 5 quintiles based on fund management skill, and estimate the relation between fund performance and stock mispricing for each quintile.

Table 9 presents the coefficient between fund performance and stock mispricing by regressing fund performance, for the 5 management skill quintiles, on fund level mispricing, while controlling for past fund performance ($Alpha_{t-1}$), 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

[14] 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.
[15] The data are available through Yu Yuan's website http://www.saif.sjtu.edu.cn/facultylist/yyuan/.
[16] Fund holdings information is manually collected through Bloomberg Portfolio Analysis Database.

performance and stock mispricing is more pronounced for funds with lower management skills. For example, when soring funds based on fund selectivity, the coefficient between fund performance and *VW_MISP* (*EW_MISP*) in the lowest skill fund quintile is -0.111 (-0.111) and significant, while the coefficient in the highest skill fund quintile is -0.069 (-0.101). This pattern is even stronger when sorting funds into quintiles using BvanB fund skill measure. In sum, consistent with our previous evidence, the results of this cross-sectional analysis demonstrate that skilled fund managers' investments are associated with undervalued stocks.

TABLE 1.9

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 BvanB Fund *Alpha* measures. Fund level mispricing is measured using two ways: (i) VW_MISP is the market value weighted average of stock mispricing for all stocks within each fund and (ii) EW_MISP is the equal weighted average of stock mispricing for all stocks within each fund. Stock mispricing value is introduced by Stambaugh et al. (2012) and the data are available through Yu Yuan's website (http://www.saif.sjtu.edu.cn/facultylist/yyuan/). Furthermore, the sample is split into quintiles based on their selectivity or BvanB skill, which are estimated using 24 month regression from October 2011 to September 2013. Fund holdings information are manually collected through Bloomberg Portfolio Analysis Database, and the data are collected for the last quarter of 2013. ***, **, * denotes significance at the 1%, 5% or 10% level.

	Fund *Alpha* (FFC model)					
	All	**Lowest Selectivity Skill**	**4**	**3**	**2**	**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
	BvanB Fund *Alpha*					
	All	**Lowest BvanB Skill**	**2**	**3**	**4**	**Highest BvanB 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

Lucky Bias Analysis

Selectivity Performance Lucky Bias Results

One criticism about the superior performance of skilled fund managers, particularly in high sentiment periods, as documented above, is that it could be attributed to luck rather than to the differing abilities of managers. To address this concern, we followed Barras et al. (2010) and conduct a lucky bias analysis for the entire sample and replicated the analysis for both high and low sentiment periods. As shown in Table 10 Panel A, using fund risk-adjusted excess return (fund *alpha*) as a performance measure, with a 20% significance level, 4.41% of the total funds beat the market significantly, and within the 4.41% funds, only 1.63% of fund managers are truly skilled. This number decreases to 0.69% when we move to the 5% significance level. This indicates that some of the mutual fund managers do possess management skill, but the proportion is very low.

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

TABLE 1.10

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	84.29%	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	0.150	0.2	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.**

BvanB Fund Added Value Lucky Bias Results

When we replicate the lucky bias analysis, using the BvanB fund *alpha*, as the performance measure, which captures the extra capital funds absorb from the financial market, we find similar results to those reported in Table 9. Specifically, as shown in Table 11 Panel A, on average, 7.52% (3.73%) of funds outperform the market benchmark at the 20% (5%) significance level. The proportion drops to 5.40% (1.48%) at a 20% (5%) significance level after we remove the lucky funds. Once again, during high sentiment periods, the percentage of skilled funds goes up to 8.60% (2.71%), but in low sentiment periods, the percentage decreases to 2.24% (0.27%).

There are three points to take away from the lucky bias analysis. First, even though the average mutual manager cannot beat the market, a small fraction of fund managers (about 0.69%, using selectivity ($1-R^2$) measure and 1.48%, using BvanB value added skill measure, both of which are below the 5% significance level) with high stock-picking skills delivers persistently superior performance than their low skill peers. Second, skilled fund managers' skills are more profitable during high sentiment periods when the market is crowded with noise traders. During low sentiment periods when stocks are more likely to be traded near their intrinsic values, only a smaller portion of skilled managers produces significantly positive fund *alpha*s 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 *alpha*s. 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.

TABLE 1.11

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

Fund performance is measured using BvanB fund *alpha* based on 11 Vanguard Index Fund orthogonal bases. Panel A shows the estimated proportions of zero-alpha, unskilled, and skilled funds in the funds population with the monthly average fund number in each category based on Barras, Scaillet, and Wermers (2010)'s methodology of false discoveries. It also exhibits the proportion of funds in the right and left tails using four significant levels (0.05, 0.10, 0.15, and 0.20). The significant proportion in left tail is divided into unlucky and unskilled categories, and the significant proportion in right tail is divided into lucky and skilled categories. Average BvanB fund *alpha* and BvanB fund *alpha* standard division are also reported. Panel B and C show the results of false discoveries analysis during high and low sentiment periods. The sentiment index data are available at Jeffrey Wurgler's website. If the BW sentiment index for the test month (t) is higher (lower) than the median number of all monthly BW sentiment index numbers, we define this month as high (low) market sentiment month.

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**
BvanB Alpha ($/month)	-3.991	-4.079	-3.674	-3.692	3.434	3.636	3.643	3.683	**BvanB Alpha ($/month)**
BvanB Alpha Stdv.	3.049	3.465	2.652	3.122	2.626	2.765	2.508	2.428	**BvanB 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**
BvanB Alpha ($/month)	-3.932	-3.874	-3.566	-3.903	3.598	3.847	3.986	4.172	**BvanB Alpha ($/month)**
BvanB Alpha Stdv.	2.916	2.650	2.323	3.612	2.203	2.58	2.37	2.291	**BvanB 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**
BvanB Alpha ($/month)	-4.052	-4.284	-3.782	-3.484	3.273	3.421	3.279	3.088	**BvanB Alpha ($/month)**
BvanB Alpha Stdv.	3.199	4.132	2.957	2.558	2.992	2.944	2.614	2.478	**BvanB Alpha Stdv.**

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 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 luck of skill.[17]

ROBUSTNESS CHECK

Sentiment beta analysis

Several studies have focused on the profitability of mutual funds' sentiment timing strategy. For example, Grinblatt, Titman, and Wermers (1995) and Carhart (1997) have showed that mutual funds tend to follow momentum. Recently, Massa and Yadav (2015) reported that mutual funds employ portfolio strategies based on market sentiment. Specifically, they find that low sentiment *beta* funds outperform the high sentiment beta funds, even after controlling for standard risk factors and fund characteristics. This result is attributed to the sentiment-contrarian strategy rather than the sentiment-momentum strategy, which, in turn, attracts significant investor flows in comparison to the sentiment-catering strategy. In a more recent study, Chen, Han, and Pan (2016) examine whether exposure to sentiment risk can explain the cross-sectional variation in hedge fund returns and find that funds with a sentiment beta in the top decile subsequently outperform those in the bottom decile by 0.67% per month on a risk-adjusted basis.

[17] These results are available upon request.

Therefore, they argue that some hedge funds can time sentiment and contribute to fund performance by increasing their exposure to a sentiment factor when the factor premium is high.

In this section, we investigate the impact of fund sentiment timing strategy on fund performance. As discussed earlier, in this study, we view investor sentiment as an economic condition, rather than as a risk factor to be exploited by its timing and argue that skilled managers invest in assets based on their superior analytic ability and private information about an asset's true value, rather than timing sentiment. This leads us to expect that the fund sentiment timing strategy is more likely to be associated with low rather than high skilled fund managers. To examine whether high (low) skilled fund managers are less (more) likely to time investor sentiment, we perform Fama–MacBeth regressions of high- and low-skilled fund portfolio returns and *alpha*s 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:

$$R_{p,t} - R_{f,t} = \alpha + \beta_1(RM - Rf)_t + \beta_2 SMB_t + \beta_3 HML_t + \beta_4 MOM_t + \beta_5 Sentiment_t \qquad (12)$$

where $R_{p,t}$ is the portfolio p's return in month t; $R_{f,t}$ is the risk-free rate in month t; $RM\text{-}Rf$ 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 (12) with a 24-month moving window. Then, we run the following cross-sectional regression of portfolio return (13) (and portfolio *alpha* obtained from FFC model (14)) on the sentiment beta, with or without fund-level control variables:

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

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

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

TABLE 1.12
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 *alpha*s, 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 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.

Fund Capital Flow Analysis

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

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

$$Net\ capital\ flow_{f,t} = TNA_{f,t} - (1 + R_{f,t}) * TNA_{f,t-1} \tag{15}$$

where $TNA_{f,t}$ is the total net assets of fund *f* in month *t*, and $R_{f,t}$ is the fund return in month *t*. To test whether and how fund performance is affected by capital flows, we include net capital flows 2 months ago (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 Eq. (9).

Consistent with our prediction, the results in Table 13 column 1 show a negative and significant correlation between the previous month capital inflows ($Flow_{t-1}$) with fund *alpha*, which reveals that extra capital inflows create more pressure on fund managers to invest resulting in lower fund *alpha*. The insignificant coefficients between the interaction *Flow*Sentiment* in t-1 and t-2 and fund *alpha* (P = 0.97 and P = 0.62 for capital inflows, respectively), as shown in column 2, indicate that the negative relationship between the previous months' capital inflows and fund performance is not sentiment-related. The coefficients between the interaction *Flow*Selectivity* in t-1 and t-2 and fund *alpha*, as reported in column 3, are positive and significant (P < 0.001), suggesting that managers with high selectivity skill direct extra capital inflows in better investment opportunities delivering high alpha than their unskilled fund counterparts. Last, the positive and significant relationship between the interaction *Selectivity*Sentiment* and fund *alpha* (0.166, P = 0.04), in column 4, shows that even after controlling for the negative effect of capital inflows from previous months, high selectivity managers still possess the ability to make significantly superior investments during high sentiment periods to the benefit fund investors.

TABLE 1.13

The Effect of Fund Flow and Investor Sentiment on Fund Performance

This table reports the regression results of following model:

$$\begin{aligned} Alpha_{i,t} = \alpha + \beta_1 Selectivity_{i,t} + \beta_2 Sentiment_t + \beta_3 Selectivity_{i,t} * Sentiment_t \\ + \beta_4 Flow_{i,t-1} + \beta_5 Flow_{i,t-2} + \beta_6 (Flow_{i,t-1} * Selectivity_{i,t}) + \beta_7 (Flow_{i,t-2} * Selectivity_{i,t}) \\ + \beta_8 (Flow_{i,t-1} * Sentiment_t) + \beta_9 (Flow_{i,t-2} * Sentiment_t) + \gamma \sum Controls_{i,t} + \varepsilon_t \end{aligned}$$

The dependent variable is fund *alpha*. The main independent variables are fund selectivity ($1\text{-}R^2_{t-1}$), market sentiment (BW sentiment index, available at Jeffrey Wurgler's website), selectivity*Sentiment, which is the product of selectivity and market sentiment, $flow_{i,p+q}$, which is the net capital flow of fund i in month t+q (q equals -2, -1); and the product of fund flow with sentiment and the product of fund flow with selectivity. Control variables contain $Alpha_{t-1}$, 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)
Intercept	-1.07***	-0.97***	-1.25***	-1.04***
	(<.001)	(<.001)	(<.001)	(<.001)
Selectivity			0.42***	0.36***
			(<.001)	(<.001)
Sentiment		-0.09***		-0.12***
		(<.001)		(<.001)
Selectivity*Sentiment				0.17**
				(0.040)
$Flow_{t-1}$	-6.40E-05**	-3.71E-05	-6.71E-04***	-3.33E-05
	(0.040)	(0.270)	(<.001)	(0.290)
$Flow_{t-2}$	2.95E-05	6.25E-05*	-2.69E-04***	5.97E-05*
	(0.350)	(0.070)	(<.001)	(0.060)
$Flow_{t-1}$*Selectivity			3.97E-03***	
			(<.001)	
$Flow_{t-2}$*Selectivity			2.30E-03***	
			(<.001)	
$Flow_{t-1}$*Sentiment		1.69E-06		
		(0.970)		
$Flow_{t-2}$*Sentiment		-2.15E-05		
		(0.620)		
$Alpha_{t-1}$	0.32***	0.34***	0.33***	0.33***
	(<.001)	(<.001)	(<.001)	(<.001)
Turnover	0.00***	0.00***	-4.84E-04***	-4.68E-04***
	(<.001)	(<.001)	(<.001)	(<.001)
Expense ratio	-0.04***	-0.04***	-0.05***	-0.05***
	(<.001)	(0.010)	(<.001)	(<.001)
Log(TNA)	0.63***	0.60***	0.71***	0.62***
	(<.001)	(<.001)	(<.001)	(<.001)
$[Log(TNA)]^2$	-0.07***	-0.06***	-0.08***	-0.07***
	(<.001)	(<.001)	(<.001)	(<.001)
Log(age)	-0.09***	-0.10***	-0.08***	-0.10***
	(<.001)	(<.001)	(<.001)	(<.001)
Adj. R^2	0.009	0.009	0.012	0.010

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, 2014; Novy-Marx, 2014; and Fama and French, 2015). Volatility anomaly basically means that the low volatility stock portfolio outperforms the high volatility stock portfolio significantly, and Jordan and Riley (2014) show that it has a large impact on mutual fund returns, which could create a significant bias when measuring managers' skills. Even though the volatility anomaly has been questioned by other studies, we assess the sensitivity of our results by controlling for the effect of the volatility anomaly.[18]

In accord with section IV.A, we sort all the funds in each month into 25 (5x5) portfolios with a different selectivity (1-$R^2_{t\text{-}1}$) 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 obtain the abnormal risk-adjusted excess return, i.e., portfolio fund *alpha*. Table 14 presents the annualized fund *alpha* and P-value for each portfolio in high (Panel A) and low (Panel B) sentiment periods, respectively.

[18] 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 *alpha*s and increases the portfolio Sharpe ratio significantly.

TABLE 1.14

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 repeats by moving the estimation and test period one month at a time. Last we regress the test period average portfolio returns on Fama-French 5 factor plus momentum model. For each portfolio cell, we present portfolio *alpha*, which is the intercept from the above regression, and the P-value. The sample period of the test months is from January 1990 to December 2014 (300 months). Panel A shows the results of high market sentiment group and Panel B shows the results of low market sentiment group. For each portfolio, we present the portfolio *alpha*, annualized, using monthly returns and the P-value. ***, **, * denotes significance at the 1%, 5% or 10% level.

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

	Fund selectivity ($1-R^2_{t-1}$)						
***Alpha*$_{t-1}$**	**Low**	**4**	**3**	**2**	**High**	**All**	**High-Low**
Low	-2.28***	-3.59***	-3.50***	-3.94***	-1.66	-3.00***	0.32
	(0.005)	(0.002)	(0.008)	(0.005)	(0.363)	(0.003)	(0.742)
2	-2.67***	-1.57*	-3.41***	-2.31**	-0.77	-2.14***	0.97
	(<.001)	(0.073)	(<.001)	(0.047)	(0.593)	(0.010)	(0.149)
3	-1.59***	-1.77**	-2.90***	-1.74*	-0.73	-1.74**	0.33
	(0.009)	(0.019)	(0.002)	(0.099)	(0.556)	(0.012)	(0.621)
4	-0.84	-0.82	-0.61	-0.20	-0.06	-0.50	0.38
	(0.265)	(0.340)	(0.491)	(0.870)	(0.967)	(0.506)	(0.628)
High	-0.41	0.59	1.70	4.54***	6.66***	2.63**	3.56***
	(0.746)	(0.707)	(0.159)	(0.003)	(0.002)	(0.013)	(0.005)
All	-1.56**	-1.44*	-1.75**	-0.75	0.68	-0.96	1.10*
	(0.013)	(0.059)	(0.038)	(0.469)	(0.563)	(0.178)	(0.087)
High-Low	0.89	1.97**	2.62***	4.06***	4.05***	2.72***	
	(0.154)	(0.018)	(<.001)	(<.001)	(0.002)	(<.001)	

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

	Fund selectivity ($1-R^2_{t-1}$)						
***Alpha*$_{t-1}$**	**Low**	**4**	**3**	**2**	**High**	**All**	**High-Low**
Low	-1.24**	-0.05	-0.85	-1.09	-2.26	-1.09	-0.60
	(0.027)	(0.953)	(0.317)	(0.274)	(0.271)	(0.173)	(0.540)
2	-0.56	-0.51	-0.04	-0.01	0.71	-0.09	0.57
	(0.244)	(0.311)	(0.943)	(0.990)	(0.566)	(0.874)	(0.309)
3	-0.20	-0.24	-0.50	-0.30	0.96	-0.05	0.44
	(0.697)	(0.650)	(0.386)	(0.680)	(0.395)	(0.916)	(0.472)
4	-1.05*	-1.08	0.74	-0.63	2.30*	0.06	1.63**
	(0.071)	(0.374)	(0.257)	(0.426)	(0.059)	(0.906)	(0.020)
High	-0.34	0.75	0.92	1.96*	1.93	1.04	1.11
	(0.629)	(0.341)	(0.277)	(0.081)	(0.247)	(0.142)	(0.215)
All	-0.68*	-0.22	0.06	-0.02	0.75	-0.02	0.64
	(0.084)	(0.648)	(0.891)	(0.969)	(0.426)	(0.961)	(0.167)
High-Low	0.63	0.62	1.06*	1.75**	2.27*	1.26**	
	(0.137)	(0.187)	(0.055)	(0.016)	(0.088)	(0.016)	

These results continue to show that skilled fund managers' performance is superior during high investor sentiment periods indicating that they are not sensitive volatility anomaly. Consistent with the pattern of our main results, fund portfolio performance (*alpha*), as shown in row "All," decreases from the high selectivity (high $1\text{-}R^2_{t-1}$) portfolio to the low selectivity (low $1\text{-}R^2_{t-1}$) 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. The hypothetical strategy of a long position in the high selectivity fund portfolio and a short position in the low selectivity fund portfolio, rightmost "High-Low," yields 1.10% (P = 0.087) extra return than the market benchmark for the entire sample. However, during low sentiment periods, as shown in Panel B, the fund portfolio with the highest selectivity and the best past performance cannot beat the market benchmark significantly (1.93%, P = 0.247). In addition, the hypothetical strategy fails to significantly outperform the market on average (0.64%, P = 0.167).[19] Taken together, these results provide supplemental evidence indicating that skilled managers produce higher fund *alpha*s during high sentiment periods, and this relationship is not biased by the volatility anomaly.

Alternative Sentiment Measures

We also ran robustness tests using two alternative sentiment measures: credit market sentiment and the Financial and Economic Attitudes Revealed by Search (FEARS) sentiment 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

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

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. Unreported results based on these two sentiment measures are qualitatively consistent with the pattern of our previous findings.[20]

CONCLUSION

In this paper, unlike most of the previous literature that has focused on the question of whether fund managers improve fund performance, we examine whether skilled mutual fund managers deliver greater value (alpha) during high sentiment periods 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 examine this conjecture and find that managers endowed with high fund management skills realize superior fund performance during high investor sentiment periods. Specifically, our result show that fund managers with the highest skill create $7.71 million of added value during high sentiment periods which exceeds the average realized fund gains ($3.74 million), while they incur a small value loss of $0.18 million in low sentiment periods. However, fund managers with the lowest skill experience a values loss of $5.64 million during high

[20] These results are available upon request.

sentiment periods which is far lower than the average realized fund gains ($3.74 million), while they incur a substantial value loss of $30.32 million in low sentiment periods.

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

REFERENCES

Amihud, Y.; and R. Goyenko. "Mutual fund's R^2 as predictor of performance." *Review of Financial Studies* 26.3 (2013): 667-694.

Amromin, G.; and S. A. Sharpe. "Expectations of risk and return among household investors: Are their Sharpe ratios countercyclical?."*Available at SSRN 1327134* (2009).

Antoniou, C.; J. A. Doukas; and A. Subrahmanyam. "Cognitive dissonance, sentiment, and momentum." *Journal of Financial and Quantitative Analysis* 48.01 (2013): 245-275.

Antoniou, C.; J. A. Doukas; and A. Subrahmanyam. "Investor sentiment, beta, and the cost of equity capital." *Management Science* 62.2 (2015): 347-367.

Avramov, D.; and R. Wermers. "Investing in mutual funds when returns are predictable." *Journal of Financial Economics* 81.2 (2006): 339-377.

Baker, M.; and J. Wurgler. "Investor sentiment and the cross-section of stock returns." *The Journal of Finance* 61.4 (2006): 1645-1680.

Baks, K.; A. Metrick; and J. Wachter. "Should investors avoid all actively managed mutual funds? A study in Bayesian performance evaluation." *The Journal of Finance* 56.1 (2001): 45-85.

Barber, B. M.; and T. Odean. "Boys will be boys: Gender, overconfidence, and common stock investment." *Quarterly journal of Economics* (2001): 261-292.

Barberis, N.; and R. Thaler. "A survey of behavioral finance."*Handbook of the Economics of Finance* 1 (2003): 1053-1128.

Barras, L.; O. Scaillet; and R. Wermers. "False discoveries in mutual fund performance: Measuring luck in estimated alphas." *The Journal of Finance* 65.1 (2010): 179-216.

Ben-Rephael, A.; S. Kandel; and A. Wohl. "Measuring investor sentiment with mutual fund flows." *Journal of Financial Economics* 104.2 (2012): 363-382.

Berk, J. B.; and R. C. Green. *Mutual fund flows and performance in rational markets*. No. w9275. National Bureau of Economic Research, 2002.

Berk, J. B.; and J. H. Van Binsbergen. "Measuring skill in the mutual fund industry." *Journal of Financial Economics* 118.1 (2015): 1-20.

Białkowski, J.; A. Etebari; and T. P. Wisniewski. "Fast profits: Investor sentiment and stock returns during Ramadan." *Journal of Banking & Finance* 36.3 (2012): 835-845.

Black, F. "Noise." *The journal of finance* 41.3 (1986): 528-543.

DeBondt, W. F.; and R. Thaler. "Does the stock market overreact?."*The Journal of finance* 40.3 (1985): 793-805.

Brands, S.; S. J. Brown; and D. R. Gallagher. "Portfolio concentration and investment manager performance." *International Review of Finance* 5.3-4 (2005): 149-174.

Carhart, M. M. "On persistence in mutual fund performance." *The Journal of finance* 52.1 (1997): 57-82.

Chen, Y.; B. Han; and J. Pan. "Sentiment Risk, Sentiment Timing, and Hedge Fund Returns." *Sentiment Timing, and Hedge Fund Returns (January 12, 2016)* (2016).

Cohen, L.; A. Frazzini; and C. Malloy. "The small world of investing: Board connections and mutual fund returns." (2007). *National Bureau of Economic Research Cambridge, Mass., USA.*

Cremers, K. M.; and A. Petajisto. "How active is your fund manager? A new measure that predicts performance." *Review of Financial Studies* 22.9 (2009): 3329-3365.

Cremers, M.; M. A. Ferreira; P. P. Matos; and L. T. Starks. "Indexing and active fund management: International evidence." *Journal of Financial Economics* 120.3 (2016): 539-560.

Cullen, G.; D. Gasbarro; K. S. Le; and G. S. Monroe. "Does Selectivity in Mutual Fund Trades Exploit Sentiment Timing?." (2013).

Da, Z., J. Engelberg; and P. Gao. "The sum of all FEARS investor sentiment and asset prices." *Review of Financial Studies* 28.1 (2015): 1-32.

Daniel, K.; M. Grinblatt; S. Titman; and R. Wermers. "Measuring mutual fund performance with characteristic-based benchmarks." *The Journal of finance* 52.3 (1997): 1035-1058.

Daniel, K.; D. Hirshleifer; and A. Subrahmanyam. "Investor psychology and security market under-and overreactions." *the Journal of Finance* 53.6 (1998): 1839-1885.

Dowling, M.; and B. M. Lucey. "Weather, biorhythms, beliefs and stock returns—some preliminary Irish evidence." *International Review of Financial Analysis* 14.3 (2005): 337-355.

Edmans, A.; D. Garcia; and Ø. Norli. "Sports sentiment and stock returns." *The Journal of Finance* 62.4 (2007): 1967-1998.

Elton, E. J.; M. J. Gruber; and C. R. Blake. "An examination of mutual fund timing ability using monthly holdings data." *Review of Finance*16.3 (2012): 619-645.

Fama, E. F.; and K. R. French. "Common risk factors in the returns on stocks and bonds." *Journal of financial economics* 33.1 (1993): 3-56.

Fama, E. F.; and K. R. French. "A five-factor asset pricing model, Fama-Miller Working Paper." (2014).

Glode, V. "Why mutual funds “underperform”." *Journal of Financial Economics* 99.3 (2011): 546-559.

Grinblatt, M.; and M. Keloharju. "How distance, language, and culture influence stockholdings and trades." *The Journal of Finance* 56.3 (2001): 1053-1073.

Grinblatt, M.; S. Titman; and R. Wermers. "Momentum investment strategies, portfolio performance, and herding: A study of mutual fund behavior." *The American economic review* (1995): 1088-1105.

Gruber, M. J. "Another puzzle: The growth in actively managed mutual funds." *The journal of finance* 51.3 (1996): 783-810.

Hirshleifer, D.; and T. Shumway. "Good day sunshine: Stock returns and the weather." *The Journal of Finance* 58.3 (2003): 1009-1032.

Hong, H.; and J. C. Stein. "A unified theory of underreaction, momentum trading, and overreaction in asset markets." *The Journal of Finance* 54.6 (1999): 2143-2184.

Jiang, G. J.; T. Yao; and T. Yu. "Do mutual funds time the market? Evidence from portfolio holdings." *Journal of Financial Economics*86.3 (2007): 724-758.

Jordan, B. D.; and T. B. Riley. "Volatility and mutual fund manager skill." *Journal of Financial Economics* 118.2 (2015): 289-298.

Kacperczyk, M.; S. V. Nieuwerburgh; and L. Veldkamp. "Time-Varying Fund Manager Skill." *The Journal of Finance* 69.4 (2014): 1455-1484.

Kacperczyk, M.; and A. Seru. "Fund manager use of public information: New evidence on managerial skills." *The Journal of Finance* 62.2 (2007): 485-528.

Kacperczyk, M.; C. Sialm; and L. Zheng. "On the industry concentration of actively managed equity mutual funds." *The Journal of Finance* 60.4 (2005): 1983-2011.

Kacperczyk, M.; S. V. Nieuwerburgh; and L. Veldkamp. “Rational attention allocation over the business cycle.” No. w15450. *National Bureau of Economic Research*, 2009.

Kacperczyk, M.; S. V. Nieuwerburgh; and L. Veldkamp. "A rational theory of mutual funds' attention allocation." *Econometrica* 84.2 (2016): 571-626.

Kaplanski, G.; and H. Levy. "Sentiment and stock prices: The case of aviation disasters." *Journal of Financial Economics* 95.2 (2010): 174-201.

Kosowski, R. "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* 1.03 (2011): 607-664.

Lamont, O. A.; and R. H. Thaler. "Anomalies: The law of one price in financial markets." *The Journal of Economic Perspectives* 17.4 (2003): 191-202.

López-Salido, D.; J. C. Stein; and E. Zakrajšek. "Credit-market sentiment and the business cycle." No. w21879. *National Bureau of Economic Research*, 2016.

Malkiel, B. G. "Returns from investing in equity mutual funds 1971 to 1991." *The Journal of finance* 50.2 (1995): 549-572.

Massa, M.; and V. Yadav. "Investor Sentiment and Mutual Fund Strategies." *Journal of Financial and Quantitative Analysis* 50.04 (2015): 699-727.

Miller, E. M. 1977. Risk, Uncertainty, and Divergence of Opinion. Journal of Finance 32:1151–1168.

Moreira, A.; and T. Muir. "Volatility managed portfolios." No. w22208. *National Bureau of Economic Research*, 2016.

Novy-Marx, R. Understanding defensive equity. No. w20591. *National Bureau of Economic Research*, 2014.

Shiller, R. J.; and J. Pound. "Survey evidence on diffusion of interest and information among investors." *Journal of Economic Behavior & Organization* 12.1 (1989): 47-66.

Shleifer, A.; and R. W. Vishny. "The limits of arbitrage." *The Journal of Finance* 52.1 (1997): 35-55.

Stambaugh, R. F.; J. Yu; and Y. Yuan. "The short of it: Investor sentiment and anomalies." *Journal of Financial Economics* 104.2 (2012): 288-302.

Von Reibnitz, A. H. "When Opportunity Knocks: Cross-Sectional Return Dispersion and Active Fund Performance." (2015). *Paper presented at the 26th Australasian Finance and Banking Conference*.

Wermers, R. "Mutual fund performance: An empirical decomposition into stock-picking talent, style, transactions costs, and expenses." *The Journal of Finance* 55.4 (2000): 1655-1703.

Zheng, L. "Is money smart? A study of mutual fund investors' fund selection ability." *The Journal of Finance* 54.3 (1999): 901-933.

APPENDIX 1.I
Data Collection Process Comparison

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

APPENDIX 1.II

Vanguard Index funds

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

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

APPENDIX 1.III

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

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

Panel A: High market sentiment periods

	Fund selectivity ($1-R^2_{t-1}$)						
***Alpha*$_{t-1}$**	**Low**	**4**	**3**	**2**	**High**	**All**	**High-Low**
Low	-2.05***	-4.14***	-2.54*	-2.85*	-2.69	-2.86***	-0.38
	(0.010)	(<.001)	(0.052)	(0.053)	(0.151)	(0.005)	(0.699)
2	-2.01***	-0.67	-1.38	-0.67	0.69	-0.81	1.31**
	(0.003)	(0.436)	(0.151)	(0.564)	(0.585)	(0.291)	(0.041)
3	-0.45	-1.29*	-1.67*	-0.60	0.93	-0.62	0.47
	(0.478)	(0.060)	(0.058)	(0.526)	(0.383)	(0.307)	(0.462)
4	-0.06	-1.48	-0.31	0.46	3.35***	0.40	1.70**
	(0.943)	(0.280)	(0.708)	(0.712)	(0.008)	(0.583)	(0.022)
High	-1.24	-1.15	0.22	4.14***	5.80***	1.56	3.48***
	(0.340)	(0.476)	(0.866)	(0.009)	(0.004)	(0.162)	(0.004)
All	-1.16*	-1.76**	-1.15	0.07	1.58	-0.49	1.30**
	(0.060)	(0.025)	(0.136)	(0.943)	(0.130)	(0.451)	(0.030)
High-Low	0.47	1.51*	1.46*	3.42***	4.27***	2.23***	
	(0.469)	(0.072)	(0.077)	(0.001)	(0.001)	(0.002)	

Panel B: Low market sentiment periods

	Fund selectivity ($1-R^2_{t-1}$)						
***Alpha*$_{t-1}$**	**Low**	**4**	**3**	**2**	**High**	**All**	**High-Low**
Low	-1.24**	-0.53	-1.92**	-2.12**	-2.12	-1.58**	-0.46
	(0.023)	(0.457)	(0.015)	(0.013)	(0.262)	(0.028)	(0.614)
2	-0.85*	-1.46***	-1.28**	-1.03	-0.77	-1.08*	0.02
	(0.055)	(0.004)	(0.032)	(0.219)	(0.548)	(0.070)	(0.967)
3	-1.16***	-0.25	-1.35**	-1.12	-0.27	-0.82	0.41
	(0.009)	(0.634)	(0.035)	(0.154)	(0.825)	(0.117)	(0.498)
4	-2.03***	-1.02*	-0.25	-1.45*	-1.20	-1.19**	0.36
	(<.001)	(0.081)	(0.707)	(0.062)	(0.355)	(0.025)	(0.602)
High	-1.14	-0.15	-0.77	0.07	0.23	-0.35	0.73
	(0.117)	(0.860)	(0.390)	(0.953)	(0.897)	(0.650)	(0.429)
All	-1.29***	-0.68	-1.10**	-1.13*	-0.79	-1.00**	0.23
	(0.001)	(0.122)	(0.030)	(0.081)	(0.436)	(0.041)	(0.644)
High-Low	0.08	0.23	0.61	1.14*	1.21	0.65	
	(0.852)	(0.628)	(0.254)	(0.061)	(0.343)	(0.179)	

APPENDIX 1.IV

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

This table presents the portfolio BvanB fund *alpha*, annualized, using monthly returns (145 months), from December 2002 to December 2014 (Panel A), high sentiment (Panel B), and low sentiment (Panel C) periods, based on the University of Michigan consumer sentiment index (UM sentiment index). If the UM sentiment index for the test month (t) is higher (lower) than the median number of all monthly UM sentiment index numbers, we define this month as high (low) market sentiment month. Portfolios are formed by sorting all funds in each month into quintiles by BvanB fund skill (Eq. 3) and then by BvanB fund $alpha_{t-1}$, and both are described in detail in section III.B.2. For each portfolio cell, we present portfolio BvanB fund *alpha*, which is the portfolio *alpha* times the average TNA of funds within the portfolio at the beginning of current month (t), and the P-value. ***, **, * denotes significance at the 1%, 5% or 10% level.

Panel A: Portfolio BvanB alpha based on alternative investment opportunity

	BvanB fund skill						
$Alpha_{t-1}$	**Low**	**4**	**3**	**2**	**High**	**All**	**High-Low**
Low	-29.64***	-11.21***	-8.13***	-8.32***	-23.35***	-16.13***	3.15
	(<.001)	(<.001)	(<.001)	(<.001)	(<.001)	(<.001)	(0.211)
4	-11.07***	-4.61***	-3.05***	-2.09	-3.86	-4.94***	3.60*
	(0.001)	(0.001)	(0.008)	(0.092)	(0.166)	(0.002)	(0.064)
3	-4.17	-1.87	-0.44	0.28	1.83	-0.87	3.00
	(0.137)	(0.166)	(0.689)	(0.817)	(0.511)	(0.555)	(0.117)
2	0.01	0.84	1.79	2.95**	8.76***	2.87*	4.38**
	(0.998)	(0.550)	(0.115)	(0.023)	(0.001)	(0.064)	(0.026)
High	18.16***	6.79***	7.32***	9.02***	30.39***	14.34***	6.11**
	(<.001)	(<.001)	(<.001)	(<.001)	(<.001)	(<.001)	(0.015)
All	-7.58**	-2.01	-0.50	0.37	2.76	-0.95	5.17**
	(0.027)	(0.159)	(0.668)	(0.775)	(0.337)	(0.548)	(0.018)
High-Low	23.90***	9.00***	7.72***	8.67***	26.87***	15.23***	
	(<.001)	(<.001)	(<.001)	(<.001)	(<.001)	(<.001)	

Panel B: Portfolio BvanB alpha in high market sentiment

$Alpha_{t-1}$	**Low**	**4**	**3**	**2**	**High**	**All**	**High-Low**
Low	-23.81***	-7.87***	-5.51***	-5.93***	-23.37***	-13.30***	0.22
	(<.001)	(0.001)	(0.007)	(0.010)	(<.001)	(<.001)	(0.955)
4	-4.55	-1.45	-0.49	0.55	-1.43	-1.47	1.56
	(0.293)	(0.511)	(0.789)	(0.780)	(0.755)	(0.549)	(0.586)
3	3.80	1.82	2.65	3.27	7.18	3.74	1.69
	(0.375)	(0.403)	(0.149)	(0.114)	(0.103)	(0.131)	(0.530)
2	9.43**	5.24**	5.48***	6.59***	12.96***	7.94***	1.77
	(0.040)	(0.028)	(0.005)	(0.004)	(0.003)	(0.003)	(0.521)
High	30.95***	12.64***	12.61***	13.69***	35.95***	21.17***	2.50
	(<.001)	(<.001)	(<.001)	(<.001)	(<.001)	(<.001)	(0.494)
All	1.59	2.07	2.95	3.64*	6.26	3.62	2.34
	(0.758)	(0.364)	(0.127)	(0.091)	(0.180)	(0.166)	(0.462)
High-Low	27.38***	10.25***	9.06***	9.81***	29.66***	17.23***	
	(<.001)	(<.001)	(<.001)	(<.001)	(<.001)	(<.001)	

Panel C: Portfolio BvanB alpha in low market sentiment

$Alpha_{t-1}$	**Low**	**4**	**3**	**2**	**High**	**All**	**High-Low**
Low	-35.40***	-14.49***	-10.71***	-10.68***	-23.33***	-18.92***	6.04*
	(<.001)	(<.001)	(<.001)	(<.001)	(<.001)	(<.001)	(0.062)
4	-17.50***	-7.73***	-5.58***	-4.70***	-6.26*	-8.35***	5.62**
	(<.001)	(<.001)	(<.001)	(0.002)	(0.051)	(<.001)	(0.035)
3	-12.02***	-5.51***	-3.49***	-2.66**	-3.44	-5.43***	4.29
	(0.001)	(0.001)	(0.003)	(0.040)	(0.315)	(0.001)	(0.118)
2	-9.28**	-3.49**	-1.86*	-0.64	4.62	-2.13	6.95**
	(0.019)	(0.018)	(0.089)	(0.603)	(0.138)	(0.162)	(0.013)
High	5.56	1.03	2.09*	4.41***	24.90***	7.60***	9.67***
	(0.192)	(0.487)	(0.082)	(0.003)	(<.001)	(<.001)	(0.005)
All	-16.63***	-6.04***	-3.91***	-2.85**	-0.70	-5.45***	7.96***
	(0.001)	(0.001)	(0.003)	(0.043)	(0.836)	(0.002)	(0.009)
High-Low	20.48***	7.76***	6.40***	7.55***	24.12***	13.26***	
	(<.001)	(<.001)	(<.001)	(<.001)	(<.001)	(<.001)	

APPENDIX 1.V

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

This table reports the results of regressing fund performance (fund *alpha* based on FFC model or fund BvanB *alpha*) on manager's skill (selectivity or BvanB skill ratio) and investor sentiment, controlling for other characteristics. The main independent variables are fund selectivity ($1\text{-}R^2_{t-1}$), market sentiment (BW sentiment index, available at Jeffrey Wurgler's website) and selectivity*sentiment, which is the product of selectivity and market sentiment. We use four macroeconomic variables to control 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. Fund-level control variables contain expense ratio, log value of fund age, fund turnover, log value of total net assets (TNA), and squared log value of TNA. The P-value and adjusted R2 for each regression are also presented. ***, **, * denotes significance at the 1%, 5% or 10% level.

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

CHAPTER 2

DOES CORPORATE MANAGERIAL ABILITY MATTER TO FUND MANAGERS?

ABSTRACT

In this paper, we examine whether skilled fund managers' value creation is linked with the performance of high managerial ability stocks—that is, the stocks of firms run by skilled chief executive officers (CEOs)—using the latter as their stock identification strategy. We find that the performance of the stocks of firms managed by skilled CEOs has strong explanatory power in the performance of actively managed mutual funds headed by highly skilled fund managers. The evidence shows that the excess value added generated by mutual fund managers is $3.47 million per year with exposure to high CEO managerial ability stocks, whereas the average performance of all mutual funds is -$1.94 million.

INTRODUCTION

Previous studies using fund holdings' deviation from the benchmark portfolio to measure mutual fund managers' management skill show that fund management skill has a positive relation with fund performance (Brands, Brown, and Gallagher, 2005; Kacperczyk, Sialm, and Zheng, 2005; Cremers and Petajisto, 2009; Cremers, Ferreira, Matos, and Starks, 2015). Furthermore, empirical studies report that skilled fund managers add value by selecting valuable stocks (Gruber, 1996; Carhart, 1997; Daniel, Grinblatt, Titman, and Wermers, 1997; Zheng, 1999) and that their talent in identifying high-performance stocks is due to their superior insight and analytical ability. Amihud and Goyenko (2013), using 1 - R^2 to measure fund selectivity without paying attention to the composition of fund portfolios, find that funds tracing less the market benchmark (i.e., skilled fund managers) are associated with higher risk-adjusted excess returns (*alpha*). Similarly, Berk and van Binsbergen (2015; hereafter BvanB), who question the long-held view that risk-adjusted returns (net or gross *alpha*) are an appropriate measure of mutual fund management skill, propose the dollar value of a fund's added value over its benchmark as the measure of skill and find that the average mutual fund adds value by extracting about $3.2 million US Dollars a year from financial markets. They also find skilled fund managers' superior performance to persist for 10 years.[21]

While most previous studies focus on whether skilled fund managers improve fund performance or how to estimate fund managerial skill, the important question of how skilled fund managers detect valuable stocks remains largely unexplored. As mentioned by Wermers, Yao, and Zhao (2012), the majority of active mutual fund managers claim that they select valuable stocks using private information generated from stocks' fundamental information. Employing the "generalized inverse alpha" (GIA) approach, the authors conclude that the private information used by active fund managers in the stock selection process is distinct from stock fundamental information, which is contained in publicly available quantitative signals. Kacperczyk and Seru (2007) show that skilled fund managers use more private information than public information to change portfolio allocation, implying that fund managers' superior analytical ability helps them to recognize and process idiosyncratic information efficiently, which, in turn, leads them to identify the most valuable stocks. Therefore, previous research argues that the superior performance of skilled mutual fund managers is rooted in private information, but only a few studies try to characterize the private information used by fund managers. For instance, Kacperczyk et al. (2005) claim that the private information may be about

[21] As BvanB argue, due to the scale effect, a fund's ability to outperform the benchmark (net or gross *alpha*) declines as the size of the fund increases and, therefore, the manager's selectivity skill should be adjusted by fund size. Net *alpha*, the authors argue, is determined in equilibrium by competition between investors and not by managerial skill. Gross *alpha* is a return measure, not a value measure, and therefore not a measure of skill either.

valuation and performance prediction for specific industries and find that fund managers have better performance if they are more familiar with and focus on specific industries.

Motivated by the growing body of literature and the business world that managers matter for firm behavior and economic performance (i.e., Bertrand and Schoar 2003; Kaplan, Klebanov, and Sorensen, 2012; Demerjian, Lev, and McVay, 2012), in this paper, we explore whether the superior fund performance delivered by skilled fund managers is associated with the performance of stocks from companies run by chief executive officers (CEOs) with high managerial ability. If, in fact, CEO skill matters and its importance varies across fund managers, it can help to explain variation in fund performance. Intuitively, we want to quantify how much of the observed variation in fund performance can be attributed to fund managers' stock selection based on CEO managerial ability.[22]

We add to this literature by testing the proposition that skilled fund managers' value creation is related to the performance of high managerial ability stocks (i.e., stocks from firms run by skilled CEOs), using the latter as their stock identification strategy. To the extent that a company's stock valuation ultimately reflects the quality of its managers through their large contributions to corporate profits, the question of whether fund manager performance is associated with the performance of stocks from companies led by adept corporate managers remains unexplored. Accordingly, if stocks are highly likely to represent firms run by more efficient (skilled) corporate managers than others, fund managers using corporate managerial ability as a stock selection identification strategy should significantly contribute to a fund's superior performance. However, whether the source of mutual fund managers' superior stock

[22] Cohen, Frazzini, and Malloy (2007) indirectly support this argument by showing that, if fund managers have more information about corporate board members through shared education networks, they will place larger bets on those firms and such funds perform significantly better in these holdings relative to their non-connected holdings.

picking ability is rooted in the stocks of firms run by CEOs with high managerial talent has not been the focus of the empirical finance literature until now. In this paper, we add to this literature by examining whether the value (fund performance improvement) created by skilled fund managers can be explained by the performance of high managerial ability stocks. That is, we explore whether CEO managerial skill, as an identification strategy, plays an important role in explaining skilled mutual fund performance by analyzing the connection between mutual fund managers' stock selectivity skill and CEO managerial ability through the relation between the performance of skilled mutual funds and high managerial ability stocks.

There are three reasons to suggest that CEO managerial ability should be an important factor for fund managers' consideration in their stock picking decisions. First, the financial literature documents that corporate managerial ability plays an important role in a firm's future performance. Hayes and Schaefer (1999) link the loss of an adept manager to abnormal negative returns. Holcomb et al. (2009), show that managerial ability can serve as the basis of value creation and superior firm performance. Chang et al. (2010) report that higher-ability CEOs receive higher compensation and that differences in CEO ability account for differences in firm value and performance. Using a manager–firm matched panel data, Bertrand and Schoar (2003) find that managerial ability, measured by manager fixed effects, shapes a large range of corporate decisions, such as mergers and acquisitions or research and development (R&D) investments.[23] Consequently, low-ability corporate managers may lead firms to adopt suboptimal strategies, hurting firm performance. Consistent with this view, Demerjian, Lev, and McVay

[23] Prior literature (i.e., Bertrand and Schoar, 2003; Gow, Kaplan, Larcker, and Zakolyukina, 2015) has explored heterogeneity across corporate managers, such as differences in managerial ability, personality traits, management styles, education, or work experience, to explain differences in corporate policies and value across firms without a narrow focus on specific executive characteristics. A different stream of research has concentrated on executive characteristics such as risk aversion, time preferences, optimism, and overconfidence (Malmendier and Tate, 2005, 2008; Graham, Harvey and Ruri, 2013) and shows their influence on corporate decisions and outcomes.

(2012) find a strong relationship between changes in managerial ability, measured by managers' efficiency in generating revenues, and changes in a firm's subsequent performance.[24] In the same vein, Andreou, Ehrlich, Karasamani, and Louca (2015) report that firms with high managerial ability had better performance even during the 2008 global financial crisis. These findings suggest that the stocks of firms under the helm of CEOs with high managerial ability are expected to have better performance than their counterparts managed by low-skilled CEOs because the former run corporate organizations more efficiently and direct capital resources to projects with favorable growth opportunities. Therefore, such stocks should attract the attention of skilled mutual fund managers if corporate managers' ability is viewed as a sign of efficiently run corporations, signaling favorable future stock price increases.

The second reason why CEO managerial ability matters as an investment identification strategy to skilled mutual fund managers is that skilled CEOs can limit firm total risk. For example, Bonsall, Holzman, and Miller (2016) document that companies with CEOs possessing higher managerial ability have lower credit risk, because of the lower likelihood that they will miss principal or interest payments. In addition, Trueman (1986) points out that CEOs with higher managerial ability are more likely to issue earnings forecasts to keep the market aware of changes in the firm's economic environment, which, in turn, lowers stock price volatility. Baik, Farber, and Lee (2011) provide empirical evidence in support of Trueman's argument and show that the frequency of earnings forecasts increases when the firm's CEO has greater managerial ability. Third, firms with strong CEO managerial abilities are subject to less information asymmetry (Andreou et al., 2015; Baik, Farber, and Lee, 2011), which increases the accuracy of

[24] Demerjian, Lev, and McVay (2012) show that their managerial ability measure is strongly associated with manager fixed effects and that stock price reactions to CEO turnover are positive (negative) when they assess the outgoing CEO as being of low (high) ability. The authors also report that replacing CEOs with CEOs with more (less) managerial ability improves (deteriorates) firm performance subsequent to executive replacement decisions.

mutual fund managers' stock valuations. Since more firm-specific information is released to the equity market by CEOs with high managerial ability, mutual fund managers' research efforts are expected to be less costly and their stock picking choices are more likely to be rewarded with higher excess returns when they invest in the stocks of such firms. The above arguments lead to the hypothesis that CEO managerial skill is likely to act as an important factor in skilled fund managers' portfolio allocation, resulting in superior fund performance.[25] Surprisingly, this question has not been the focus of empirical investigation and the aim of this study is to address this issue.

To address this question, we first examine whether heterogeneity across stock valuations is associated with differences in managerial ability, using the managerial ability score (MA-Score) data proposed by Demerjian et al. (2012). This MA-Score estimates corporate managerial ability based on how efficiently superior managers, especially CEOs, can transform corporate resources into revenue relative to their industry peers. In their research, Demerjian et al. first use data envelopment analysis to estimate firm efficiency and then remove any firm-specific characteristics that are expected to assist or hamper the management's efforts to obtain an accurate managerial efficiency measure. The unexplained portion of firm efficiency is attributed to managerial ability. In the context of this study, the MA-Score is employed as a proxy for corporate managerial ability to assess its predictive power on firm performance (i.e., stock *alpha*) using portfolio analysis. Consistent with the evidence of Demerjian et al., we find firms with higher managerial ability, as measured by the company's MA-Score one year prior, have better performance than their peers. Specifically, the stocks of companies with the highest managerial ability generate a 4.74% abnormal return every year (P = 0.017), which exceeds the average

[25]The literature on managerial compensation dynamics (i.e., Lucas, 1978) argues that managerial ability (competitive advantage) is rewarded with higher compensation because it enables shareholders to earn positive rents, implying that the stocks of such companies are very likely to be the most valuable.

managerial ability performance (1.57%, P = 0.077), whereas the stocks of companies with the lowest managerial ability experience a negative 5.00% abnormal return every year (P = 0.042), which is far lower than the average. Therefore, given this evidence, if managerial ability is used by skilled fund managers as a stock selection strategy, fund performance should be positively and significantly related to the stock performance of high managerial ability firms.

Next, we estimate fund manager skill and fund performance by employing two different measures over the 1990–2014 sample period. First, fund management selectivity skill is assessed by employing the method of Amihud and Goyenko (2013). Then, we estimate fund manager skill and fund performance using the measures of management skill (i.e., skill ratio) and performance (i.e., the value extracted by a fund from capital markets) of BvanB. The evidence based on both measures consistently shows that fund managers with the highest skill create $3.74 million of value added, which exceeds the average realized fund loss of $1.97 million, while fund managers with the lowest skill experience a value loss of $18.06 million every year. To determine whether the performance of mutual funds managed by skilled fund managers is linked with the stocks of firms run by managers of high managerial ability, we sort all sampled firms into high managerial ability firms (top 50%, top 33%, or top 20%) and low managerial ability (bottom 50%, bottom 33%, or bottom 20%) firms based on their previous year's managerial ability score. If skilled mutual fund managers do have stock picking skills by detecting firms of high managerial ability and investing in such firms, their fund performance should be positively and significantly correlated with the performance of high managerial ability firms.

To examine the relationship between highly skilled mutual fund performance and the performance of high managerial ability stocks, we sort all mutual funds into quintiles based on managers' stock picking skill measures (i.e., fund selectivity or the BvanB skill ratio) and the performance for each mutual fund is measured by the abnormal return, which is the difference between the real return and the expected return of the test month, with a 24-month moving estimation window. This procedure enables us to inspect the merit of our hypothesis without requiring knowledge of the fund's portfolio holdings. The results of these tests support the hypothesis that skilled fund managers' performance is positively and significantly associated with the performance of firms run by managers possessing high managerial skill, suggesting that fund managers' superior stock picking ability is linked with investments in high managerial ability stocks. Conversely, the *alpha*s of skilled mutual funds are insignificantly related with the average performance of low CEO managerial ability firms, implying that the superior performance of skilled fund managers comes from investing in high CEO ability stocks, since low CEO ability stocks fail to improve fund performance. Furthermore, we find a significant negative relation between skilled funds' BvanB *alpha*s and the stock performance of firms led by CEOs with low managerial ability. These results provide additional support for the view that skilled fund managers' superior fund performance comes through investing in firms headed by CEOs with superior managerial ability.

Next, we apply an analysis using the composition of each fund to confirm whether funds with highly skilled fund managers are loaded with a higher proportion of high–MA-Score stocks. By calculating the value-weighted MA-Score for each fund, we find that the highest-skilled fund quintile is linked with the highest average fund level MA-Score value. This provides additional evidence that skilled fund managers' stock holdings are associated with high managerial ability stocks.

In addition, to test the persistence of the relationship between corporate managerial ability and fund management performance, the previous analysis is replicated by sorting firms based on the average MA-Score of the past two years instead of the previous year. The results of this test demonstrate consistently that the superior performance of skilled mutual fund managers is closely linked with the performance of high managerial ability stocks, revealing that this link is not a short-lived phenomenon.

Pan, Wang, and Weisbach (2015) show that investors update their expectations about the future outcomes of firms dynamically when there is uncertainty about the managerial ability of top corporate managers. Along this argument, skilled mutual fund managers are expected to respond to corporate managerial skill changes and improve fund performance in anticipation of investors' revised expectations about managerial skill. We investigate this hypothesis by sorting firms in our sample into two groups based on each firm's MA-Score change in the previous year. Then, we estimate the average performance of the firms in each group and examine their relation with the performance of mutual funds run by skilled managers. The results ascertain that skilled mutual fund managers can accurately assess CEO managerial ability ahead of their peers and other investors generating superior fund performance. Furthermore, this finding confirms that CEO managerial ability is an essential source of value creation by fund managers possessing superior stock picking ability.

Kacperczyk, van Nieuwerburgh, and Veldkamp (2014, 2016) argue that mutual fund managers successfully pick stocks in economic expansions and time the market in recessions. Accordingly, one would expect CEO managerial ability to be more precious for skilled fund managers during economic expansions, since CEO managerial ability information is mainly used during fund managers' stock selection process. The evidence supports this hypothesis by showing that the performance of high managerial ability stocks contributes significantly more in the performance of mutual funds run by skilled managers during economic expansions than in recessions.

In the next two robustness checks, we examine whether the indispensable role of CEO managerial ability assessment in fund managers' stock selection skill is concentrated in picking stocks from specific industries or is based on certain fund trading strategies. Even though the results based on the selectivity measure show that fund performance is more pronounced in mutual funds adopting the *Value* strategy and only appears when the underlying stocks are from certain industries (i.e., mining, construction, manufacturing, transportation, communications, electric, gas, and sanitary services), the results based on the BvanB skill measure indicate that the corporate managerial ability-based stock picking strategy of skilled fund managers produces superior abnormal returns in all types (*Value*, *Growth*, and *Blend*) of mutual funds and across industries.

The remainder of the paper is organized as follows. Section 1 describes the data and the empirical methodology. Section 2 discusses the results. Section 3 presents the results from robustness tests. Section 4 concludes the paper.

DATA AND EMPIRICAL METHODOLOGY

Data and sample selection

The data cover actively managed US mutual funds and US public traded companies. The mutual fund data are obtained from the Bloomberg Fund Dataset, which is widely used in the finance industry but has not been used in academic studies. Hence, this dataset does not suffer from the standard sample bias. The data sample period covers 25 years, from 1990 to 2014. To estimate mutual fund manager skill and past fund *alpha*s for the current year, we use the monthly data for the previous two years (24 months). Therefore, our data collection starts in January 1988. We collect monthly raw returns for each fund if the fund has complete data for more than two years. We also collect fund-level control variables that could be associated with fund performance: turnover, which is the minimum of the aggregated sales or aggregated purchases of securities divided by each fund's total net assets (TNA), age, and expense ratio (i.e., the fund's annual expense ratio). We control for survivorship bias by collecting data for both alive and dead funds. We also use several criteria to restrict our sample to actively managed US equity mutual funds: 1) The geographical focus is the United States, 2) the country of domicile is the United States, 3) the asset class is equity, 4) the fund type is an open-ended mutual fund, and 5) the inception date is no later than December 2012. Furthermore, we exclude other types of funds, such as index funds, balance funds, international funds, and sector funds, by deleting funds whose name contains the term *index, ind, S&P, DOW, Wilshire, Russell, global, fixed-income, international, sector,* or *balanced.* In addition, we require funds to have a minimum TNA of \$15 million (in December 2013 dollars). Overall, the sample contains 2,190 mutual funds over the period from 1990 to 2014.[26]

To collect company data, we first match the list of companies having managerial ability score data with the list of companies, both alive and dead, listed in the NASDAQ, New York Stock Exchange (NYSE), and American Stock Exchange (AMEX) stock exchanges. The managerial ability score data, introduced by Demerjian et al. (2012), are from Sarah McVay's UW faculty website.[27] Finally, our sample consists of 2,469 companies and covers the period from 1989 to 2013. Other firm-level annual variables, such as a firm's total debt-to-total equity

---

[26] The top and bottom 1% of R^2 observations were deleted. The reason for their exclusion is that funds with the highest R^2 should be index funds, which have not been filtered out by the sample selection criteria. The lowest R^2 values of funds may be due to estimation error.
[27] See http://faculty.washington.edu/pdemerj/data.html.

ratio (D/E), return on equity (ROE), market-to-book ratio (M/B), and market capitalization, are obtained from the Bloomberg database for all the companies in the sample.[28] The summary statistics for the annual data of mutual funds and companies are reported in Table 1.

TABLE 2.1

Summary statistics

This table shows the summary statistics of US actively managed equity mutual funds and US public-traded companies with CEO managerial ability scores (MA-Scores). Panel A gives the statistics for mutual funds. R^2_{t-1} is calculated by regressing each fund's excess return (fund monthly raw return minuses risk free rate of that month) on the multifactor model of Fama-French (1993) and Carhart (1997) (FFC model) over a time window of 24 months. The risk factors are accessible online through the Kenneth French data library. Expense ratio is the annual expense ratio of each fund. TNA is each fund's total net assets in millions. Turnover is the minimum of aggregated sales or aggregated purchases of securities divided by the total net assets of the fund. Our sample contains 2,190 actively-managed equity mutual funds over the period from January 1990 to December 2014. Panel B shows the summary statistics of US public-traded companies with CEO managerial ability scores. The companies are collected by matching companies having managerial ability data with companies listed in NASDAQ, NYSE, and AMEX stock exchanges. The managerial ability score data are introduced by Demerjian and McVay (2012) and are public available online. Finally we have 2,469 companies in our sample and the time period is from 1990 to 2014. Debt to equity ratio is the ratio of total debt to the total equity hold by the company in each year. Market to book ratio is the ratio of the company's market capitalization to its accounting value for each year. ROE is the return on equity of the company. Size is captured using the company's total market capitalization.

Panel A: Mutual fund summary statistics				
Variable	**Mean**	**25%**	**Median**	**75%**
Age (Year)	12.83	7.00	11.00	17.00
Expense Ratio (%)	1.18	0.92	1.15	1.35
R^2_{t-1}	0.88	0.85	0.92	0.95
TNA (Million $)	1,105.42	57.93	190.06	782.90
Turnover	67.94	27.00	48.92	83.00
Panel B: Company summary statistics				
Variable	**Mean**	**25%**	**Median**	**75%**
Firm MA-Score	0.01	-0.08	0.00	0.08
Debt to Equity Ratio (%)	64.48	2.66	30.44	72.36
Excess Return (%)	15.77	-18.35	7.13	35.72
Market to Book Ratio (%)	3.28	1.32	2.14	3.58
ROE (%)	4.81	1.28	10.89	18.61
Size (Million $)	5,340.08	135.04	589.81	2,323.17

As shown in Table 1, the R^2 estimates for mutual funds have a mean value of 0.88 and a median value of 0.92. This reveals a clear negatively skewed distribution, which indicates that more than 80% of the funds' excess return variance can be explained by the variance of market

[28] Similar to the mutual fund data, the top and bottom 1% of performance observations were deleted, because these observations are more likely to be affected by firm-specific events or estimation errors.

indexes. On the other hand, the MA-Score values show an average of 0.01, with a median number of 0.00.

Methodology

In this section, we describe in detail the corporate managerial ability, mutual fund performance, and fund manager's skill measures used in our analysis.

Corporate managerial ability measure

The CEO managerial ability measure is the MA-Score measure introduced by Demerjian et al. (2012), which is defined as management's efficiency, relative to its industry peers, in transforming corporate resources into firm revenue. Compared with previous CEO skill measures, such as the manager's fixed effects skill measure, the MA-Score measure is more precise and easier to implement.

Specifically, Demerjian et al., (2012) use a two-step process to measure a firm's managerial ability score. First, they employ data envelopment analysis to optimize firm performance across different inputs and outputs and then they compare each firm to the most efficient outcome. They then distinguish managerial performance from firm performance by regressing the total firm efficiency score on the firm's size, market share, cash availability, life cycle, operational complexity, and foreign operations and collect the residual from this estimation as the measure of managerial ability. This measure is highly correlated with previous management skill measurements, such as managers' fixed effects and historical stock returns. Demerjian et al. also conduct tests to establish the validity of this managerial ability measure and find that abnormal stock returns around the time of a CEO turnover announcement are negatively associated with the managerial ability score. In addition, changes in the CEO ability score are shown to be positivity associated with the firm's future stock return and profitability. These results suggest that the MA-Score managerial ability measure can be used as a reliable proxy to gauge CEO managerial skill in the context of our study.

Furthermore, we take another step to verify whether the MA-Score measure is an appropriate CEO managerial skill measure by using a firm's MA-score in the previous year to predict the stock's mispricing level during the current year.[29] With firm-level controls, along with year and industry fixed controls, we find that the MA-score has significantly negative predictive power in the mispricing level of the firm's stock. Hence, our evidence demonstrates that the CEO skilled-based stock-picking identification strategy of fund managers is equivalent to identifying and investing in stocks subject to low mispricing, since mispricing will introduce greater volatility to stock performance and skilled CEOs can protect the stocks from unpredictable price changes caused by market anomalies for the interests of their stockholders.

Fund selectivity and performance measures

To examine whether a positive relationship between skilled fund managers' performance and the performance of firms run by skilled CEOs exists, we first assess fund manager skill by employing the method of Amihud and Goyenko (2013). In their research, Amihud and Goyenko calculate fund manager skill, which they refer to as selectivity, using a fund's R^2 obtained by regressing fund returns on multifactor benchmark models. The benchmark multifactor model used in this study is that proposed by Fama and French (1993) and Carhart (1997) and is denoted the FFC model, which contains market excess returns (R_M - R_f), small minus big size stocks

---

[29] The mispricing data are introduced by Stambaugh, Yu, and Yuan (2012) and can be collected from Robert F. Stambaugh's website, at http://finance.wharton.upenn.edu/~stambaug/. The firm-level control variables contain the industry-adjusted return on assets, monthly stock return, number of total analysts following, M/B, monthly stock volatility, firm size (sales), capital expenditure, and industry-adjusted R&D expenses. The results are available upon request.

(SMB), high minus low book-to-market ratio stocks (HML), and winner minus loser stocks (MOM), and all the data are accessible online through *Kenneth French's data library*. Amihud and Goyenko argue that a low level of co-movement with the benchmark model (i.e., the FFC model), which is reflected by a low R^2, shows high fund management skill because highly skilled fund managers manage funds based on private information, which makes the fund less sensitive to public information variations. Selectivity, as for Amihud and Goyenko, is measured as

$$Selectivity = 1 - R^2 = \frac{RMSE^2}{Total\,Variance} = \frac{RMSE^2}{Systematic\ Risk^2 + RMSE^2} \tag{1}$$

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 shown in Eq. (1), fund selectivity will be higher when the fund's strategy is based less on market information, which is reflected in systematic risk. The advantage of this method is that it does not require knowledge of fund holdings or the benchmark index that the fund is using. However, as shown in Table 1, the distribution of R^2 is negatively skewed, which means that the distribution of selectivity should be heavily positively skewed. Therefore, we used the logistic transformation of selectivity, *TSelectivity*, as shown in Eq. (2), as the first fund manager skill measure:

$$TSelectivity = \log\left(\frac{Selectivity}{1 - Selectivity}\right) \tag{2}$$

We use the average fund abnormal return before fees, the fund gross *alpha*, to measure fund performance. The reason for using the fund gross *alpha* rather than the net *alpha* is that, as Berk and Green (2002) 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 fund manager performance.

BvanB fund skill and performance measures

Besides the selectivity measure of Amihud and Goyenko (2013), fund manager skill is also estimated using the method of BvanB, who deduce fund manager skill based on the extra value added to the fund divided by its standard error (the BvanB measure). Compared with the selectivity measure, the BvanB measure is a more suitable way to measure fund performance. As argued by BvanB, the gross abnormal return has to be adjusted by fund size to estimate fund performance. In addition, the authors also question the benchmark used in previous research (e.g., FFC model, Fama–French three-factor model, capital asset pricing model) and argue that, for a reliable market benchmark, the return of the benchmark should be known to investors and the benchmark should be tradable. Unfortunately, the benchmarks used in factor models do not meet these criteria. To solve this problem, BvanB use 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.

Following BvanB, we also use the 11 Vanguard index funds as the benchmark.[30] We started collecting data when all the index funds have data and, therefore, our data period covers 14 years, from 2001 to 2014. As BvanB, we construct an orthogonal basis set out of these index funds by regressing the *n*th fund on the orthogonal basis produced by the first n - 1 funds over the whole sample 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 nth index fund of the whole period.

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

After we obtain the new benchmark, we regress the excess returns of each fund on the 11 Vanguard index fund orthogonal benchmark for the whole sample period, from 2003 to 2014, using 24-month rolling window regression and moving forward one year each time. We calculate fund performance using the abnormal capital inflow of each fund in the test year (denoted BvanB *alpha*), which is calculated as the fund's gross abnormal return (real raw return over its expected return) multiplied by the inflation-adjusted TNA of the fund at the beginning of the current year. The fund expected return is the product of the loading of each Vanguard index fund on the orthogonal basis on the fund excess return from the preceding 24-month estimation period by the real numbers of each Vanguard index fund on the orthogonal basis in the current year.

As BvanB, we use the skill ratio measure (denoted BvanB skill) to capture fund management skill, as shown in Eq. (3). Each fund's BvanB skill in each year is calculated as the fund's abnormal return (fund *alpha*) multiplied by the inflation-adjusted fund size at the beginning of the last year, divided by the standard error of the fund *alpha*, collected from the 24-month rolling window regression of fund excess returns over the alternative investment opportunity formed with the 11 Vanguard index funds:

$$BvanB\ Fund\ Skill_{f,t} = \frac{alpha_{f,t-1} * TNA_{f,t-2}}{SE_{f,t-1}} \tag{3}$$

EMPIRICAL RESULTS

Effect of CEO managerial ability on stock performance

To examine whether CEO managerial ability works as a means of fund managers' stock picking identification strategy, we examine whether high (low) fund performance is associated with the performance of the stocks of firms run by CEOs with high (low) managerial skill. Consequently, we first investigate whether high CEO managerial ability is linked with superior stock performance. If the stocks of firms managed by skilled CEOs are associated with abnormal gains, they should be attractive to mutual fund managers and beneficial to fund performance. Therefore, discovering firms run by talented CEOs and investing in these companies should assist fund managers in improving fund performance. That is, using corporate managerial skill as an investment strategy, skilled fund managers should be able to deliver value. To explore the relation between stock performance and a company's CEO's ability, we first sort all companies in each year (*t*) into quintiles based on their CEOs' managerial ability scores (MA-Score) in year *t* - 1. The managerial ability score data are from Demerjian and McVay (2012) and are available online. Then, within each quintile, we further sort all firms into five groups based on their past performance (i.e., firm $alpha_{t-1}$). The firm $alpha_{t-1}$ values are the intercepts of regressing each company's monthly stock excess returns (over the T-bill rate) on the factors from the FFC model for a 24-month estimation period. This procedure produces 25 (5×5) portfolios of different corporate managerial abilities and past performances. Then, we report the equally weighted firm annualized abnormal returns and P-values for each portfolio during the whole sample period (January 1990 to December 2014) in Table 2. To estimate the monthly abnormal return for each company, we calculate the difference between the company's monthly excess return (over the risk-free rate) and the expected excess return of the same month. To calculate the expected excess return for each company in the current month, we multiply the FFC model factor loadings, which are also obtained from the preceding 24-month estimation period (*t* - 2 to *t* - 1) by the FFC model factors in the same month. This process is repeated by moving the estimation and test period one month at a time.

TABLE 2.2

Portfolio firm *alpha*, sorting on lagged CEO managerial ability score and *alpha*

The table presents the portfolio average of firm annual abnormal return (firm *alpha*) in the whole sample periods from January 1990 to December 2014. Portfolios are formed by sorting all companies in each year into quintiles by lagged CEO managerial ability score (MS-Score) and then by firm $alpha_{t-1}$. The managerial ability score data are introduced by Demerjian and McVay (2012) and are public available online. Firm $alpha_{t-1}$ data are obtained from the 24-month estimation period by regressing each company's monthly stock excess returns (over the T-bill rate) on the factors from FFC model. Then, we calculate the abnormal return in month t for each company as the difference between company excess return (over risk free rate) in month t and the expected excess return of the same month. The expected excess return for each company in month t is calculated by multiplying the FFC model factor loadings from the 24 month preceding estimation period (t-2 to t-1) by the FFC model factors in current month. The process repeats by moving the estimation and test period one month at a time. We report the equal weighted firm abnormal returns for each portfolio and the P-value. ***, **, * denotes significance at the 1%, 5% or 10% level.

	CEO Managerial Ability$_{t-1}$						
Stock Alpha$_{t-1}$	**Low**	**4**	**3**	**2**	**High**	**All**	**High-Low**
Low	-5.00**	3.94*	1.97	4.02**	1.47	1.28	3.23***
	(0.042)	(0.056)	(0.271)	(0.023)	(0.409)	(0.391)	(0.008)
4	-2.39	0.76	0.98	4.14***	3.52**	1.40	2.95***
	(0.126)	(0.619)	(0.505)	(0.004)	(0.026)	(0.183)	(0.002)
3	-2.22	3.72***	3.10**	2.37*	3.88***	2.17**	3.05***
	(0.113)	(0.005)	(0.025)	(0.083)	(0.005)	(0.020)	(<.0001)
2	-0.99	2.99**	2.48*	4.26***	3.26**	2.40**	2.13**
	(0.532)	(0.039)	(0.077)	(0.007)	(0.027)	(0.017)	(0.019)
High	-6.93***	0.77	2.54	1.84	4.74**	0.59	5.84***
	(0.002)	(0.699)	(0.122)	(0.330)	(0.017)	(0.654)	(<.0001)
All	-3.51***	2.43**	2.22**	3.33***	3.37***	1.57*	3.44***
	(0.006)	(0.016)	(0.026)	(0.002)	(0.002)	(0.077)	(<.0001)
High-Low	-0.96	-1.58	0.29	-1.09	1.64	-0.34	
	(0.490)	(0.215)	(0.800)	(0.331)	(0.195)	(0.681)	

Consistent with the findings of Demerjian et al. (2012), the results in Table 2 show that firms under the helm of high CEO ability (a high CEO MA-Score in the prior year) earn high abnormal stock returns (i.e., stock *alpha*).[31] The highest abnormal return is 4.74% (P = 0.017) for the portfolio with the highest managerial ability and best past performance, while the average abnormal return for the whole sample is 1.57% (P = 0.077).[32] Meanwhile, the results indicate that, if active mutual funds aggressively invest in the stocks of firms managed by CEOs with high managerial ability, they can reap large rewards for fund investors. We also perform a

[31] Even though this relation has been documented by Demerjian et al. (2012), we confirm this relation in our context by narrowing the data to only public companies traded on the AMEX, NYSE, and NASDAQ stock exchanges, because those stocks are available for mutual fund managers to invest in and their financials are more reliable.

[32] We replicate the portfolio analysis using yearly data and the results are consistent with the monthly data results.

regression analysis by regressing stock *alpha* on CEO MA-Score$_{t-1}$ and stock *alpha*$_{t-1}$, controlling for firms' total D/E, ROE, M/B, and market capitalization. The regression results, reported in Appendix II, for the sample period from 1990 through 2014, consistently show that the stocks of firms managed by CEOs with higher managerial ability have significant better performance than other stocks. Jointly, these findings confirm that investing in the stocks of firms under the directorship of skilled CEOs is expected to be very attractive to skilled mutual fund managers because such stocks represent valuable investment opportunities that could improve fund performance.

Effect of fund manager skill on fund performance

In this section, we examine the predictive power of the two fund manager skill measures on fund performance used in our analysis. First, we test the predictive power of the selectivity measure (i.e., the logistic transformation of 1 - R^2_{t-1}) on fund performance (i.e., fund annual *alpha*). As stated by Amihud and Goyenko (2013), this selectivity measure captures the proportion of fund performance that is explained by trading on private information and, therefore, we expect a significant positive relation between high fund selectivity and the fund *alpha*. We estimate R^2 using a 24-month window rolling regression procedure and R^2 is used only if the mutual fund has 24 months of complete continuous data in the estimation period. Then, for each month, we rank all mutual funds in the quintiles based on their 1 - R^2 value. Within each quintile, we sort funds into five portfolios based on their *alpha*$_{t-1}$, which is the intercept from the estimation regression. This procedure produces 25 (5×5) portfolios with different fund manager selectivities and past performances. For each portfolio, we report the equally weighted firm abnormal returns and P-values during the whole sample period (January 1990 to December 2014) and report the results in Table 3, Panel A. To estimate the fund *alpha* in month t for each mutual fund, we calculate the difference between the fund excess return (over the risk-free rate) in month t and the expected excess return for the same month. To calculate the expected excess return for each fund in month t, we multiply the FFC model factor loadings, which are also collected from the preceding 24-month estimation period (t - 2 to t - 1) by the FFC model factors in the current month. This procedure is repeated by moving the estimation and test period one month at a time.

The results in Table 3, Panel A, show that, when the overall mutual fund industry cannot beat the market benchmark significantly (-0.57%, P = 0.166), funds in the highest selectivity quintile generate a significant, positive 3.05% annual *alpha* (P = 0.023). In addition, the return of the hypothetical portfolio of a long position in high-selectivity funds and a short position in low-selectivity funds delivers a significant positive annual *alpha* (0.92%, P = 0.019 for the whole sample; 2.24%, P = 0.003 for funds with the best past performance). These results confirm that fund selectivity is positively associated with fund *alpha*.

We re-examine the effect of fund management skill on fund performance using the BvanB skill measure. The main difference with the previous portfolio analysis is that the BvanB skill and performance (BvanB *alpha*) measures are used, as defined in Section 1.2.3. This metric permits us to gauge the success of a fund manager based on the value added of an investment opportunity (i.e., the net present value of an investment) rather than the return a fund earns (i.e., the internal rate of return), since bigger funds could generate more value even if they have lower *alpha*s. These results are presented in Table 3, Panel B.

TABLE 2.3

Fund portfolio performance, based on sorting on fund manager skill and lagged fund performance

This table presents the fund portfolio performance (fund *alpha* and fund BvanB *alpha*), annualized, using monthly returns. In *panel A*, 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 for the period from January 1990 to December 2014. 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. *Panel B* presents the portfolio BvanB fund *alpha*, annualized, using monthly returns (145 months), from December 2002 to December 2014. Portfolios are formed by sorting all funds in each month into quintiles by BvanB fund skill (Eq. 3) and then by BvanB fund $alpha_{t-1}$, and both are described in detail in section 1.2.3. For each portfolio cell, we present portfolio BvanB fund *alpha*, which is the portfolio *alpha* times the average TNA of funds within the portfolio at the beginning of current month (t), and the P-value. ***, **, * denotes significance at the 1%, 5% or 10% level.

Panel A: Portfolio fund alpha for the entire sample period

	Fund selectivity ($1-R^2_{t-1}$)						
***Alpha*$_{t-1}$**	**Low**	**4**	**3**	**2**	**High**	**All**	**High-Low**
Low	-1.75***	-2.04***	-1.84**	-1.97**	-2.06	-1.93***	-0.20
	(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	0.87**
	(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	0.65
	(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	1.05**
	(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	2.24***
	(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	0.92**
	(0.001)	(0.012)	(0.110)	(0.754)	(0.426)	(0.166)	(0.019)
High-Low	0.19	0.62	0.91*	2.03***	2.57**	1.27**	
	(0.606)	(0.191)	(0.061)	(0.001)	(0.004)	(0.004)	

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

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

Consistent with our previous findings (Table 3, Panel A), the results in Table 3, Panel B, reveal that funds with superior management skills, based on the BvanB fund skill measure, exhibit better performance than the average mutual fund. The highest annualized BvanB fund *alpha* is \$3.74 million (P = 0.337) for the fund portfolio with the highest BvanB fund skill and the best past performance, while the average performance of all mutual funds is -\$1.94 million (P = 0.280). The results for the hypothetical portfolio of a long position in a high BvanB fund skill portfolio and a short position in a low BvanB fund skill portfolio, presented in the rightmost column of Panel B under "High–Low", indicate that the return from this strategy is positive and significant (\$5.30 million, P = 0.044). For the highest and BvanB $alpha_{t-1}$ quintiles, the hypothetical portfolio yields an annualized *alpha* of \$4.27 million (P = 0.061). Overall, these results confirm the existence of a positive relationship between those funds with the greatest management skill and performance.[33]

We also perform regression analysis to assess the validity of the linear relationship between fund manager skill and fund performance, controlling for other effects. For both measures, we regress fund performance (fund *alpha* or fund BvanB *alpha*) on fund manager skill (TSelectivity or BvanB skill), controlling for fund past performance (fund $alpha_{t-1}$ or fund BvanB $alpha_{t-1}$), the expense ratio, the log value of fund age, TNA, and the squared log value of TNA and report these results in Appendix III. Consistent with the results from portfolio analysis, the regression results show that fund manager skill in all the regression specifications is positive and significantly associated with fund performance. Jointly, in accordance with previous studies, these results demonstrate that both fund selectivity and BvanB fund management skill measures are reliable metrics that allow us to capture fund managers' stock picking skill. Both measures

[33] We replicate the portfolio analysis using yearly data and the results are consistent with the monthly data results.

demonstrate that skilled managers at the helm of mutual funds significantly outperform their peers.

Skilled fund performance and CEO managerial ability

The central hypothesis of this research is that the superior performance of mutual funds headed by skilled fund managers (i.e., top 20% of funds with the highest stock picking skill in each year) relative to their low-skilled peers is associated with the stocks of firms run by CEOs possessing high managerial skills. To address this issue, at the beginning of each year from 1990 to 2014, we assign all funds in our sample to one of five equally weighted portfolios based on managers' stock picking skill inferred from the selectivity measure, as defined in Section 1.2. In each year, we treat the mutual funds in the top selectivity quintile as the funds with skilled managers. To proxy for the performance of firms with high and low CEO skill, we sort all firms into two groups (each group contains 50% of the companies in the sample), three groups (each group contains 33% of the companies in the sample), and five groups (each group contains 20% of the companies in the sample) based on each firm's past year MA-Score and compute the average performance for each group. The performance of the groups consisting of the top 50%, 33%, or 20% of the firms is used to identify the performance of firms with skilled CEOs, while the performance of the groups containing the bottom 50%, 33%, or 20% of firms is used to indicate the performance of firms with low managerial ability CEOs. We then regress the highest-skilled funds' annual fund *alpha*, obtained from the top 20% of funds in terms of selectivity, on the performance of the two company groups managed by CEOs with high (top 50%, top 33%, or top 20%) or low (bottom 50%, bottom 33%, or bottom 20%) managerial ability scores, controlling for other fund characteristics. The results are illustrated in Table 4.

TABLE 2.4

High and low managerial ability stocks' performance and high selectivity funds' performance (*Alpha*)

This table reports the results of regressing high selectivity (top 20%) fund annual *alpha* on the performance of firms assigned in groups with high (top 50%, 33%, and 20%) and low (bottom 50%, 33%, and 20%) lagged CEO managerial ability scores, controlling for other fund characteristics. The dependent variable is the annual *alpha* of high selectivity funds, representing the top 20% funds with the highest selectivity in each year. The annual fund *alpha* is the difference between fund excess return (over risk free rate) in year t and the expected excess return of the same year. The expected excess return for each fund in year t is calculated by multiplying the FFC model factor loadings from the 24 month preceding estimation period by the FFC model factors in current year. The process is repeated by moving the estimation and test period one year at a time. The main independent variables are the average abnormal firm returns (firm *alpha*) with MA-Scores in the high (top 50%, 33%, and 20%) and low (bottom 50%, 33%, and 20%) groups. Companies are sorted into groups based on their CEO MA-Scores in prior year. The abnormal return in year t for each company is calculated as the difference between company excess return (over risk free rate) in year t and the expected excess return of the same year. The expected excess return for each company in year t is calculated by multiplying the FFC model factor loadings from the 24 month preceding estimation period by the FFC model factors in current year. The process repeats by moving the estimation and test period one year at a time. Fund-level control variables contain expense ratio, log value of fund age, value of total net assets (TNA), and squared log value of TNA. Sample period covers from 1990 through 2014. We present the P values and adjusted R^2 for each regression. ***, **, * denotes significance at the 1%, 5% or 10% level.

	Top 20% Selectivity Fund *Alpha*								
	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]
Intercept	-0.88	-0.29	-0.47	-0.81	-0.29	-0.64	-1.06	-0.62	-1.07
	(0.815)	(0.940)	(0.902)	(0.829)	(0.940)	(0.866)	(0.777)	(0.870)	(0.776)
***Alpha* of Top 50% MA-Score Firms**	0.15***		0.25***						
	(0.002)		(0.001)						
***Alpha* of Bottom 50% MA-Score Firms**		0.05	-0.08						
		(0.174)	(0.106)						
***Alpha* of Top 33% MA-Score Firms**				0.15***		0.17***			
				(0.002)		(0.006)			
***Alpha* of Bottom 33% MA-Score Firms**					0.04	-0.03			
					(0.158)	(0.505)			
***Alpha* of Top 20% MA-Score Firms**							0.16***		0.16***
							(<.0001)		(0.002)
***Alpha* of Bottom 20% MA-Score Firms**								0.06**	0.00
								(0.023)	(0.973)
Fund *Alpha*$_{t-1}$	1.61***	1.71***	1.57***	1.63***	1.71***	1.61***	1.66***	1.70***	1.66***
	(0.001)	(<.0001)	(0.001)	(0.001)	(<.0001)	(0.001)	(<.0001)	(<.0001)	(<.0001)
Expense Ratio	-0.25**	-0.25**	-0.25**	-0.25**	-0.25**	-0.25**	-0.25**	-0.25**	-0.25**
	(0.013)	(0.014)	(0.013)	(0.013)	(0.014)	(0.013)	(0.014)	(0.013)	(0.014)
Turnover	-0.01***	-0.01***	-0.01***	-0.01***	-0.01***	-0.01***	-0.01***	-0.01***	-0.01***
	(<.0001)	(<.0001)	(<.0001)	(<.0001)	(<.0001)	(<.0001)	(<.0001)	(<.0001)	(<.0001)
Log(Age)	-0.70	-0.79	-0.77	-0.70	-0.79	-0.73	-0.69	-0.72	-0.69
	(0.222)	(0.171)	(0.178)	(0.220)	(0.169)	(0.204)	(0.225)	(0.208)	(0.229)
Log(TNA)	1.27	1.28	1.24	1.27	1.29	1.26	1.30	1.30	1.30
	(0.309)	(0.306)	(0.319)	(0.308)	(0.303)	(0.312)	(0.297)	(0.298)	(0.297)
[Log(TNA)]^2	-0.13	-0.13	-0.12	-0.13	-0.13	-0.13	-0.13	-0.13	-0.13
	(0.236)	(0.236)	(0.241)	(0.234)	(0.234)	(0.237)	(0.223)	(0.230)	(0.223)
Strategy Control	*YES*	*YES*	*YES*	*YES*	*YES*	*YES*	*YES*	*YES*	*YES*
Adj. R^2	0.036	0.030	0.038	0.036	0.031	0.036	0.040	0.033	0.040

TABLE 2.5

High and low managerial ability stocks' performance and high BvanB skill funds' performance (value added)

This table reports the results of regressing high (Top 20%) BvanB skill fund annual BvanB *alpha* on the performance of company groups with high and low CEO ability scores controlling for other fund characteristics. The dependent variable is the annual *alpha* of high BvanB skill funds, representing the top 20% funds with the highest BvanB skill in each year. The main independent variables are added value of high (top 50%, 33%, and 20%) and low (bottom 50%, 33%, and 20%) MA-Score firms, which is the average of company's abnormal return timing the company's market capitalization at the beginning of year t in each group. Companies are sorted into groups based on their CEO MA-Scores in prior year. Fund-level control variables contain expense ratio, log value of fund age, fund turnover, log value of TNA, squared log value of TNA, and BvanB $alpha_{t-1}$, which is the product of fund $alpha_{t-1}$ and fund TNA at the beginning of last year in the estimation period and fund $alpha_{t-1}$ is the intercept from the 24 month preceding estimation period. Sample period ranges from 2003 through 2014. The P-value and adjusted R^2 for each regression are also presented. ***, **, * denotes significance at the 1%, 5% or 10% level.

	Top 20% BvanB Skill Fund *Alpha*								
	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]
Intercept	453.04***	705.06***	540.05***	415.51***	756.59***	633.34***	425.96***	661.11***	499.81***
	(<.0001)	(<.0001)	(<.0001)	(<.0001)	(<.0001)	(<.0001)	(<.0001)	(<.0001)	(<.0001)
Added Value of Top 50% MA-Score Firms	0.20***		0.35***						
	(<.0001)		(<.0001)						
Added Value of Bottom 50% MA-Score Firms		-0.34***	-0.49***						
		(<.0001)	(<.0001)						
Added Value of Top 33% MA-Score Firms				0.32***		0.42***			
				(<.0001)		(<.0001)			
Added Value of Bottom 33% MA-Score Firms					-0.21***	-0.31***			
					(<.0001)	(<.0001)			
Added Value of Top 20% MA-Score Firms							0.26***		0.25***
							(<.0001)		(<.0001)
Added Value of Bottom 20% MA-Score Firms								-0.08***	-0.06***
								(<.0001)	(<.0001)
Fund BvanB $Alpha_{t-1}$	0.04	0.80	0.65	-0.01	0.53	0.31	0.06	0.35	0.14
	(0.961)	(0.339)	(0.417)	(0.993)	(0.533)	(0.693)	(0.938)	(0.683)	(0.856)
Expense Ratio	-32.12**	-31.59***	-18.33	-24.84**	-33.20***	-13.52	-15.08	-35.50***	-13.21
	(0.011)	(0.010)	(0.119)	(0.042)	(0.008)	(0.243)	(0.200)	(0.005)	(0.259)
Turnover	-0.05	-0.07	-0.02	-0.04	-0.07	-0.02	-0.02	-0.07	-0.01
	(0.417)	(0.284)	(0.713)	(0.544)	(0.265)	(0.747)	(0.808)	(0.279)	(0.858)
Log(Age)	18.14**	7.59	8.18	17.08*	6.74	3.94	16.14*	13.66	14.30*
	(0.044)	(0.391)	(0.331)	(0.051)	(0.452)	(0.636)	(0.055)	(0.133)	(0.087)
Log(TNA)	-223.06***	-291.73***	-246.16***	-213.72***	-302.07***	-267.34***	-218.93***	-278.82***	-237.99***
	(<.0001)	(<.0001)	(<.0001)	(<.0001)	(<.0001)	(<.0001)	(<.0001)	(<.0001)	(<.0001)
$[Log(TNA)]^2$	26.22***	30.39***	27.25***	25.84***	31.12***	29.00***	26.19***	29.73***	27.30***
	(<.0001)	(<.0001)	(<.0001)	(<.0001)	(<.0001)	(<.0001)	(<.0001)	(<.0001)	(<.0001)
Strategy Control	*YES*	*YES*	*YES*	*YES*	*YES*	*YES*	*YES*	*YES*	*YES*
Adj. R^2	0.329	0.356	0.416	0.366	0.340	0.433	0.414	0.318	0.421

As hypothesized, skilled mutual fund *alpha* values are positively and significantly linked with the average performance of firms run by high-ability CEOs. This indicates that the high *alpha* delivered by skilled fund managers is strongly associated with the superior stock performance of firms managed by CEOs with high managerial skills (0.25, P = 0.001 for the top 50% of firms; 0.17, P = 0.006 for the top 33%; 0.16, P = 0.002 for the top 20%). On the other hand, the skilled mutual fund *alpha* values are insignificantly related with the average performance of low CEO managerial ability firms, suggesting that investing in the stocks of firms run by low-ability CEOs fails to improve fund performance (-0.08, P = 0.106 for the bottom 50% of firms; -0.03, P = 0.505 for the bottom 33%; 0.00, P = 0.973 for the bottom 20%), further corroborating that skilled fund managers' superior fund performance comes from investing in firms managed by CEOs of superior managerial ability. In sum, the results clearly show that the highest quintile of skilled fund managers generates the highest *alpha* when investing in the stocks of firms operating under the helm of highly skilled corporate managers.

We repeat the previous analysis using the BvanB measures of fund management skill and fund performance. Specifically, we regress the high BvanB skill funds' annual *alpha*, obtained from the top 20% of funds with the highest BvanB skill, on the performance of the two company groups managed by CEOs with high (top 50%, top 33%, or top 20%) or low (bottom 50%, bottom 33%, or bottom 20%) managerial ability scores, controlling for other fund characteristics. Furthermore, in accord with the argument of BvanB, we use a firm's value added to measure each firm's performance for year t, which is calculated by its abnormal return (stock *alpha*) times the firm's inflation adjusted market capitalization at the beginning of year t. We then regress the high BvanB skill funds' annual BvanB *alpha*, obtained from the top 20% of funds with the highest BvanB skill, on the average value added of the two company groups managed by CEOs with high or low managerial ability, controlling for other fund characteristics, and report these results in Table 5.

The pattern of these results provides additional support for our hypothesis that the superior performance of mutual funds, under the helm of skilled mutual managers, is associated with the stocks of firms run by CEOs of high managerial talent. Specifically, the regression results in Table 5 show that the performance of firms run by CEOs with high managerial ability significantly contributes to the performance of mutual funds managed by skilled fund managers (0.35, $P < 0.0001$ for the top 50% of firms; 0.42, $P < 0.0001$ for the top 33%; 0.25, $P < 0.0001$ for the top 20%). Additionally, we find a significant, negative relation between the skilled funds' BvanB *alpha* values and the stock performance of firms led by CEOs with low managerial ability (-0.49, $P < 0.0001$ for the bottom 50% of firms; -0.31, $P < 0.0001$ for the bottom 33%; -0.06, $P < 0.0001$ for the bottom 20%). This negative relation reveals two things. First, even within the top 20% highest skilled mutual funds, a portion of the mutual funds show a significant performance correlation with low managerial ability stocks, which consequently harm fund performance. A probable reason for this negative relationship (i.e., investing in firms with low managerial ability) may be related to increased capital inflows due to past superior performance, limiting options to invest in firms with superior managerial ability. In addition, due to short selling restrictions, the majority mutual funds can only hold long stock positions. Hence, investing in stocks of firms with low managerial ability while they hold stock positions in firms with high managerial ability could be viewed as a way of creating a short selling position to protect fund performance. The last regression (regression [9]) shows that when highly skilled fund managers invest in both high and low managerial ability firms, this both improves (0.25, $P < 0.0001$) and harms (-0.06, $P < 0.0001$) fund performance, respectively, significantly improving net fund performance (0.19). This pattern also holds for regression (regression [6]) for the top 33% of skilled fund managers, but not for the top 50% of skilled fund managers (regression [3]). Second, when skilled fund managers correctly anticipate the negative effects of a CEO's managerial ability, one would expect them to cash out the investment in this company quickly and take a hedge position on the company's stock by investing in the company's competitors or in companies with the opposite operating strategy. The latter activity can cause a negative relation between skilled fund performance based on the BvanB value measure and the stock performance of firms led by CEOs with low managerial ability.[34]

Skilled fund performance, fund manager skill, and CEO managerial ability

Subsequently, we perform multivariate regression analysis to examine the effect of fund manager skill, high/low MA-Score firm performance, and their interactions on fund performance for the entire sample period (1990–2014). First, we estimate the following model:

$$\textit{Skilled Fund Alpha}_{f,t} = \textit{TSelectivity}_{f,t} + \textit{Alpha of High MA-Score Firms}_t + \textit{Alpha of Low MA-Score Firms}_t + \textit{TSelectivity}_{f,t} * \textit{Alpha of High MA-Score Firms}_t + \sum \textit{Controls}_{f,t} \quad (4)$$

Based on the central prediction of our hypothesis, skilled mutual fund managers are expected to invest in the stocks of firms run by skilled CEOs to improve fund performance. Therefore, a positive and significant relation between the interaction of fund selectivity and the average stock return performance of firms managed by CEOs with high managerial ability, *TSelectivity* Alpha of High (top 50%, 33%, or 20%) MA-Score Firms*, and fund performance (*Alpha*) is expected to emerge from the regression analysis.

---

[34] We also replicate the same analyses in Section 2.2 by replacing high/low MA-Score firm performance by the average CEO MA-Score values for each group in the previous year. The results can be found in Appendix VI, which are similar to those reported and support our argument.

TABLE 2.6

High and low managerial ability stocks' performance, fund selectivity, and high selectivity funds' performance (*Alpha*)

This table reports the results of regressing top 20% highest selectivity fund *alpha*s on manager's selectivity, high and low CEO MA-Score firms' performance, and the interactive variable of fund selectivity timing high MA-Score firms' performance, controlling for other fund characteristics. The dependent variable is the annual *alpha* of high selectivity funds, representing the top 20% funds with the highest selectivity in each year. The main independent variables are *alpha* of high (top 50%, 33%, and 20%) and low (bottom 50%, 33%, and 20%) MA-Score firms, calculated as the average abnormal returns of companies in high and low CEO MA-Score scores groups, and the interactive variable of fund selectivity timing high MA-Score firms' *alpha*. We present the P values and adjusted R^2 for each regression. ***, **, * denotes significance at the 1%, 5% or 10% level

	Top 20% Selectivity Fund *Alpha*								
	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]
Intercept	0.76	1.00	-0.13	0.84	0.87	0.00	0.57	0.45	-0.34
	(0.839)	(0.790)	(0.972)	(0.823)	(0.817)	(0.998)	(0.880)	(0.904)	(0.927)
Fund TSelectivity	2.51***	2.43***	0.91	2.47***	2.46***	1.27*	2.49***	2.52***	1.40**
	(<.0001)	(<.0001)	(0.211)	(<.0001)	(<.0001)	(0.074)	(<.0001)	(<.0001)	(0.047)
***Alpha* of Top 50% MA-Score Firms**	0.15***	0.21***	0.38***						
	(0.002)	(0.005)	(<.0001)						
***Alpha* of Bottom 50% MA-Score Firms**		-0.06	-0.04						
		(0.261)	(0.395)						
TSelectivity* *Alpha* of top 50% MA-Score Firms			0.29***						
			(0.001)						
***Alpha* of Top 33% MA-Score Firms**				0.13***	0.14**	0.27***			
				(0.005)	(0.023)	(<.0001)			
***Alpha* of Bottom 33% MA-Score Firms**					-0.01	0.01			
					(0.889)	(0.867)			
TSelectivity* *Alpha* of top 33% MA-Score Firms						0.23***			
						(0.004)			
***Alpha* of Top 20% MA-Score Firms**							0.15***	0.14***	0.25***
							(<.0001)	(0.006)	(<.0001)
***Alpha* of Bottom 20% MA-Score Firms**								0.02	0.02
								(0.592)	(0.481)
TSelectivity* *Alpha* of top 20% MA-Score Firms									0.19***
									(0.006)
Fund *Alpha*$_{t-1}$	1.41***	1.39***	1.34***	1.43***	1.43***	1.39***	1.46***	1.46***	1.45***
	(0.003)	(0.003)	(0.004)	(0.002)	(0.002)	(0.003)	(0.002)	(0.002)	(0.002)
Expense Ratio	-0.29***	-0.29***	-0.28***	-0.29***	-0.29***	-0.28***	-0.28***	-0.29***	-0.27***
	(0.005)	(0.005)	(0.006)	(0.005)	(0.005)	(0.006)	(0.005)	(0.005)	(0.007)
Turnover	-0.01***	-0.01***	-0.01***	-0.01***	-0.01***	-0.01***	-0.01***	-0.01***	-0.01***
	(<.0001)	(<.0001)	(<.0001)	(<.0001)	(<.0001)	(<.0001)	(<.0001)	(<.0001)	(<.0001)
Log(Age)	-0.84	-0.89	-0.76	-0.85	-0.86	-0.76	-0.84	-0.81	-0.70
	(0.137)	(0.117)	(0.183)	(0.134)	(0.133)	(0.184)	(0.140)	(0.155)	(0.220)
Log(TNA)	1.38	1.36	1.23	1.38	1.38	1.28	1.41	1.42	1.30
	(0.265)	(0.273)	(0.321)	(0.264)	(0.266)	(0.303)	(0.255)	(0.252)	(0.293)
$[\text{Log(TNA)}]^2$	-0.13	-0.13	-0.12	-0.13	-0.13	-0.12	-0.13	-0.13	-0.12
	(0.219)	(0.223)	(0.265)	(0.217)	(0.218)	(0.249)	(0.207)	(0.206)	(0.241)
Adj. R^2	0.050	0.050	0.058	0.049	0.048	0.054	0.053	0.053	0.058

TABLE 2.7

High and low managerial ability stocks' performance, fund BvanB skill, and high BvanB skill funds' performance (value added)

This table reports the results of regressing top 20% highest BvanB skill fund *alpha*s on manager's BvanB skill, high and low CEO MA-Score firms' performance, and the interactive variable of fund BvanB skill timing high MA-Score firms' performance, controlling for other fund characteristics. The main dependent variable is the annual BvanB *alpha* of high BvanB skill funds, representing the top 20% funds with the highest BvanB skill ratio in each year. The main independent variables are added value of high (top 50%, 33%, and 20%) and low (bottom 50%, 33%, and 20%) MA-Score firms, calculated as the average of company's abnormal return (*alpha*) timing the company's market capitalization at the beginning of the current year, for high and low CEO MA-Score groups, and the product of fund BvanB skill and added value of high MA-Score firms. We present the P values and adjusted R2 for each regression. ***, **, * denotes significance at the 1%, 5% or 10% level.

	Top 20% BvanB Skill Fund *Alpha*								
	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]
Intercept	402.66***	504.80***	541.10***	365.77***	593.57***	684.57***	377.57***	452.80***	551.79***
	(<.0001)	(<.0001)	(<.0001)	(<.0001)	(<.0001)	(<.0001)	(<.0001	(<.0001)	(<.0001)
BvanB skill	1.36***	0.93**	0.46	1.36***	1.04**	0.66	1.33***	1.26***	0.92**
	(0.003)	(0.028)	(0.290)	(0.002)	(0.013)	(0.113)	(0.002)	(0.003)	(0.026)
Added Value of Top 50% MA-Score Firms	0.20***	0.35***	0.32***						
	(<.0001)	(<.0001)	(<.0001)						
Added Value of Bottom 50% MA-Score Firms		-0.49***	-0.50***						
		(<.0001)	(<.0001						
BvanB Skill* Added Value of Top 50% MA-Score Firms			0.01***						
			(<.0001)						
Added Value of Top 33% MA-Score Firms				0.32***	0.42***	0.35***			
				(<.0001)	(<.0001)	(<.0001)			
Added Value of Bottom 33% MA-Score Firms					-0.31***	-0.33***			
					(<.0001)	(<.0001)			
BvanB Skill* Added Value of Top 33% MA-Score Firms						0.01***			
						(<.0001)			
Added Value of Top 20% MA-Score Firms							0.26***	0.25***	0.20***
							(<.0001)	(<.0001)	(<.0001)
Added Value of Bottom 20% MA-Score Firms								-0.06***	-0.08***
								(<.0001)	(<.0001)
BvanB Skill* Added Value of Top 20% MA-Score Firms									0.01***
									(<.0001)
BvanB $Alpha_{t-1}$	-2.09*	-0.83	0.16	-2.14**	-1.33	0.20	-2.03*	-1.83*	-0.17
	(0.060)	(0.428)	(0.882)	(0.048)	(0.194)	(0.845)	(0.051)	(0.077)	(0.865)
Expense Ratio	-31.25**	-17.82	-17.91	-23.98**	-12.94	-12.74	-14.24	-12.47	-12.55
	(0.013)	(0.129)	(0.125)	(0.050)	(0.263)	(0.263)	(0.226)	(0.286)	(0.271)
Turnover	-0.05	-0.02	-0.02	-0.04	-0.02	-0.03	-0.01	-0.01	-0.03
	(0.452)	(0.744)	(0.694)	(0.585)	(0.783)	(0.632)	(0.856)	(0.903)	(0.675)
Log(Age)	17.80**	8.01	7.37	16.73*	3.77	2.30	15.79*	14.01*	13.69*
	(0.048)	(0.341)	(0.379)	(0.056)	(0.650)	(0.779)	(0.060)	(0.094)	(0.093)
Log(TNA)	-203.31***	-232.42***	-245.39***	-194.15***	-251.93***	-284.08***	-199.85***	-219.65***	-256.03***
	(<.0001)	(<.0001)	(<.0001)	(<.0001)	(<.0001)	(<.0001)	(<.0001)	(<.0001)	(<.0001)
$[Log(TNA)]^2$	24.31***	25.92***	27.10***	23.93***	27.51***	30.32***	24.33***	25.53***	28.73***
	(<.0001)	(<.0001)	(<.0001)	(<.0001)	(<.0001)	(<.0001)	(<.0001)	(<.0001)	(<.0001)
Adj. R^2	0.331	0.417	0.421	0.368	0.434	0.452	0.416	0.423	0.451

Consistent with the tests presented earlier and the above prediction, the results in Table 6 show that the average performance of firms run by skilled CEOs, *Alpha of High (Top 50%, 33%, or 20%) MA-Score Firms*, in all the regression specifications is positive and significantly correlated with high selectivity fund *alpha*. Furthermore, the interaction of fund management selectivity and the average performance of skilled CEO firms, *TSelectivity* Alpha of High (top 50%, 33%, or 20%) MA-Score Firms*, is also positively and significantly associated with high selectivity fund *alpha* (0.29, P = 0.001 in regression [3]; 0.23, P = 0.004 in regression [6]; 0.19, P = 0.006 in regression [9]), suggesting that skilled fund managers create more value by investing in the stocks of firms run by CEOs with high managerial ability than in those of firms run by CEOs with low managerial ability. Interestingly, while the interactive term in the horserace, *TSelectivity* Alpha of High (top 50%, 33%, or 20%) MA-Score Firms* in regressions [3], [6], and [9], remains positive and significant, fund selectivity (*Fund TSelectivity*), however, turns out to be less significant (0.09, P = 0.211 for regression [3]; 1.27, P = 0.074 for regression [6]; 1.40, P = 0.047 for regression [9]), indicating that fund managers' stock picking skill delivers greater value to fund performance when they invest in the stocks of firms managed by CEOs with superior managerial ability.

Next, we replicate the previous regression analysis using the BvanB skill and performance measures and report the results in Table 7, Panel A. Consistent with the pattern of results in Table 6, these regression results show that the average performance of firms run by skilled CEOs is positive and significantly correlated with a high BvanB fund *alpha*, suggesting that investing in the stocks of firms headed by skilled CEOs improves fund performance. The interaction of the BvanB skill and the average performance of skilled CEO firms, *BvanB Skill* Added Value of Top (50%, 33%, and 20%) MA-Score Firms*, is also positively and significantly associated with high selectivity fund *alpha* (0.01, P < 0.0001 in regressions [3], [6], and [9]), respectively, indicating that skilled fund managers' investment in such firms improves fund performance. On the other hand, as in Table 5, the contribution of the stocks of firms run by low-skilled CEOs (*Added Value of Bottom 50% MA-Score Firms*) to fund performance, BvanB *alpha*, is significantly negative (-0.50, P < 0.0001 in regression [3]; -0.33, P < 0.0001 in regression [6]; -0.08, P < 0.0001 in regression [9]). Jointly, the results from the multivariate regression analysis lend support to the hypothesis that skilled mutual fund managers' CEO managerial ability-based stock selection investment strategy has a positive and significant impact on mutual fund performance. Funds earn higher (lower) subsequent returns by investing in the stocks of companies managed by CEOs with high (low) managerial ability. Hence, adopting corporate managerial ability as a stock identification and investment strategy is an essential component of mutual fund performance success.[35,36,37]

Skilled fund performance and CEO managerial ability change

Since CEO managerial ability is not expected to be static over time and is not accurately known at a point of time, it is interesting to examine how its changes (i.e., increases or decreases) influence fund performance, to the extent that managerial ability is considered

---

[35] From now on, we only report the results using the top and bottom 50% MA-Score firm performance, since the 33% and 20% measures give consistent results.

[36] We replicate the analyses by exploring the performance relation between high managerial ability stocks and mutual funds in the lowest fund managers' skill quintile (bottom 20%) compared to mutual funds in the highest managers' skill quintile (top 20%). Unsurprisingly, the coefficients for the performance of funds with less-skilled managers and the average performance of high managerial ability stocks, using both fund selectivity and the BvanB skill measures, are insignificant, at zero (-0.01, P = 0.719 for the selectivity measure and 0.04, P = 0.379 for the BvanB measure).

[37] Furthermore, to assess the persistence of the impact of CEO ability on fund performance, we use the previous two-year average MA-Score to identify firms with high or low managerial ability. The new evidence is consistent with the previous results based on both skill measures and provides additional support for the positive and significant association between skilled fund performance and the stocks of firms managed by CEOs with high managerial ability, even when using the previous two-year average MA-Score to measure corporate managerial ability.

important by fund managers for their stock picking decisions. To examine this effect, we sort the firms into two groups based on each firm's previous year MA-Score change (MA-Score$_{t-2}$ - MA-Score$_{t-1}$) and then estimate the relation between each group's performance change (i.e., high and low CEO ability change firms' *alpha*) and skilled mutual fund performance. The results are reported in Table 8.

TABLE 2.8

High and low managerial ability change stocks' performance and skilled funds' performance

This table reports the results of regressing top 20% highest selectivity (BvanB skill) fund *alpha* on fund manager's selectivity (BvanB skill) and performances of firm groups with high/low previous year CEO MA-Score changes controlling for other fund characteristics. Firms are sorted into two groups based on their previous year CEO MA-Score changes. For regression [1] and [2], the dependent variable is the annual *alpha* of high selectivity funds, representing the top 20% funds with the highest selectivity in each year. The main independent variables are firm *alpha*s of high and low previous year CEO MA-Score changes, which are the average abnormal returns of companies in high and low previous year CEO MA-Score change groups. For regression [3] and [4], the dependent variable is the annual BvanB *alpha* of high BvanB skill funds, representing the top 20% funds with the highest BvanB skill ratio in each year. The main independent variables are value added of high and low previous year CEO MA-Score changes, which are the average abnormal returns of companies in high and low previous year CEO MA-Score change groups time the company's market capitalization at the beginning of each year. Fund-level control variables contain expense ratio, log value of fund age, value of total net assets (TNA), and squared log value of TNA. We present the P values and adjusted R^2 for each regression. ***, **, * denotes significance at the 1%, 5% or 10% level.

	Top 20% Selectivity Fund *Alpha*		**Top 20% BvanB Skill Fund *Alpha***	
	[1]	[2]	[3]	[4]
Intercept	-1.53	0.13	612.50***	563.68***
	(0.686)	(0.974)	(<.0001)	(<.0001)
TSelectivity		2.59***		
		(<.0001)		
BvanB Skill				1.30***
				(0.005)
High CEO Ability Change Firm *Alpha*	0.21***	0.19***		
	(0.001)	(0.003)		
Low CEO Ability Change Firm *Alpha*	-0.14**	-0.11		
	(0.039)	(0.114)		
High CEO Ability Change Firm Added Value			0.06*	0.07**
			(0.080)	(0.045)
Low CEO Ability Change Firm Added Value			-0.15***	-0.16***
			(0.001)	(0.001)
Fund $Alpha_{t-1}$	1.82***	1.55***		
	(0.001)	(0.001)		
Fund BvanB $Alpha_{t-1}$			0.21	-1.86
			(0.813)	(0.102)
Expense Ratio	-0.24**	-0.28***	-36.96***	-36.06***
	(0.018)	(0.006)	(0.004)	(0.005)
Turnover	-0.01***	-0.01***	-0.08	-0.07
	(0.001)	(0.001)	(0.270)	(0.298)
Log(Age)	-0.74	-0.88	14.83	14.58
	(0.196)	(0.122)	(0.105)	(0.110)
Log(TNA)	1.47	1.59	-270.32***	-251.51***
	(0.241)	(0.200)	(<.0001)	(<.0001)
$[Log(TNA)]^2$	-0.14	-0.14	29.21***	27.38***
	(0.190)	(0.172)	(<.0001)	(<.0001)
Strategy Control	*YES*	*YES*	*YES*	*YES*
Adj. R^2	0.039	0.052	0.310	0.313

These results show a positive and significant relation between CEO ability increases and fund performance. Specifically, the performance of mutual funds run by skilled managers is positively and significantly associated with the performance of firms experiencing large CEO ability improvement (0.19, P = 0.003 based on the selectivity measure, controlling for lagged fund selectivity; 0.07, P = 0.045 based on the BvanB skill measure, controlling for lagged fund BvanB skill). The opposite pattern is observed when firms experience CEO ability declines, especially when the BvanB *alpha* and BvanB skill measures are used. In sum, these results suggest that skilled fund managers' performance is linked with CEO managerial ability changes, implying that the stock picking decisions of highly skilled fund managers based on the high CEO managerial ability strategy (preference) contribute significantly to fund *alpha*. That is, the investment exposure of skilled fund managers to the stocks of firms headed by high-ability CEOs pays off.

ROBUSTNESS CHECKS

Fund portfolios sorted by high managerial ability (MA-Score) stocks

Our earlier results provide support for the hypothesis that skilled fund managers' value creation is related to the performance of high managerial ability stocks. In this section, we examine the robustness of this result by analyzing the composition of fund portfolios. The fund portfolio information is manually collected from the Bloomberg Portfolio Analysis database. [38] Specifically, using cross-sectional analysis for each year, we investigate whether the portfolios of highly skilled fund managers are loaded with a higher proportion of high–MA-Score stocks than the portfolios of less-skilled fund managers. To address this, we first identify the MA-Score for

[38] Only funds with full information in the 24-month estimation period and have no less than 10 stocks with MA-Score information are included.

each stock held within each fund portfolio and then we calculate the value-weighted score of each fund, as follows:

$$FundScore_j = \frac{\sum(MAScore_{i,j} \times MarketValue_{i,j})}{\sum MarketValue_{i,j}} \quad (5)$$

where $FundScore_j$ is the value-weighted MA-Score for fund j, $MAScore_{i,j}$ is the MA-Score of stock i in fund j, and $MarketValue_{i,j}$ is the total market value of stock i in fund j. Finally, for each fund portfolio quintile, we estimate the average *FundScore* value and report the results for 2012 and 2013.[39]

TABLE 2.9

Fund portfolio MA-Score, based on sorting on fund manager skill

This table presents the average value-weighted fund MA-Scores of each fund portfolio. Fund portfolios are formed by sorting all funds in each year into quintiles by fund selectivity (logistic transformed 1-R^2) or fund BvanB skill. Fund selectivity (Eq. 1 and 2) and fund BvanB skill (Eq. 3) are estimated separately using 24-month monthly fund data in current year and one year before. Within each portfolio, we estimate the portfolio MA-Score by averaging the value-weighted average fund MA-Score of all the funds containing in the portfolio, and the value-weighted average fund MA-Score is calculated as the sum of market value weighted MA-Scores of the stocks holding by the fund. Fund portfolio holdings information are manually collected from Bloomberg Portfolio Analysis database, and stock MA-Score data are available through Sarah McVay's UW faculty website. We report the cross sectional analysis results for the last two years of our sample period (2012 and 2013).

Fund Manager Skill	Fund Portfolio MA-Score			
	Selectivity Skill Measure		BvanB Skill Measure	
	2012	2013	2012	2013
Q1 (Highest Skill)	0.074	0.068	0.072	0.074
Q2	0.069	0.066	0.070	0.063
Q3	0.070	0.067	0.062	0.073
Q4	0.071	0.068	0.065	0.073
Q5 (Lowest Skill)	0.062	0.066	0.070	0.073
All	0.069	0.067	0.068	0.071

The average portfolio *FundScore* results, presented in Table 9, provide additional support for our hypothesis by showing that the highest-skilled fund quintile (Q1) has the highest average *FundScore*, among all five quintiles, indicating that skilled fund managers' stock holdings are

[39] The cross-sectional analysis results for other years are consistent with our findings and are available upon request.

associated with high managerial ability stocks. On the other hand, the portfolios of low-skilled fund managers appear to be tilted in favor of low managerial ability stocks.

Skilled fund performance, CEO ability, and economic states

Previous studies have shown that fund managers' value creation varies with the state of the economy (Glode, 2011; Kosowski, 2011; Kacperczyk, van Nieuwerburgh, and Veldkamp, 2014, 2016). Specially, Kacperczyk et al. (2014, 2016) argue that mutual fund managers pick stocks in economic expansions and time the market in recessions. Along this argument, one would expect CEO managerial ability to be more precious for skilled fund managers during economic expansions, since CEO managerial ability information is mainly used during fund managers' stock selection process. To test the sensitivity of our results, we condition our previous regression analysis to the state of the economy. We follow Kacperczyk et al. (2014) and use the Chicago Fed National Activity Index (CFNAI) to capture the business state. The CFNAI is a coincident indicator of national economic activity comprising 85 macroeconomic time series. For the whole sample period, if the CFNAI index in year t is higher (lower) than the median number of the sample of all the index numbers, year t is defined as an economic expansion (recession). Separately, we perform a regression of fund performance on skilled-CEO firm performance while controlling for other fund-level control variables in economic expansions and recessions. The results can be found in Table 10.

TABLE 2.10

High managerial ability stocks' performance, skilled funds' performance, and business states

This table reports the results of regressing high skill (selectivity and BvanB skill) fund annual *alpha* on the performance of company groups with high and low CEO ability scores in economic expansions and economic recessions, controlling for other fund characteristics. If the 12-month average Fed National Activity Index (CFNAI) for the test year (t) is higher (lower) than the median number of all yearly 12-month average CFNAI index numbers, we define this year as economic expansion (recession) year. The dependent variable is the annual *alpha* of high selectivity (BvanB skill) funds, which are the top 20% funds with the highest selectivity (BvanB skill) in each year. For the selectivity skill measurement, the main independent variable is *alpha* of top 50% MA-Score firms, which is the average abnormal performance of companies in high CEO ability scores group. For the BvanB skill measurement, the main independent variable is added value of top 50% MA-Score firms, which is the average of each company's abnormal performance timing the company's market capitalization at the beginning of year t in high CEO ability scores group. Companies are sorted into two CEO ability groups (high and low) based on their CEO ability score in prior year (t-1). Fund-level control variables contain expense ratio, log value of fund age, fund turnover, log value of TNA, squared log value of TNA, and fund $alpha_{t-1}$ (BvanB $alpha_{t-1}$). Sample period ranges from 1990 through 2014 for selectivity measurement and from 2003 to 2014 for BvanB skill measurement. The P-value and adjusted R^2 for each regression are also presented. ***, **, * denotes significance at the 1%, 5% or 10% level.

	Top 20% Selectivity Fund *Alpha*		**Top 20% BvanB Skill Fund *Alpha***	
	Expansion	*Recession*	*Expansion*	*Recession*
Intercept	-3.83	0.97	636.16***	451.31***
	(0.478)	(0.852)	(<.0001)	(<.0001)
***Alpha* of Top 50% MA-Score Firms**	0.46***	0.12**		
	(<.0001)	(0.054)		
Added Value of Top 50% MA-Score Firms			0.38***	0.21***
			(0.010)	(<.0001)
Fund $Alpha_{t-1}$	2.09***	1.35**		
	(0.001)	(0.044)		
BvanB $Alpha_{t-1}$			3.43***	-3.33**
			(<.0001)	(0.016)
Expense Ratio	-0.54***	-0.07	-19.45	-36.84**
	(<.0001)	(0.611)	(0.193)	(0.043)
Turnover	-0.01*	-0.01***	0.02	-0.06
	(0.071)	(0.001)	(0.897)	(0.466)
Log(Age)	0.63	-1.57**	-0.36	38.11***
	(0.436)	(0.046)	(0.972)	(0.005)
Log(TNA)	0.71	1.68	-258.03***	-243.14***
	(0.696)	(0.322)	(<.0001)	(<.0001)
$[Log(TNA)]^2$	-0.06	-0.17	28.08***	28.52***
	(0.683)	(0.225)	(<.0001)	(<.0001)
Strategy Control	*YES*	*YES*	*YES*	*YES*
Adj. R^2	0.090	0.028	0.490	0.271

In line with previous studies, the results in Table 10 demonstrate that, even though a positive relation exists in both economic states, the performance of skilled mutual funds has a markedly stronger relation with the performance of firms run by skilled CEOs during economic expansions than in economic recessions. Using the fund selectivity measure, we find the coefficient decreases from 0.46 ($P < 0.0001$) in economic expansions to 0.12 ($P = 0.054$) in economic recessions, while, based on the BvanB fund skill measure, the coefficient decreases from 0.38 ($P = 0.010$) in economic expansions to 0.21 ($P < 0.0001$) in economic recessions. Thus, consistent with the findings of Kacperczyk et al. (2014, 2016), our results show that the performance relation between skilled fund managers and the stocks of firms managed by skilled CEOs is more pronounced during economic expansions than in recessions. In sum, controlling for the state of the economy, our evidence continues to point out that skilled fund managers' performance is reliably linked with the stocks of firms run by CEOs of high managerial ability.

Skilled fund performance, CEO ability, and fund trading strategy

We next investigate whether the positive relation between the performance of skilled fund managers and the performance of high managerial ability that we have documented so far is driven by certain (asset class) fund investment strategies. To address this issue, we classify mutual funds within the highest management skill quintile into three groups based on their fund management strategy: *Growth*, *Value*, and *Blend*.[40] For each group, we reexamine the association between the fund performance of the fund managers with the highest skill with the performance of those firms run by the CEOs with the high managerial ability. The results are reported in Table 11. When the fund selectivity measure is used, only *Value* strategy funds are positively

[40] Within our 2,190 mutual fund sample, we have 7 types of trading strategies based on their Bloomberg trading strategy classification, and 98% of the funds are covered in the main three strategies: Growth, Value, and Blend. Besides that, 2% of the mutual funds have strategies of Market Neutral, Long Short, Bear Market, and no trading strategy data.

and significantly associated with the stocks of firms managed by CEOs with high managerial ability (0.22, P = 0.001), while the other two fund strategies (i.e., *Growth* and *Blend*) show a positive but not significant (0.08, P = 0.394 for *Growth* strategy; 0.14, P = 0.111 for *Blend* strategy) relation with high managerial ability stocks. When switched to the BvanB fund skill measure, all three fund strategy groups show a significant positive relationship with high managerial ability stocks (0.17, P < 0.0001 for *Growth* strategy; 0.15, P < 0.0001 for *Value* strategy; 0.32, P < 0.0001 for *Blend* strategy). Since the BvanB fund skill measure, as argued by BvanB, represents a more accurate fund management skill measure because it measures fund performance adjusted by total assets under management, these results indicate that skilled fund managers, no matter which fund management strategy they follow, consistently generate excess value through their ability to recognize the value of corporate managerial ability and to pick the stocks of firms managed by adept CEOs.

Skilled fund performance, CEO ability, and firm industry

Our last robustness check examines whether the positive relation between the performance of skilled fund managers and high managerial ability stocks is more pronounced in certain industries. We first group all companies based on their two-digit Standard Industrial Classification code and then, within each industry, we assign each firm into a high or a low CEO ability group, based on the firm's CEO MA-Score the previous year. Then, we calculate the average performance of firms with skilled CEOs (in the top 50% based on the prior year's MA-Score) in each industry annually and regress the skilled mutual fund performance on the average performance of firms with skilled CEOs in each industry, controlling for other fund-level variables. The coefficients with their corresponding P-values are shown in Table 12. The pattern of these results, similar with that reported in Table 11, indicates that the relationship between skilled fund manager performance and high managerial ability stocks holds across industries. The explanations of these results are analogous to those of the results reported in Table 11. When we use the fund selectivity to measure fund manager skill, the positive and significant relation between the performance of skilled fund managers and high managerial ability stocks is documented for only four industries (mining, construction, manufacturing, transportation, communications, electric, gas, and sanitary services). However, when the BvanB fund skill measure is used, the evidence indicates this relationship is not industry specific. While the relation between skilled fund manager performance and high managerial ability stocks is somewhat stronger in some industries than others, it holds across all industries.

TABLE 2.11

High managerial ability stocks' performance, skilled funds' performance, and fund trading strategies

This table reports the results of regressing high skill (selectivity and BvanB skill) fund annual *alpha*, grouped based on their investment strategies (growth, value, and blend), on the performance of high managerial ability stocks, controlling for other fund characteristics. The dependent variable is the annual *alpha* of high selectivity (BvanB skill) funds, which are the top 20% funds with the highest selectivity (BvanB skill) in each year. For the selectivity skill measurement, the main independent variable is the performance of high managerial ability stocks, which is the average abnormal performance of stocks from companies in high CEO MA-Score group (top 50%). For the BvanB skill measurement, the main independent variable is the average added value of top 50% MA-Score firms, which is the average of each stock's abnormal performance timing the company's market capitalization at the beginning of year t in high CEO MA-Score group (top 50%). Companies are sorted into two CEO ability groups (high and low) based on their CEO MA-Score in prior year (t-1). Fund-level control variables contain expense ratio, log value of fund age, fund turnover, log value of TNA, squared log value of TNA, and fund $alpha_{t-1}$ (BvanB $alpha_{t-1}$). Sample period ranges from 1990 through 2014 for selectivity measurement and from 2003 to 2014 for BvanB skill measurement. The P-value and adjusted R^2 for each regression are also presented. ***, **, * denotes significance at the 1%, 5% or 10% level.

	Top 20% Selectivity Fund *Alpha*			Top 20% BvanB Skill Fund *Alpha*		
Fund Strategy	*Growth*	*Value*	*Blend*	*Growth*	*Value*	*Blend*
Intercept	1.60	8.11	-12.24	333.08**	624.25***	398.58**
	(0.820)	(0.135)	(0.105)	(0.014)	(<.0001)	(0.016)
***Alpha* of Top 50% MA-Score Firms**	0.08	0.22***	0.14			
	(0.394)	(0.001)	(0.111)			
Added Value of Top 50% MA-Score Firms				0.17***	0.15***	0.32***
				(<.0001)	(<.0001)	(<.0001)
Fund $Alpha_{t-1}$	1.51**	0.41	1.48*			
	(0.033)	(0.697)	(0.081)			
BvanB $Alpha_{t-1}$				-0.95	-1.25	0.79
				(0.524)	(0.564)	(0.522)
Expense Ratio	-2.56***	-0.86	-0.16	-11.65	-16.52	-95.12***
	(<.0001)	(0.574)	(0.167)	(0.515)	(0.468)	(0.001)
Turnover	-0.01	-0.03***	-0.01**	-0.15	0.07	0.01
	(0.206)	(0.010)	(0.045)	(0.195)	(0.724)	(0.906)
Log(Age)	0.39	-1.06	-2.46**	23.70	19.48	8.72
	(0.700)	(0.177)	(0.034)	(0.110)	(0.185)	(0.630)
Log(TNA)	0.32	-1.68	7.49***	-186.21***	-294.66***	-182.61***
	(0.890)	(0.283)	(0.007)	(<.0001)	(<.0001)	(0.001)
$[Log(TNA)]^2$	-0.01	0.11	-0.71***	22.83***	32.14***	23.85***
	(0.951)	(0.372)	(0.004)	(<.0001)	(<.0001)	(<.0001)
Adj. R^2	0.063	0.046	0.047	0.291	0.342	0.362

TABLE 2.12

High managerial ability stocks' performance, skilled funds' performance, and stock industries

This table reports the coefficients between the performance of high managerial ability stocks in different industries and the performance of funds having high skill (selectivity and BvanB skill) managers. Companies are sorted into industry groups based on their 2-digit SIC code. Within each group, companies are sorted into two CEO ability subgroups (high and low) based on their CEO MA-Score in prior year (t-1). The dependent variable is the annual *alpha* of high selectivity (BvanB skill) funds, which are the top 20% funds with the highest selectivity (BvanB skill) in each year. For the selectivity skill measurement, the main independent variable is the performance of high managerial ability stocks, which is the average abnormal performance of stocks from companies in high CEO MA-Score group (top 50%). For the BvanB skill measurement, the main independent variable is the average added value of top 50% MA-Score firms, which is the average of each stock's abnormal performance timing the company's market capitalization at the beginning of year t in high CEO MA-Score group (top 50%). Companies are sorted into two CEO ability groups (high and low) based on their CEO MA-Score in prior year (t-1). Fund-level control variables contain expense ratio, log value of fund age, fund turnover, log value of TNA, squared log value of TNA, and fund $alpha_{t-1}$ (BvanB $alpha_{t-1}$). Sample period ranges from 1990 through 2014 for selectivity measurement and from 2003 to 2014 for BvanB skill measurement. The P-values for each coefficient are also presented. ***, **, * denotes significance at the 1%, 5% or 10% level.

Industry Division	**Top 20% Selectivity Fund *Alpha***	**Top 20% BvanB Skill Fund *Alpha***
agriculture, forestry and fishing	0.00 (0.678)	0.26*** (<.0001)
mining	0.05*** (<.0001)	0.78*** (<.0001)
construction	0.03*** (0.010)	0.02*** (<.0001)
manufacturing	0.13*** (0.007)	0.46*** (<.0001)
transportation, communications, electric, gas and sanitary service	0.14*** (<.0001)	0.49*** (<.0001)
wholesale trade	0.00 (0.881)	0.31*** (<.0001)
retail trade	0.01 (0.567)	0.44*** (<.0001)
finance, insurance and real estate	0.00 (0.898)	0.45*** (<.0001)
services	0.04 (0.187)	0.50*** (<.0001)
non-classifiable	0.00** (0.042)	0.25*** (<.0001)

CONCLUSION

In this paper, we examine whether the value created by skilled fund managers can be attributed to the performance of high managerial ability stocks. Prior research on CEO ability has shown a strong prediction power of CEOs' managerial skill in future firm performance. We hypothesize that this predictive power makes CEO's managerial ability valuable for mutual fund managers and using CEOs' high managerial ability as an identification strategy should be associated with superior mutual fund performance, especially for funds managed by highly skilled fund managers. Hence, a significant positive connection should exist between the performance of mutual funds run by skilled managers and the performance of high managerial ability stocks.

Consistent with this prediction, this paper shows that the excess value added generated by mutual fund managers with exposure to high managerial ability stocks ($3.47 million per year) is much higher than the average performance of all mutual funds (-$1.94 million per year). Consequently, this research provides strong evidence that the performance of high managerial ability stocks has strong explanatory power for the performance of actively managed mutual funds headed by highly skilled fund managers. Furthermore, this positive relation exists for stocks across all industries and for funds with different types of trading strategies.

The results of this paper enable us to characterize the private information used by skilled fund managers and to suggest that their stock selection is based on information about the level of CEO managerial ability, while previous research mainly focuses on firm- and industry-level explanations. In sum, our research suggests that skilled mutual fund managers' superior performance (alpha) stems from allocating capital in corporations run by CEOs with high managerial skill.

REFERENCES

Allen, F. & Babus, A. (2008). Networks in finance. *Available at SSRN.*

Amihud, Y. & Goyenko, R. (2013). Mutual fund's R^2 as predictor of performance. *Review of Financial Studies* 26(3): 667-694.

Andreou, P. C., Ehrlich, D., Karasamani, I., & Louca, C. (2015). Managerial ability and firm performance: Evidence from the global financial crisis. *Available at SSRN*.

Baik, B. O. K., Farber, D. B., & Lee, S. S. (2011). CEO ability and management earnings forecasts. *Contemporary Accounting Research* 28(5), 1645-1668.

Berk, J. B. & Green, R. C. (2002). Mutual fund flows and performance in rational markets. *National Bureau of Economic Research*.

Berk, J. B. & van Binsbergen, J. H. (2015). Measuring skill in the mutual fund industry. *Journal of Financial Economics* 118(1): 1-20.

Bertrand, M. & Schoar, A. (2002). Managing with style: The effect of managers on firm policies. *Available at SSRN.*

Bonsall IV, S. B., Holzman, E. R., & Miller, B. P. (2016). Managerial Ability and Credit Risk Assessment. *Management Science* 2016 May 2.

Brands, S., Brown, S. J., & Gallagher, D. R. (2005). Portfolio concentration and investment manager performance. *International Review of Finance*, 5(3-4), 149-174.

Carhart, M. M. (1997). On persistence in mutual fund performance. *The Journal of finance*, 52(1), 57-82.

Cohen, L., Frazzini, A., & Malloy, C. (2007). The small world of investing: Board connections and mutual fund returns. *NBER Working Paper*.

Cremers, K. J., Martijn, M. A. F., Pedro, P. M., & Laura, T. S. (2015).Indexing and Active Fund Management. *Available at SSRN*.

Cremers, K. M. & Petajisto, A. (2009). How active is your fund manager? A new measure that predicts performance. *Review of Financial Studies*. 22(9): 3329-3365.

Daniel, K., Grinblatt, M., Titman, S., & Wermers, R. (1997). Measuring mutual fund performance with characteristic-based benchmarks. *The Journal of finance*, 52(3), 1035-1058.

Demerjian, P., Lev, B., & McVay, S. (2012). Quantifying managerial ability: A new measure and validity tests. *Management Science*, 58(7), 1229-1248.

Fama, E. F., & French, K. R. (1993). Common risk factors in the returns on stocks and bonds. *Journal of financial economics*. 33(1), 3-56.

Glode, V. (2011). Why mutual funds "underperform". *Journal of Financial Economics*. 99(3): 546-559.

Gruber, M. J. (1996). Another puzzle: The growth in actively managed mutual funds. *The Journal of Finance.* 51(3): 783-810.

Kacperczyk, M., Nieuwerburgh, S. V., & Veldkamp, L. (2014). Time-Varying Fund Manager Skill. *The Journal of Finance*. 69(4), 1455-1484.

Kacperczyk, M. & Seru, A. (2007). Fund manager use of public information: New evidence on managerial skills. *The Journal of Finance*. 62(2): 485-528.

Kacperczyk, M., Sialm, C., & Zheng, L. (2005). On the industry concentration of actively managed equity mutual funds. *The Journal of Finance*. 60(4), 1983-2011.

Kacperczyk, M., Van Nieuwerburgh, S., & Veldkamp, L. (2016). A rational theory of mutual funds' attention allocation. *Econometrica*. 84(2), 571-626.

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(03): 607-664.

Pan, Y., Wang, T. Y., & Weisbach, M. S. (2015). Learning about CEO ability and stock return volatility. *Review of Financial Studies*, hhv014.

Stambaugh, R. F., Yu, J., & Yuan, Y. (2014). The long of it: Odds that investor sentiment spuriously predicts anomaly returns. *Journal of Financial Economics*, *114*(3), 613-619.

Trueman, B. (1986). Why do managers voluntarily release earnings forecasts? *Journal of accounting and economics.* 8(1): 53-71.

Van Nieuwerburgh, S. & Veldkamp, L. (2009). Information immobility and the home bias puzzle. *The Journal of Finance*. 64(3): 1187-1215.

Wermers, R., Yao T., & Zhao J. (2012). "Forecasting stock returns through an efficient aggregation of mutual fund holdings." *Review of Financial Studies* 25.12: 3490-3529.

Zheng, L. (1999). Is money smart? A study of mutual fund investors' fund selection ability. *The Journal of Finance*. 54(3): 901-933.

APPENDIX 2.I

Vanguard Index funds

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

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

APPENDIX 2.II

CEO managerial ability and firm's stock performance

This table reports the results of regressing firm's stock *alpha* on this firm's CEO MA-Score score in previous year controlling for other firm level characteristics. The dependent variable is firm *alpha*, which is the difference between stock excess return (over risk free rate) in year t and the expected excess return of the same year. The expected excess return for each stock in year t is calculated by multiplying the FFC model factor loadings from the 24 month preceding estimation period (t-2 to t-1) by the FFC model factors in current year. This process is repeated by moving the estimation and test period one year at a time. The main independent variables are CEO MA-Score in previous year (t-1), which is introduced by Demerjian et al. (2012) and available online, and stock $alpha_{t-1}$, which is the intercept from the 24 month preceding estimation period (t-2 to t-1). Firm-level control variables contain firm total debt to total equity ratio (D/E ratio), return on equity (ROE), market to book ratio (M/B ratio), and market capitalization. Sample period covers from 1990 through 2014. We show the regression results with and without $alpha_{t-1}$ and results with and without industry control. We present the P values and adjusted R^2 for each regression. ***, **, * denotes significance at the 1%, 5% or 10% level.

	Firm *Alpha*	
Intercept	13.12*	13.12*
	(0.068)	(0.068)
CEO MA-Score	4.14*	4.12*
	(0.093)	(0.096)
Firm $Alpha_{t-1}$		0.02
		(0.840)
D/E Ratio	0.01***	0.01***
	(<.0001)	(<.0001)
M/B Ratio	-0.32***	-0.32***
	(<.0001)	(<.0001)
ROE	0.01	0.01
	(0.455)	(0.470)
Log(Size)	-3.05***	-3.05***
	(<.0001)	(<.0001)
Industry Control	*YES*	*YES*
Adj. R^2	0.013	0.012

APPENDIX 2.III

Fund management skill and fund performance

This table reports the results of regressing fund performance on fund manager's skill, controlling for other fund characteristics. In regression [1] and [2], the dependent variable is fund annual *alpha*, which is the difference between fund excess return (over risk free rate) in year t and the expected excess return of the same year. The expected excess return for each fund in year t is calculated by multiplying the FFC model factor loadings from the 24 month preceding estimation period by the FFC model factors in current year. This process is repeated by moving the estimation and test period one year at a time. The main independent variables are fund selectivity, which is the logistic transformed value of ($1\text{-}R^2_{t-1}$), and fund $alpha_{t-1}$, which is the intercept from the 24 month preceding estimation period. In regression [3] and [4], the dependent variable is fund's BvanB *alpha*, which is the product of fund total net assets (TNA) in year t-1 and the difference between fund excess return (over T-bill rate) in year t and the expected excess return of the same year. The expected excess return for each fund in year t is calculated by multiplying the 11 Vanguard Index fund orthogonal bases factor loadings from the 24 month preceding estimation period (t-2 to t-1) by the 11 Vanguard Index fund orthogonal bases factors in current year. The process repeats by moving the estimation and test period one year at a time. The main independent variable is fund BvanB skill, which is measured as the product of fund $alpha_{t-1}$ and fund TNA at the beginning of the last year (t-1) in the estimation period (t-2 to t-1) divided by the standard error of the fund $alpha_{t-1}$. Fund-level control variables for all regressions contain expense ratio, log value of fund age, fund turnover, log value of TNA, squared log value of TNA, and BvanB $alpha_{t-1}$, which is the product of fund $alpha_{t-1}$ and fund TNA at the beginning of the last year (t-1) in the estimation period (t-2 to t-1) and fund $alpha_{t-1}$ is the intercept from the 24 month preceding estimation period (t-2 to t-1). The P-value and adjusted R^2 for each regression are also presented. ***, **, * denotes significance at the 1%, 5% or 10% level.

	Fund *Alpha*		**BvanB *Alpha***	
	[1]	[2]	[3]	[4]
Intercept	0.83	0.26	743.39***	743.25***
	(0.562)	(0.854)	(<.0001)	(<.0001)
Fund TSelectivity	0.50***	0.37*		
	(0.010)	(0.052)		
Fund *Alpha*$_{t-1}$		1.34***		
		(<.0001)		
Fund BvanB Skill			1.36***	1.38***
			(<.0001)	(<.0001)
BvanB *Alpha*$_{t-1}$				-0.07
				(0.847)
Expense Ratio	-0.30***	-0.25***	-20.25***	-20.29***
	(<.0001)	(0.001)	(<.0001)	(<.0001)
Log(TNA)	0.35	0.40	-0.02	-0.02
	(0.460)	(0.397)	(0.309)	(0.308)
$[\text{Log(TNA)}]^2$	-0.04	-0.04	14.50***	14.49***
	(0.360)	(0.309)	(<.0001)	(<.0001)
Turnover	-0.01***	-0.01***	-333.22***	-333.13***
	(<.0001)	(<.0001)	(<.0001)	(<.0001)
Log(Age)	-0.37*	-0.33	35.83***	35.82***
	(0.086)	(0.127)	(<.0001)	(<.0001)
Strategy Control	*YES*	*YES*	*YES*	*YES*
Adj. R^2	0.011	0.016	0.330	0.330

APPENDIX 2.IV

High and low CEO MA-Score and skilled funds' performance

This table reports the results of regressing high selectivity (BvanB skill) fund annual *alpha* on the average MA-Score in high and low CEO managerial ability groups. The dependent variable is the annual *alpha* of high selectivity (BvanB skill) funds, representing the top 20% funds with the highest selectivity (BvanB skill) in each year. The main independent variables are high MA-Score *1,000 and low MA-Score*1,000, which are the average CEO MA-Score of companies in high CEO MA-Score group and low MA-Score group, timing 1,000. Companies are sorted into two groups (high and low) based on their CEO MA-Scores in prior year (t-1). The process repeats by moving the estimation and test period one year at a time. Fund-level control variables contain expense ratio, log value of fund age, value of total net assets (TNA), and squared log value of TNA. Sample period covers from 1990 through 2014 for selectivity measure and from 2003 to 2014 for BvanB skill measure. We present the P values and adjusted R^2 for each regression. ***, **, * denotes significance at the 1%, 5% or 10% level.

	Top 20% Selectivity Fund *Alpha*	**Top 20% BvanB Skill Fund *Alpha***
Intercept	-44.97***	-614.81**
	(<.0001)	(0.044)
High MA-Score *1,000	0.18***	4.49***
	(<.0001)	(<.0001)
Low MA-Score *1,000	-0.23***	-6.63***
	(<.0001)	(<.0001)
Fund $Alpha_{t-1}$	1.69***	
	(<.0001)	
BvanB $Alpha_{t-1}$		0.59
		(0.499)
Expense Ratio	-0.26**	-36.50**
	(0.011)	(0.004)
Turnover	-0.01***	-0.08
	(<.0001)	(0.264)
Log(Age)	-0.92	16.48*
	(0.106)	(0.071)
Log(TNA)	1.16	-268.21***
	(0.352)	(<.0001)
$[Log(TNA)]^2$	-0.12	29.02***
	(0.263)	(<.0001)
Strategy Control	*YES*	*YES*
Adj. R^2	0.045	0.313

CHAPTER 3

THE PAYBACK OF MUTUAL FUND SELECTIVITY: EVIDENCE FROM EUROPEAN COUNTRIES

ABSTRACT

Using a sample of 2,947 actively-managed domestic equity mutual funds from 11 European countries, we investigate the performance of mutual fund selectivity across markets. The evidence of this paper supports the argument that selectivity (1-R2) still benefits fund investors outside US. Our analysis is robust after controlling for investor sentiment and market dispersion. In addition, we investigate the mediating effect of country characteristics on the profitability of fund selectivity, indicating that managers' selectivity ability is more valuable in countries with high economic development, strong legal strength, small but highly liquid equity markets, and young mutual fund industries.

INTRODUCTION

Since their invention in 1924, mutual funds have become an increasingly important investment instrument and attract a large amount of capital from individual investors to the financial markets. By the end of 2014, the total value of assets managed by mutual funds exceeded US$31 trillion, which reflected a 20% growth rate since 2007 (Investment Company Institute, 2015). With a value of US$16 trillion, the United States has the largest mutual fund industry in the world. Numerous studies have confirmed the extremely important role of the mutual fund industry in US financial markets, showing the relation between US mutual fund performance and fund managers' skills (Malkiel, 1995; Carhart, 1997; Daniel, Grinblatt, Titman, and Wermers, 1997; Brands, Brown, and Gallagher, 2005; Kacperczyk, Sialm, and Zheng, 2005; Cremers and Petajisto, 2009; Berk and van Binsbergen, 2015; Cremers, Ferreira, Amihud and Goyenko, 2015). However, only a few studies have explored these questions in other settings, such as European countries.

This gap is noteworthy because the mutual fund industry in Europe is the second largest mutual fund industry in the world. As of the end of 2014, the European mutual fund industry had more than US$9.5 trillion in assets under management, which is 31% of the world's total mutual fund industry. Among the current mutual funds worldwide, 44% are from European countries. Meanwhile, the net sale of European mutual funds in 2014 was US$617 billion, more than twice that in 2013, while the net sale of mutual funds in the United States was US$318 billion. Given the important role the European mutual fund industry plays in the world economy and its dramatic growth in recent years, academic studies of its workings are very relevant but lacking. In this paper, we investigate whether fund selectivity, an established measure of fund management skill, is associated with superior fund performance for actively managed domestic equity mutual funds in European countries.

Several studies have investigated the determinants of fund performance in the European mutual fund industry, but only at a very macro level. Both Grünbichler and Pleschiutschnig (1999) and Otten and Bams (2002) have conducted aggregate research on the European mutual fund industry's performance and Otten and Bams (2002) find that, unlike US mutual funds, European mutual funds as a whole slightly outperform the market benchmark. Banegas, Gillen, Timmermann, and Wermers (2013) show that European mutual fund performance can be explained by macroeconomic state variables, such as the default yield spread, the term spread, or the dividend yield. Ferreira, Keswani, Miguel, and Romos (2012), using the data of actively managed equity mutual funds from 27 countries, find that both fund-level variables and country characteristics can determine fund performance and, in particular, mutual funds show superior performance if they are located in countries with highly liquid markets and strong legal protection. Many other studies focus on specific European countries (e.g., Dermine and Roller, 1992; Shukla and van Imwegen, 1995; Blake and Timmermann, 1998; Dahlquist, Engstrom, and Soderlind, 2000; Cesari and Panetta, 2002). However, these focus on evaluating the overall performance of the European mutual fund industry and more valuable questions from the investor’s perspective—whether fund management skills exist and whether managers with higher skills can generate more profits for their clients—have received less attention from academia. Abinzano, Muga, and Santamaria (2010) use stochastic dominance techniques to show that some European mutual fund managers do possess management skills. Cuthbertson, Nitzsche, and O’Sullivan (2008) employ a cross-sectional bootstrap methodology and find evidence that some top-performing UK equity mutual fund managers have stock-picking abilities. Furthermore, Franck and Kerl (2013) point out that European fund managers actively change their portfolio allocations based on sell-side analyst information and this strategy benefits fund performance. However, as far as we know, no study has been conducted to measure European mutual fund managers’ skill (i.e., fund selectivity) directly and there is no evidence that managerial skill leads to superior fund performance. The aim of our analysis is to address those issues.

Empirical studies based on the US mutual fund industry show that mutual fund managers with high managerial skills do add value for their clients by selecting valuable stocks (Gruber, 1996; Carhart, 1997; Daniel et al., 1997; Zheng, 1999). The skill may be due to their superior analytical ability to anticipate macro or micro fundamental information (Kacperczyk, van Nieuwerburgh, and Veldkamp, 2011) or special knowledge of specific industries or companies (Cohen, Frazzini, and Malloy, 2007; Kacperczyk et al., 2005). Petajisto (2013) uses active share, which is measured as the aggregate stock-holding dispersion between a manager’s portfolio and the benchmark index, to capture fund managers' selectivity skill and finds a strong relation between active management and fund performance. Amihud and Goyenko (2013), using a lower fund R^2 value from regressing its returns on multifactor benchmark models to proxy for higher selectivity skill, find similar results. One advantage of Amihud and Goyenko's method is that it does not require the knowledge of fund holdings or the fund's benchmark index. Following their methodology and using a special sample of 2,947 actively managed domestic equity mutual funds from 11 European countries over the years 2000–2015, we add to this literature by estimating fund manager's stock-picking skill directly and investigating the relation between managerial skills and fund performance. To measure fund manager skill, we first construct the benchmark factors in the Fama–French (1993) and Carhart (1997) four-factor model (FFC model) for each individual country, using all the stocks included in the Bloomberg database, and calculate fund selectivity following Amihud and Goyenko (2013). Our analysis reveals evidence that, as in the US mutual fund industry, a significantly positive relationship exists between fund selectivity and fund performance in the European mutual fund industry.

Subsequently, our analysis is robust to adjusting for two market conditions, investor sentiment and market dispersion, which can strongly influence fund performance. First, investors are not consistently rational and investor sentiment can influence the profitability of a fund manager's skill. Previous literature on investor sentiment has shown that it can affect both overall market returns and individual stock returns (Daniel, Hirshleifer, and Subrahmanyam, 1998; Hong and Stein, 1999; Amromin and Sharpe, 2009; Antoniou, Doukas, and Subrahmanyam, 2015). During high-sentiment periods, the equity market is filled with greater noise than during low-sentiment periods. Hence, asset prices are more likely to be noisy and it is more difficult to identify good investment opportunities. On average, stock-picking ability during high-sentiment periods is limited, thus resulting in fund underperformance. During low-sentiment periods, stocks are traded around their fundamental values and overall mutual fund performance should be higher during low-sentiment periods, when asset prices are less noisy. The above argument indicates that the relation between fund selectivity and fund performance should be affected by market sentiment. We estimate market sentiment for each country based on the European market Consumer Confidence Indicator (CCI) and further test the sensitivity of our results by replacing the major sentiment index with four alternative market sentiment measures. The results show the same trend as our previous findings.

Second, von Reibnitz (2013) shows that market dispersion, which is used to measure the level at which stocks prices are affected by firm-specific information, can also influence the market state and consequently impact the effectiveness of fund manager skill. If fund manager skills result from their great insight and analytical ability, average mutual funds cannot yield high risk-adjusted returns during periods of low market dispersion when access to firm-specific information is costly. Thus, mutual fund manager selectivity should be more profitable during periods of high market dispersion, when more firm-specific information is available in the market. Our results also support this argument.

Next, we study how the profitability of fund selectivity relates to country-level characteristics. Unlike previous studies, which examine the direct effects of country-level variables on fund performance (e.g., Ferreira et al., 2012), we argue that those factors, such as equity market development or legal protection strength, could influence the validity of fund manager skills, which consequently affect mutual fund performance. To address this question, we employ a two-step regression procedure and find that fund manager skill is more valuable and profitable for fund investors if the fund is in countries with high economic development, strong legal protection, small but highly liquid equity markets, and a young mutual fund industry.

The remainder of the paper is organized as follows. Section 1 describes the data and empirical methodology. Section 2 presents the empirical findings, along with a discussion of the results. Section 3 concludes with a discussion of the implications of this study for the literature on mutual fund performance and managerial skill.

DATA AND METHODOLOGY

In this section, we describe our sample selection process and then present the methodology used to calculate fund performance and fund selectivity. Lastly, we explain the other market variables and country-level characteristics in our analysis.

Sample Description

We first collect data for European actively managed domestic equity mutual funds. The source is Bloomberg mutual fund database and the time period is from January 1998 to December 2015 (the first 24 months of data are used to estimate fund selectivity and fund performance as of January 2000). The criteria used to collect data are 1) whether the fund status is active or dead, 2) whether the country of domicile is European, 3) whether the asset focus is equity, 4) whether the inception date is before December 31, 2013, and 5) whether the fund type is an open-end mutual fund. To eliminate index funds or international funds, funds with a description containing any of the partial terms are deleted: *index, ind, global, fixed-income, international, sector, balanced, bond, money-market,* and *convertible debt*. In addition, each fund must have more than 25 months of continuous data. Our final sample consists of 3,388 mutual funds from 17 European countries. The list of countries and the numbers of mutual funds in each country is shown in Table 1.

TABLE 3.1
List of European countries in the database
This table lists all the European countries in Bloomberg with actively-managed domestic equity mutual fund database, along with the number of mutual funds within each country. Totally we have 3,388 actively-managed European domestic equity mutual funds, both active and dead status, from January 2000 to December 2015.

Country	Number of Funds
Austria	371
Belgium	13
Denmark	138
Finland	156
France	15
Germany	339
Greece	74
Ireland	641
Italy	308
Luxembourg	207
Netherlands	111
Norway	83
Portugal	49
Spain	399
Sweden	147
Switzerland	185
United Kingdom	152
Total	3,388

To ensure reliable results, we narrow down the list of countries to those with more than 100 months of available mutual funds data. Of the 17 European countries, 12 remain. We then delete Luxembourg, because it often functions as an offshore mutual fund market for other countries. Finally, we have 11 countries in the database, with 2,947 actively managed mutual funds. The summary statistics for these funds are reported in Table 2. The average monthly raw return for all European mutual funds is 0.49%, Sweden has the highest average monthly return (0.81%), and Austria has the lowest (0.36%). The average of total net assets (TNA) for all funds in the sample is US$235.15 million and the average age is 10.11 years.

TABLE 3.2
Summary statistics of actively managed equity mutual funds' characteristics from 11 selected European countries
This table shows the means of mutual funds' descriptive statistics in each country and the number of funds from each country for 11 European countries with more than 100 mutual funds data in Bloomberg actively-managed domestic mutual fund database. Expense ratio is the annual expense ratio of each fund. TNA is each fund's total net assets in millions. Our sample contains 2,947 actively-managed equity mutual funds over the period from January 1998 to December 2015.

Country	Age (years)	TNA (Million $)	Expense Ratio (%)	Raw Return (%)	Number of Funds
Austria	10.87	81.93	1.68	0.36	371
Denmark	13.19	173.71	1.93	0.78	138
Finland	8.66	169.66	1.84	0.51	156
Germany	11.69	208.98	2.27	0.57	339
Ireland	7.74	599.02	1.83	0.46	641
Italy	10.90	181.62	2.24	0.39	308
Netherlands	10.93	170.71	1.57	0.57	111
Spain	8.98	76.20	2.05	0.41	399
Sweden	14.17	433.88	1.63	0.81	147
Switzerland	11.13	186.60	1.73	0.54	185
United Kingdom	7.98	171.96	1.83	0.59	152
All	10.11	235.15	1.95	0.49	2,947

Measuring Fund Selectivity and Performance

The next step is to estimate fund performance (fund *alpha*) and fund selectivity for all mutual funds in our sample. Following Amihud and Goyenko (2013), we use 1 - R^2 to measure fund selectivity, where R^2 is obtained from regressing each fund's returns on the multifactor benchmark model (i.e., the FFC model). According to this study, a low R^2 value indicates that fund performance has a low level of co-movement with the market benchmark and the higher a manager's selectivity skill, the more private information the manager will use and the less sensitive the fund's performance will be to market benchmark movement. The model to estimate R^2 is the following:

$$R_{i,t} = \alpha_i + \beta_{1,i}(RM_t - Rf_t) + \beta_{2,i}SMB_t + \beta_{3,i}HML_t + \beta_{4,i}MOM_t + \varepsilon_{i,t} \qquad (1)$$

where $R_{i,t}$ is the return in US dollars of fund *i* in month *t* over the one-month US Treasury bill rate in month *t*; RM_t - Rf_t is the market excess return in US dollars in month *t*; SMB_t (small minus big) is the return difference between a large capitalization portfolio and a small capitalization portfolio in month *t*; HML_t (high minus low) is the return difference between a high–book-to-market ratio portfolio and a low book-to-market ratio portfolio in month *t*; and MOM_t (momentum) is the return difference between the past 12 months' winners and the past 12 months' losers. To employ this model, we first construct the monthly benchmark factors from the FFC model for each country using all equity values included in the Bloomberg equity database traded in each country. The variable *RM* is calculated as the value-weighted average return of all stocks, active or dead. We then form the *SMB*, *HML*, and *MOM* factors following the method described by Fama and French (1993) and Carhart (1997). To test the validity of our estimation, we calculate the correlation between each market return factor and the same country's major market index return.[41] The summary statistics are shown in Table 3.

[41] The following are the major markets: Austrian Traded Index (ATX Index) for Austria, OMX Copenhagen Index (KFX Index) for Denmark, OMX Helsinki Index (HEX Index) for Finland, German Stock Index (DAX Index) for Germany, Irish Stock Exchange Overall Index (ISEQ Index) for Ireland, FTSE Italia All-Share Index (FTSEMIB Index) for Italy, Amsterdam Exchange index (AEX Index) for the Netherlands, Spanish Continuous Market Index (IBEX Index) for Spain, Stockholm Stock Exchange Index (OMX Index) for Sweden, Swiss Market Index (SMI Index) for Switzerland, and FTSE 100 Index (UKX Index) for the United Kingdom.

TABLE 3.3
Market risk factor summary and correlations between market premium and major market index return for each country
This table gives the average of the risk factors in the estimated Fama-French (1993) and Carhart (1997) model (FFC model) for each country. The table also shows the coefficient between the market return factor (RM) and the major market index return for each country. (Austrian Traded Index (ATX Index) for Austria, OMX Copenhagen Index (KFX Index) for Denmark, OMX Helsinki Index (HEX Index) for Finland, German Stock Index (DAX Index) for Germany, Irish Stock Exchange Overall Index (ISEQ Index) for Ireland, FTSE Italia All-Share Index (FTSEMIB Index) for Italy, Amsterdam Exchange index (AEX Index) for Netherlands, Spanish Continuous Market Index (IBEX Index) for Spain, Stockholm Stock Exchange Index (OMX Index) for Sweden, Swiss Market Index (SMI Index) for Switzerland, and FTSE 100 Index (UKX Index) for United Kingdom). *** stands for Pearson's P value at 1% significant level.

Country	RM	SMB	HML	MOM	Market Index	Correlation
Austria	1.203	-0.238	0.150	0.510	ATX Index	0.928***
Denmark	1.774	0.388	-1.008	0.698	KFX Index	0.868***
Finland	1.548	-0.170	0.296	0.555	HEX Index	0.987***
Germany	1.111	1.032	1.152	0.873	DAX Index	0.926***
Ireland	0.969	-0.325	0.166	0.062	ISEQ Index	0.749***
Italy	0.637	-0.063	1.293	0.101	FTSEMIB Index	0.963***
Netherlands	0.800	0.018	-0.158	0.581	AEX Index	0.951***
Spain	0.951	0.113	0.748	0.660	IBEX Index	0.972***
Sweden	1.315	0.184	0.306	0.531	OMX Index	0.985***
Switzerland	0.994	-0.192	0.393	0.332	SMI Index	0.865***
United Kingdom	0.787	0.390	0.284	0.656	UKX Index	0.966***
All	1.099	0.103	0.329	0.505		
Std. Dev.	0.341	0.391	0.622	0.249		

We calculate fund performance (the fund's *alpha*), past performance (the fund's $alpha_{t-1}$), and fund selectivity (logistically transformed 1 - R^2) using a 24-month moving window regression based on the estimated FFC model for each individual country. The fund *alpha* is the difference between the fund's return in month *t* and the expected return of the same month. The expected return for each fund in month *t* is calculated by multiplying the FFC model factor loadings from the preceding 24-month estimation period (months *t* - 24 to *t* - 1) by the FFC model factors in the current month. The process repeats by moving the estimation and test period one month at a time. The fund's $alpha_{t-1}$ is the intercept from the preceding 24-month estimation period (months *t* - 24 to *t* - 1). As Amihud and Goyenko (2013) explain, the distribution of R^2 is negatively skewed, which means that the distribution of 1 - R^2 should be heavily positively skewed. Therefore, we use the following logistic transformation of (1 - R^2) to measure fund manager selectivity skill:

$$Selectivity = log\left(\frac{1-R^2}{1-(1-R^2)}\right) = log\left(\frac{1-R^2}{R^2}\right) \quad (2)$$

One thing to be noted here is that, based on the argument of Berk and Green (2004), the performance measure based on fund return (the fund's *alpha*) is inaccurate due to economic scale, since superior performance can be detected by investors and abstract capital inflows. Consequently, managers with more capital must choose suboptimal investment opportunities due to the limited number of investment opportunities in the market, which harms fund performance. However, Ferreira et al. (2012) show that this scale effect is not present outside the US mutual fund industry.

Investor Sentiment and Market Dispersion

In this section, we estimate market sentiment and market dispersion and incorporate these two factors into the analysis. We argue that, on average, high market sentiment signals a high level of noise trader participation, which will hurt the performance of the overall mutual fund industry because the asset prices are more likely to be noisy and, therefore, it will be more difficult to identify good investment opportunities. To measure European market sentiment, we use the CCI, a survey-based index designed to measure consumer confidence in European countries. This index is available through the European Commission database. To ensure that the sentiment measure is free of macroeconomic influences, we use the residual from the regression of the CCI index on a set of macroeconomic variables that includes Europe's inflation rate, the growth rate of Europe's employment rate, the growth rate of Europe's industrial production, the growth rate of Europe's durable consumer goods production, the growth rate of Europe's nondurable goods production, the consumer price index change in Europe's service industry, and European recession indicators based on the Organisation for Economic Co-operation and Development (OECD). The data reflect the period from January 2000 through December 2015.

We also estimate the market dispersion for each European country in our sample. Market dispersion, as argued by von Reibnitz (2013), measures how the level of stock price is affected by firm-specific information. During a period of high market dispersion, more firm-specific information is available in the market and stock prices are more affected by firm-specific information than by market conditions. This improves the profitability of fund managers' selectivity skills, since using private information to estimate assets value is more reliable. On the other hand, during periods of low market dispersion, all stocks closely follow market benchmarks. Fund selectivity may not be profitable or may even hurt fund performance, since the benefits of active bets are expected to be less pronounced and actively building a portfolio based on firm-specific information will draw more risk into the fund when fund performance is more related to market-level information, such as economic shocks. Following von Reibnitz (2013), we measure market dispersion using the standard deviation of stock returns for all stocks in each country in month t:

$$Dispersion_{j,t} = \sqrt{\frac{1}{n-1}\sum_{i=1}^{n}\left(R_{i,j,t} - R_{m,j,t}\right)^2} \qquad (3)$$

where n is the number of stocks traded within country *j* in month *t*, $R_{i,j,t}$ is month *t*'s return for each stock *i* in country *j*, and $R_{m,j,t}$ is the equally weighted average return of all stocks traded in country *j* for month *t*. The data for both active and delisted stocks are from the Bloomberg database and our data for market dispersion range from January 2000 to December 2015.

Country-Level Characteristics

Previous studies have documented that, besides fund-level variables, country-level characteristics are essential determinants of mutual fund performance (Otten and Bams, 2002; Ferreira et al., 2012). Rather than investigate the direct relationship between funds' domicile country characteristics and fund performance, in our study we investigate whether those country-level variables can influence the profitability of fund selectivity skills. In other words, we examine which country-level factors will make fund managerial skills more valuable and produce superior fund performance. To address this issue, we use a two-step regression procedure. First, for each year from 2001 to 2015, we regress fund performance (fund *alpha*) on fund selectivity, controlling for other fund-level variables using monthly data for the current year and one year prior. Only funds with data for the full 24-month period are considered. Then we collect the coefficients of fund selectivity for each year from the prior regression, which is used as a proxy of fund selectivity profitability, and run a regression of the coefficients on various country-level variables. Similar to the country-level variables used by Ferreira et al. (2012), we classify our country characteristics into different groups: economic development, equity market development, investor protection and legal strength, and mutual fund industry development. The details of country-level characteristics can be found in the Appendix.

First, we use the gross domestic product (GDP) per capita and the percentage of Internet users to capture economic development. Both sets of data are collected from the World Development Indicators (WDI) database. The GDP per capita is the GDP divided by the mid-year population, while the percentage of Internet users measures the percentage of individuals who have used the Internet in each country in the last year. Greater economic development is associated with higher income and education levels and, in our scenario, we expect a positive relationship between fund selectivity, profitability, and country economic development, since information quality should be higher with better-informed and more educated investors, which places more value on the accuracy of fund managers' selectivity ability.

To capture equity market development, we use equity share turnover and the total size of equity markets. These two variables are also accessible from the WDI database. Share turnover, which is the value of domestic shares traded divided by their market capitalization, measures the liquidity of the equity market in each country. A higher share turnover ratio, that is, higher equity market liquidity, will help fund managers to establish and change portfolios based on new information. This argument indicates a positive relation between fund selectivity profitability and the share turnover ratio. On the other hand, a large equity market size may have an ambiguous effect on the implementation of fund managerial skills. First, a large equity market means more investment opportunities, which allows skilled managers to find profitable investment opportunities much more easily. On the contrary, a large equity market contains more noise, which hinders selectivity skills from being profitable.

We use a dummy variable that equals one for a common-law country and zero otherwise to capture common-law countries and securities regulation to capture investor protection and legal strength. According to La Porta, Lopez-de-Silanes, Shleifer, and Vishny (1997), common-law systems provide more protection for investors than civil-law systems do and enhance the enforcement of business contracts. Another variable used as a proxy for a country's legal strength is securities regulation, which combines disclosure requirements, liability standards, and public enforcement, introduced by La Porta Lopez-de-Silanes, and Shleifer (2006). We expect a strong positive relationship between fund selectivity profitability and investor protection and legal strength, since strong legal strength and strong securities market regulation limit insider trading activities and promote informed arbitrage, which makes fund managerial skills based on analytical ability more valuable (Morck, Yeung, and Yu, 1999). In addition, stock markets in countries with weak property rights protection are more influenced by political events and rumors, which create more noise in the markets and harm the profitability of fund managers' selectivity ability.

Finally, we use fund industry age and the mutual fund industry's proportion of the equity market to capture mutual fund industry development. We collect mutual fund industry age data from Ferreira et al. (2012). We argue that the older the mutual fund industry, the more competitive it is and the harder it is, therefore, for fund managers to achieve superior performance, since they will generate fewer risk-adjusted returns due to a higher market competition. To estimate the mutual fund industry proportion, which is calculated as the percentage of total mutual fund equity within the total capitalization of the equity market, we collect mutual fund industry equity data from the annual Asset Management Report of the European Fund and Asset Management Association. From our perspective, a larger mutual fund industry proportion means a more competitive mutual fund industry, which will hurt the profitability of fund managers' selectivity skills.

EMPIRICAL FINDINGS

Effect of Fund Selectivity on Fund Performance

We begin our examination of whether high fund selection ability leads to superior fund performance in the European mutual fund industry by predicting fund performance (fund *alpha*) based on the fund's selectivity, estimated using the lagged logistically translated 1 - R^2. The model we estimate is as follows:

$$Fund\ Alpha = \beta_1 * Selectivity + \beta_2 * Alpha_{t-1} + \beta_3 * Expense\ Ratio + \beta_4 * Log(TNA) + \beta_5 * Log(TNA)^2 + \beta_6 * Log(Age) + Fund\ Strategy \quad (4)$$

The dependent variable is the fund *alpha*, which is the difference between the fund's excess return in month t and the expected excess return the same month. The expected excess return for each fund in month t is calculated by multiplying the FFC model factor loadings from the preceding 24-month estimation period (months t - 24 to t - 1) by the FFC model factors in the current month. The process repeats by moving the estimation and test period one month at a time. The main independent variable is fund selectivity, which is the logistically transformed value of (1 - R^2_{t-1}). Fund-level control variables contain the fund $alpha_{t-1}$, which is the intercept from the preceding 24-month estimation period (months t - 24 to t - 1), the expense ratio, the log value of fund age, the value of TNA, and the squared log value of TNA. All control variables are lagged by one month. Following Amihud and Goyenko (2013), we report the results with and without $alpha_{t-1}$ as a control variable. Our sample period ranges from January 2000 through December 2015. If a positive relation between fund selectivity and fund performance exists in the European mutual fund industry, as we predicted, we hypothesize that β1 >0. The regression results are reported in Table 4.

TABLE 3.4
The effect of fund selectivity on fund performance
This table reports the results of regressing fund *alpha* on manager's selectivity controlling for other fund characteristics. The dependent variable is fund *alpha*, which is the difference between fund excess return 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 preceding estimation period (t-24 to t-1) by the FFC model factors in current month. The process repeats by moving the estimation and test period one month at a time. The main independent variable is fund selectivity, which is the logistic transformed value of ($1\text{-}R^2_{t-1}$). Fund-level control variables contain fund $alpha_{t-1}$, which is the intercept from the 24 month preceding estimation period (t-24 to t-1), expense ratio, log value of fund age, value of total net assets (TNA), and squared log value of TNA. Sample period covers from January 2000 through December 2015. ***, **, * denotes significance at the 1%, 5% or 10% level.

	Fund *Alpha*			
Intercept	-0.194***	-0.140**	-0.162**	-0.083
	(0.002)	(0.022)	(0.022)	(0.241)
Fund Selectivity	0.115***	0.090***	0.113***	0.088***
	(<.0001)	(<.0001)	(<.0001)	(<.0001)
***Alpha*$_{t-1}$**		0.099***		0.101***
		(<.0001)		(<.0001)
Expense Ratio	-0.008	-0.007	-0.009	-0.008
	(0.427)	(0.469)	(0.387)	(0.407)
Log(Age)	0.130***	0.118***	0.131***	0.120***
	(<.0001)	(<.0001)	(<.0001)	(<.0001)
Log(TNA)	0.063***	0.051**	0.064***	0.053**
	(0.003)	(0.016)	(0.003)	(0.012)
Log(TNA)^2	-0.005**	-0.005**	-0.005**	-0.005**
	(0.039)	(0.044)	(0.038)	(0.042)
Strategy Control	NO	NO	YES	YES
Adj. R^2	0.12%	0.17%	0.12%	0.17%

Consistent with the above prediction, the results in Table 4 show that selectivity in all regression specifications is positive and significantly correlated with the fund *alpha* ($p < 0.0001$). These results present strong evidence that the positive relationship between fund selectivity and fund performance exists in the European mutual fund industry. In addition, logistically translated lagged 1 - R^2 values, in accordance with the literature focusing on US mutual fund industry, can be used to proxy fund managers' selectivity ability.

Next, we repeat the regression, as shown by Eq. (4), for each country and we present the coefficients of fund selectivity, along with p-values, in Table 5.

TABLE 3.5

The effect of fund selectivity on fund performance for each country

This table reports the coefficients of fund selectivity from regressing fund *alpha* on manager's selectivity controlling for other fund characteristics for each country. Sample period covers from January 2000 through December 2015. P value for each coefficient is also reported. ***, **, * denotes significance at the 1%, 5% or 10% level.

	Selectivity Coefficient
Austria	0.106***
	(<.0001)
Denmark	0.127***
	(0.007)
Finland	-0.013
	(0.819)
Germany	0.236***
	(<.0001)
Ireland	0.166***
	(<.0001)
Italy	0.039
	(0.110)
Netherlands	0.263***
	(0.002)
Spain	-0.029
	(0.128)
Sweden	0.146***
	(<.0001)
Switzerland	0.298***
	(<.0001)
United Kingdom	0.030
	(0.549)

The results in Table 5 show that, of 11 European countries, seven show significantly positive relationships between fund selectivity and fund performance. On the other hand, we find no evidence that the above relationship exists in Finland, Italy, Spain, or the United Kingdom, but none of the coefficients of selectivity within those four countries is significantly negative. Jointly, these results support the hypothesis that managerial skill exists among European mutual fund managers and high fund selectivity leads to better performance for European actively managed domestic mutual funds.

Effect of Selectivity, Market Sentiment, and Market Dispersion on Fund Performance

We then re-examine the effect of fund management skill on fund performance by incorporating market sentiment and market dispersion into the analysis. The purpose of this analysis is to see whether selectivity still contributes to fund performance after controlling for investor sentiment and market dispersion. First, we divide the sample periods into periods of high and low investor sentiment based on the median number of the monthly CCI index, orthogonalized with respect to a set of macroeconomic conditions. If month *t*'s CCI is higher (lower) than the median number of the monthly CCI for all sample periods (January 2000 to December 2015), we define month *t* as a period of high (low) sentiment. Then, we estimate the model as shown in Eq. (4) in periods of high and low investor sentiment separately. The results are shown in Table 6, columns (1) and (2), respectively. As predicted, fund selectivity has a stronger relationship with fund performance during low-sentiment periods (0.154, $p < 0.0001$), when asset prices are around fundamental values, than in high-sentiment periods (0.001, $p = 0.094$), when the market is filled with noisy information.

TABLE 3.6

The effect of fund selectivity on fund performance in high/low market sentiment and market dispersion periods

This table reports the results of regressing fund *alpha* on manager's selectivity controlling for other fund characteristics during high/low market sentiment periods and during high/low market Dispersion periods. The dependent variable is fund *alpha*, which is the difference between fund excess return (over risk free 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 preceding estimation period (t-24 to t-1) by the FFC model factors in current month. The process repeats by moving the estimation and test period one month at a time. The main independent variable is fund selectivity, which is the logistic transformed value of ($1-R^2_{t-1}$). Consumer Confidence Indicator (CCI) free of macroeconomic influences is used to capture the market sentiment for all countries. If month t's CCI is higher (lower) than the median number of monthly CCI for all sample periods, we define month t as high (low) sentiment period. Market Dispersion is measured as the stock return standard division for all stocks in each country in month t. Then, if the country's Dispersion for this month is higher (lower) than the median market Dispersion of this country for all sample periods, we define this month as high (low) market Dispersion period. Fund-level control variables contain fund $alpha_{t-1}$, expense ratio, log value of fund age, value of total net assets (TNA), and squared log value of TNA. Sample period covers from January 2000 through December 2015. ***, **, * denotes significance at the 1%, 5% or 10% level.

	Market Sentiment		**Market Dispersion**	
	High	*Low*	*High*	*Low*
Intercept	-0.005	-0.141	-0.671***	0.476***
	(0.962)	(0.129)	(<.0001)	(<.0001)
Fund Selectivity	0.001*	0.154***	0.230***	-0.051***
	(0.094)	(<.0001)	(<.0001)	(<.0001)
***Alpha*$_{t-1}$**	0.222***	0.029**	0.039**	0.166***
	(<.0001)	(0.038)	(0.016)	(<.0001)
Expense Ratio	0.017	-0.022*	-0.014	-0.002
	(0.273)	(0.086)	(0.339)	(0.892)
Log(Age)	0.134***	0.108***	0.262***	-0.041
	(<.0001)	(<.0001)	(<.0001)	(0.102)
Log(TNA)	-0.013	0.097***	0.059*	0.035
	(0.690)	(0.001)	(0.071)	(0.206)
Log(TNA)^2	0.000	-0.008**	-0.003	-0.006**
	(0.973)	(0.012)	(0.520)	(0.049)
Strategy Control	YES	YES	YES	YES
Adj. R^2	0.30%	0.21%	0.42%	0.18%

As with investor sentiment, we separate our sample into periods of high and low market dispersion based on the median of the market dispersion index for the whole sample period (January 2000 to December 2015). If a country's market dispersion for month *t* is higher (lower) than the median market dispersion of this country for all sample periods, we define month *t* as a period of high (low) market dispersion. The regression results showing the relationship between fund selectivity and fund performance periods of high and low market dispersion are presented in Table 6, columns (3) and (4), respectively. Interestingly, during periods of high market dispersion, when private information is more valuable, fund selectivity skill is positively and significantly related to fund performance (0.230, $p < 0.0001$). On the contrary, during periods of low market dispersion, the relationship is negative and significant (-0.051, $p < 0.0001$). Our explanation is that, during periods of low market dispersion, when market-level information (i.e., economic shocks) is more important for estimating stock prices, increased attention on private information will not generate visible abnormal returns and will bring more risk into the portfolio. In this scenario, a strategy of building a portfolio deviating from market movements during periods of low market dispersion is costly and will decrease fund performance.

Next, we incorporate investor sentiment and market dispersion into the main regression (Eq. 4). The results are shown in Table 7.

TABLE 3.7

The effect of fund selectivity, market sentiment, and market Dispersion on fund performance

This table reports the results of regressing fund *alpha* on manager's selectivity controlling for other fund characteristics during high/low market sentiment periods and during high/low market Dispersion periods. The dependent variable is fund *alpha*, which is the difference between fund excess return (over risk free 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 preceding estimation period (t-24 to t-1) by the FFC model factors in current month. The process repeats by moving the estimation and test period one month at a time. The main independent variables are fund selectivity, which is the logistic transformed value of ($1-R^2_{t-1}$), consumer Confidence Indicator (CCI) free of macroeconomic, and market Dispersion, which is the stock return standard division for all stocks in each country in month t. Fund-level control variables contain fund $alpha_{t-1}$, expense ratio, log value of fund age, value of total net assets (TNA), and squared log value of TNA. Sample period covers from January 2000 through December 2015. ***, **, * denotes significance at the 1%, 5% or 10% level.

	Fund *Alpha*		
Intercept	-0.167**	-0.279***	-0.331***
	(0.019)	(0.001)	(<.0001)
Fund Selectivity	0.116***	0.099***	0.124***
	(<.0001)	(<.0001)	(<.0001)
Sentiment	-0.042***		-0.039***
	(<.0001)		(<.0001)
Dispersion		0.017***	0.014***
		(<.0001)	(<.0001)
$\boldsymbol{Alpha_{t-1}}$	0.111***	0.100***	0.110***
	(<.0001)	(<.0001)	(<.0001)
Expense Ratio	-0.010	-0.005	-0.006
	(0.327)	(0.639)	(0.510)
Log(Age)	0.120***	0.112***	0.113***
	(<.0001)	(<.0001)	(<.0001)
Log(TNA)	0.059***	0.064***	0.067***
	(0.006)	(0.003)	(0.002)
Log(TNA)^2	-0.005*	-0.007***	-0.006**
	(0.052)	(0.010)	(0.016)
Strategy Control	YES	YES	YES
Adj. R^2	0.33%	0.25%	0.39%

First the regression results in Table 7 show that fund selectivity is still positively related with fund performance (0.124, $p < 0.0001$) after controlling for market sentiment and market dispersion. In addition, market sentiment can hurt overall fund performance (-0.042, $p < 0.0001$ without market dispersion in the regression; -0.039, $p < 0.0001$ with market dispersion in the regression) and market dispersion, on average, can benefit fund performance (0.017, $p < 0.0001$ without investor sentiment in the regression; 0.014, $p < 0.0001$ with investor sentiment in the regression). Jointly, these results confirm our previous findings that fund selectivity is positively and significantly related to fund performance and this relationship remains significant even when controlling for investor sentiment and market dispersion.

Next, we repeat the above analysis for each country and we report the coefficients of selectivity, investor sentiment, and market dispersion in Table 8.

After we consider investor sentiment and market dispersion, the results, as shown in Table 8, are consistent with previous findings. Of all 11 European countries, eight show positive and significant relationships between fund selectivity and fund performance, which indicates that, after controlling for investor sentiment and market dispersion, fund selectivity still has strong predictive power for future fund performance in the majority of European mutual fund industries. Even though the selectivity coefficients for the remaining three countries are not significant, they still show positive signs (0.007, $p = 0.900$ for Finland; 0.013, $p = 0.502$ for Spain; 0.058, $p = 0.253$ for the United Kingdom). The sentiment coefficients for nine of the 11 countries appear to be significantly negative, while the market dispersion coefficients for seven of the 11 countries are significantly positive.

TABLE 3.8

The effect of fund selectivity, market sentiment, and market Dispersion on fund performance for each country

This table reports the coefficients of selectivity, market sentiment, and market Dispersion from regressing fund *alpha* on manager's selectivity, market sentiment, and market Dispersion, controlling for other fund characteristics for each country. P value for each coefficient is also presented. Sample period ranges from January 2000 through December 2015. ***, **, * denotes significance at the 1%, 5% or 10% level.

	Selectivity Coeff.	Sentiment Coeff.	Dispersion Coeff.
Austria	0.159***	-0.018***	0.089***
	(<.0001)	(0.002)	(<.0001)
Denmark	0.163***	-0.002	0.105***
	(0.001)	(0.904)	(<.0001)
Finland	0.007	-0.051***	0.327***
	(0.900)	(<.0001)	(<.0001)
Germany	0.272***	-0.066***	0.042***
	(<.0001)	(<.0001)	(<.0001)
Ireland	0.120***	-0.033***	-0.091***
	(0.001)	(<.0001)	(<.0001)
Italy	0.064***	-0.088***	-0.091***
	(0.009)	(<.0001)	(<.0001)
Netherlands	0.334***	-0.058***	0.040***
	(0.001)	(0.001)	(0.006)
Spain	0.013	-0.104***	-0.053***
	(0.502)	(<.0001)	(<.0001)
Sweden	0.190***	-0.018*	0.066***
	(<.0001)	(0.058)	(<.0001)
Switzerland	0.265***	-0.025**	-0.103***
	(<.0001)	(0.014)	(<.0001)
United Kingdom	0.058	-0.015	0.012**
	(0.253)	(0.109)	(0.032)

To examine the sensitivity of our finding of the relation between the European mutual fund industry’s performance and market sentiment, in this section we replace our major sentiment measure (CCI) with four alternative market sentiment measures, including the Economic Sentiment Indicator (ESI), which is from the European Commission's Business and Consumer Surveys and is constructed from the following indicators: the industrial confidence indicator (40%), the service confidence indicator (30%), the CCI (20%), the construction confidence indicator (5%), and the retail trade confidence indicator (5%); the Economic Climate Index (ENOMWLEC), which is drawn from surveys of business conditions in Germany among a broad range of business executives across the manufacturing, construction, wholesale, and retail sectors; and the German Consumer Confidence Index (GECSI), where a value of 100 indicates an equal number of optimists and pessimists and figures below 100 indicate more pessimists than optimists (and vice versa). The same as with the CSI sentiment index, we use the residual from the regression of the each index on a set of macroeconomic variables, including Europe’s inflation rate, the growth rate of Europe’s employment rate, the growth rate of Europe’s industrial production, the growth rate of Europe’s durable consumer goods production, the growth rate of Europe’s nondurable goods production, the consumer price index change in Europe’s service industry, and OECD-based European recession indicators.

Since no financial market in the world is isolated with the others, especially large and developed ones, we also use the Baker–Wurgler (BW) sentiment index, orthogonalized with respect to a set of macroeconomic conditions to replace the European sentiment measures. This index is formed to measure US market sentiment but the argument here is that the US equity market, which is the largest and most developed equity market in the world, can influence other financial markets. Information from the US equity market (e.g., investor optimism and pessimism) can transfer to other markets. The time series plots of all the sentiment indexes used are shown in Figure 1. The regression results for this analysis are shown in Table 9.

FIGURE 1

Time series plot of each sentiment measure (free of macroeconomic influences) from January 2000 to December 2015

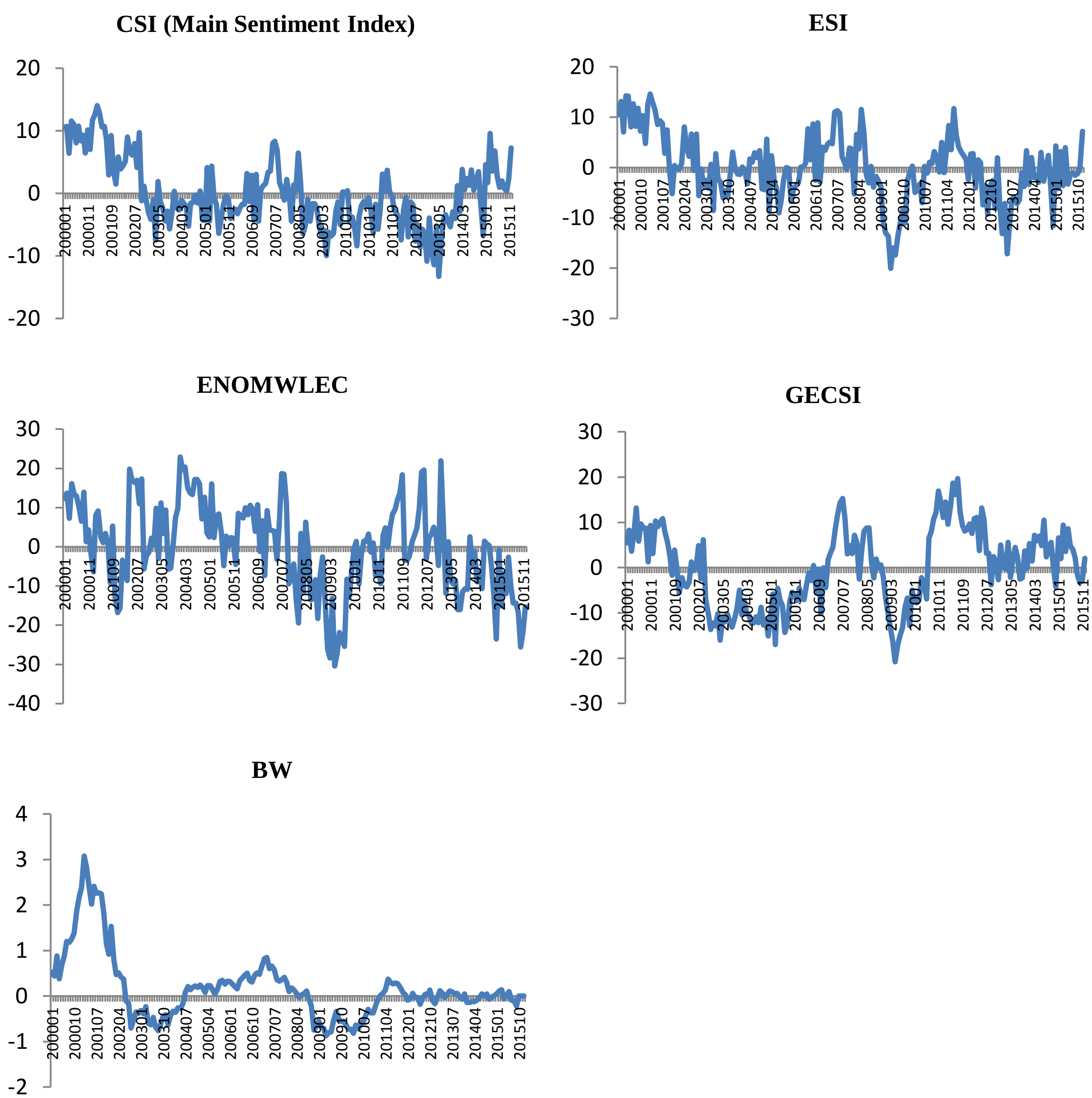

TABLE 3.9

The effect of market sentiment on fund performance, using alternative European Sentiment measures

This table reports the results of regressing fund *alpha* on manager's selectivity and different market sentiment measures, controlling for other fund characteristics. The dependent variable is fund *alpha*, which is the difference between fund excess return (over risk free 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 preceding estimation period (t-24 to t-1) by the FFC model factors in current month. The process repeats by moving the estimation and test period one month at a time. The main independent variables are fund selectivity, which is the logistic transformed value of ($1-R^2_{t-1}$), and market sentiment. We use 4 alternatives to measure market sentiment:
ESI, which is the Economic Sentiment Indicator calculated from the European Commission's Business and Consumer Surveys; ENOMWLEC, which comes from surveys of business conditions in Germany; GECSI, which is the German Consumer Confidence Indicator, and BW, which is Baker and Wurgler sentiment index (BW sentiment index, available at Jeffrey Wurgler's website). All the sentiment indexes are free of macroeconomic influences. Fund-level control variables contain fund $alpha_{t-1}$, expense ratio, log value of fund age, value of total net assets (TNA), and squared log value of TNA. Sample period covers from January 2000 through September 2015. ***, **, * denotes significance at the 1%, 5% or 10% level.

	Fund *Alpha*			
Intercept	-0.105	-0.068	-0.263***	-0.081
	(0.138)	(0.339)	(0.000)	(0.258)
Fund Selectivity	0.113***	0.089***	0.076***	0.114***
	(<.0001)	(<.0001)	(<.0001)	(<.0001)
ESI	-0.044***			
	(<.0001)			
ENOMWLEC		-0.002**		
		(0.016)		
GECSI			-0.025***	
			(<.0001)	
BW				-0.392***
				(<.0001)
***Alpha*$_{t-1}$**	0.131***	0.102***	0.162***	0.122***
	(<.0001)	(<.0001)	(<.0001)	(<.0001)
Expense Ratio	-0.009	-0.008	-0.011	-0.006
	(0.340)	(0.416)	(0.269)	(0.553)
Log(Age)	0.104***	0.116***	0.162***	0.096***
	(<.0001)	(<.0001)	(<.0001)	(<.0001)
Log(TNA)	0.063***	0.055***	0.043**	0.070***
	(0.003)	(0.010)	(0.044)	(0.001)
Log(TNA)^2	-0.005**	-0.005**	-0.004*	-0.006**
	(0.039)	(0.039)	(0.086)	(0.022)
Strategy Control	YES	YES	YES	YES
Adj. R^2	0.005	0.002	0.004	0.002

The results in Table 9 are consistent with the previous ones shown in Table 7 using the CCI to measure investor sentiment. All the alternative sentiment indexes show a strong negative relationship with fund performance and fund selectivity remains positively and significantly correlated with fund performance.

Effect of Country-Level Variables on Fund Selectivity Profitability

In this section, we use a two-step regression procedure, as described in Section 1.4, to investigate the country-level characteristics' influence on the profitability of fund managers' selectivity ability. Unlike the previous literature, which focuses on the direct influence of those variables on fund performance, we treat the country characteristics as mediating variables.. The results of regressing the selectivity coefficient on a list of country-level variables are reported in Table 10.

The results in Table 10 confirm our hypothesis that country-level characteristics work as mediators and affect the relationship between fund selectivity and fund performance. First, we find no evidence that a country's GDP per capita can influence the profitability of mutual fund managers' selectivity ability. As Ferreira et al. (2012), we argue that, after incorporating other country-level variables, the effect of this broad economic indicator is diluted. However, we find a strong relationship between fund selectivity profitability and Internet usage, as we expected. We conclude that higher Internet usage proxies for better-educated investors in the equity markets, which consequently increases the information quality and benefits skilled fund managers.

Both of our variables capturing the quality of a country's legal system show a positive and significant relationship with selectivity profitability, which confirms our hypothesis that legal strength limits insider trading and market noise, thus making fund managerial skills based on analytical ability more valuable.

Market liquidity, measured by the share turnover ratio, has a strong positive relation with selectivity profitability. The results, in line with our expectation, indicate that fund managers' skill will raise more profits for fund clients if the fund strategy can be quickly adjusted to incorporate new information. On the other hand, we find a significant negative relationship between equity market size and fund selectivity profitability. This might be caused by noisier information in the equity market.

TABLE 3.10

The effect of country level variables on the relationship between fund performance and selectivity

This table presents the regression results from the two-step procedure. First we calculate the coefficient between fund selectivity and fund performance by regressing fund *alpha* on fund selectivity, controlling for other fund level control variables, for 24 months. Only funds have full 24 months' data within current year and the prior year will be included. Then we have an annual time series data for each coefficient for 15 years (2001 to 2015). Second, we run regression of each coefficient (selectivity profitability) on 8 country level variables. The country level variables contain GDP per capital, percentage of Internet user, total size of equity market, equity share turnover, dummy variable for common law (if common then 1, otherwise 0), securities regulation, mutual fund industry age, and mutual fund industry proportion within equity market. We also show adjusted R^2 and P values. ***, **, * denotes significance at the 1%, 5% or 10% level.

	Selectivity Profitability	
Intercept	-34.117***	-53.177***
	(<.0001)	(<.0001)
GDP per Capital (million $)	-0.059	0.135
	(0.660)	(0.309)
Internet (%)	0.877***	1.209***
	(<.0001)	(<.0001)
Common Law	9.636***	
	(0.001)	
Securities Regulation		4.367***
		(<.0001)
Equity Market Size (billion $)	-0.003***	-0.001***
	(<.0001)	(0.005)
Share Turnover (%)	0.061***	0.030***
	(<.0001)	(<.0001)
Mutual Fund Industry Age (years)	-0.607***	-0.930***
	(<.0001)	(<.0001)
Mutual Fund Industry Proportion	-0.107	-0.064
	(0.788)	(0.858)
Adj. R^2	15.20%	16.50%

Finally, we find that fund managers' selectivity ability is more profitable if the country's mutual fund industry is young. Since the older the mutual fund industry is, the more competitive it is, it is harder for fund managers to achieve superior performance by competing with each other. In addition, the mutual fund industry proportion of the equity market shows no evidence of affecting the relationship between fund selectivity and fund performance.

Briefly, the results provide strong evidence that country-level characteristics work as mediators between fund selectivity and fund performance and that better economic development and legal protection, a less developed mutual fund industry, a smaller equity market, and greater equity market liquidity will make fund managers' selectivity ability more profitable.

CONCLUSION

This study investigates the predictive power of fund selectivity on fund performance (i.e., fund *alpha*) within the European mutual fund industry using a unique sample of actively managed domestic equity mutual funds from 11 European countries. Our study reveals empirical evidence that, as in the US mutual fund industry, selectivity is a valid skill measure in the European mutual fund industry and mutual fund managers with higher levels of selectivity ability can generate superior performance for their clients. Even though mutual fund performance can be influenced by financial market conditions, such as market sentiment and market dispersion, the positive relationship between fund selectivity and fund performance still holds after controlling for those effects. We also find that country-level characteristics serve as mediating variables between fund selectivity and fund performance. Fund selectivity is more valuable and profitable if the fund is from a country with better economic development, stronger legal protection, a less developed mutual fund industry, a smaller equity market, and greater equity market liquidity.

REFERENCES

Abinzano, I., Muga, L., & Santamaria, R. (2010). Do managerial skills vary across fund managers? results using European mutual funds. *Journal of Financial Services Research*, *38*(1), 41-67.

Amihud, Y., & Goyenko, R. (2013). Mutual fund's R2 as predictor of performance. *Review of Financial Studies*, 26(3), 667-694.

Amromin, G., & 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., & Subrahmanyam, A. (2015). Investor sentiment, beta, and the cost of equity capital. *Management Science*.

Baker, M., & Wurgler, J. (2006). Investor sentiment and the cross-section of stock returns. *The Journal of Finance*, 61(4), 1645-1680.

Banegas, A., Gillen, B., Timmermann, A., & Wermers, R. (2013). The cross section of conditional mutual fund performance in European stock markets.*Journal of Financial economics*, *108*(3), 699-726.

Berk, J. B., & Green, R. C. (2002). Mutual fund flows and performance in rational markets: *National Bureau of Economic Research*.

Berk, J. B., & Van Binsbergen, J. H. (2015). Measuring skill in the mutual fund industry. *Journal of financial economics*, 118(1), 1-20.

Blake, D., & Timmermann, A. (1998). Mutual fund performance: evidence from the UK. *European Finance Review*, *2*(1), 57-77.

Brands, S., Brown, S. J., & Gallagher, D. R. (2005). Portfolio Concentration and Investment Manager Performance. *International Review of Finance*, 5(3-4), 149-174.

Carhart, M. M. (1997). On persistence in mutual fund performance. *The Journal of Finance*, 52(1), 57-82.

Cesari, R., & Panetta, F. (2002). The performance of Italian equity funds.*Journal of Banking & Finance*, *26*(1), 99-126.

Cohen, L., Frazzini, A., & 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., & Petajisto, A. (2009). How active is your fund manager? A new measure that predicts performance. *Review of Financial Studies*, 22(9), 3329-3365.

Cremers, M., Ferreira, M. A., Matos, P. P., & Starks, L. T. (2015). Indexing and active fund management: International evidence. *Journal of Financial Economics*, Forthcoming.

Cuthbertson, K., Nitzsche, D., & O'Sullivan, N. (2008). UK mutual fund performance: Skill or luck?. *Journal of Empirical Finance*, *15*(4), 613-634.

Dahlquist, M., Engström, S., & Söderlind, P. (2000). Performance and characteristics of Swedish mutual funds. *Journal of Financial and quantitative Analysis*, *35*(03), 409-423.

Daniel, K., Grinblatt, M., Titman, S., & Wermers, R. (1997). Measuring mutual fund performance with characteristic-based benchmarks. *The Journal of Finance*, 52(3), 1035-1058.

Daniel, K., Hirshleifer, D., & Subrahmanyam, A. (1998). Investor psychology and security market under-and overreactions. *The Journal of Finance*, 53(6), 1839-1885.

Dermine, J., & Röller, L. H. (1992). Economies of scale and scope in French mutual funds. *Journal of Financial Intermediation*, *2*(1), 83-93.

Fama, E. F., & French, K. R. (1993). Common risk factors in the returns on stocks and bonds. *Journal of Financial Economics*, 33(1), 3-56.

Ferreira, M. A., Keswani, A., Miguel, A. F., & Ramos, S. B. (2012). The determinants of mutual fund performance: A cross-country study. *Review of Finance*, rfs013.

Franck, A., & Kerl, A. (2013). Analyst forecasts and European mutual fund trading. *Journal of Banking & Finance*, *37*(8), 2677-2692.

Gruber, M. J. (1996). Another puzzle: The growth in actively managed mutual funds. *The Journal of finance*, 51(3), 783-810.

Grünbichler, A., & Pleschiutschnig, U. H. (1999). *Performance persistence: evidence for the European mutual funds market*.

Hong, H., & Stein, J. C. (1999). A unified theory of underreaction, momentum trading, and overreaction in asset markets. *The Journal of Finance*, 54(6), 2143-2184.

Kacperczyk, M., Sialm, C., & Zheng, L. (2005). On the industry concentration of actively managed equity mutual funds. *The Journal of Finance*, 60(4), 1983-2011.

Kacperczyk, M., Van Nieuwerburgh, S., & Veldkamp, L. (2011). Rational attention allocation over the business cycle. *Unpublished working paper.* New York University.

La Porta, R., Lopez-de-Silanes, F., & Shleifer, A. (2006). What works in securities laws?. *The Journal of Finance*, *61*(1), 1-32.

La Porta, R., Lopez-de-Silanes, F., Shleifer, A., & Vishny, R. (1999). The quality of government. *Journal of Law, Economics, and organization*, *15*(1), 222-279.

Malkiel, B. G. (1995). Returns from investing in equity mutual funds 1971 to 1991. *The Journal of Finance*, 50(2), 549-572.

Morck, R., Yeung, B., & Yu, W. (2000). The information content of stock markets: why do emerging markets have synchronous stock price movements? *Journal of financial economics*, *58*(1), 215-260.

Otten, R., & Bams, D. (2002). European mutual fund performance. *European Financial Management*, 8(1), 75-101.

Petajisto, A. (2013). Active share and mutual fund performance. *Financial Analysts Journal*, *69*(4), 73-93.

Shukla, R. K., & Van Inwegen, G. B. (1995). Do locals perform better than foreigners?: An analysis of UK and US mutual fund managers. *Journal of Economics and Business*, *47*(3), 241-254.

von Reibnitz, A. H. (2013). When Opportunity Knocks: Cross-Sectional Return Dispersion and Active Fund Performance. *Paper presented at the 26th Australasian Finance and Banking Conference*.

Zheng, L. (1999). Is money smart? A study of mutual fund investors' fund selection ability. *The Journal of finance*, 54(3), 901-933

APPENDIX 3

Country level variable description and data resource

Variable name	Variable Group	Description	Data Type	Data Resource
GDP per Capital (Million)	Economic development	Gross domestic product divided by midyear population. Data are in constant 2010 U.S. dollars.	Time-series	World Development Indicators (WDI) database
Internet	Economic development	Percentage of individuals who have used the Internet (from any location) in the last 12 months. Internet can be used via a computer, mobile phone, personal digital assistant, games machine, digital TV etc.	Time-series	World Development Indicators (WDI) database
Equity Market Size	Equity market development	The total number of shares traded, both domestic and foreign, multiplied by their respective matching prices. Data are end of year values converted to U.S. dollars using corresponding year-end foreign exchange rates.	Time-series	World Development Indicators (WDI) database
Share Turnover	Equity market development	The value of domestic shares traded divided by their market capitalization. The value is annualized by multiplying the monthly average by 12.	Time-series	World Development Indicators (WDI) database
Common Law	Investor protection and legal strength	1 if the legal origin is common law and 0 if the legal origin is civil law	Dummy	La Porta et al. 1997
Securities Regulation	Investor protection and legal strength	Combination of disclosure requirements, liability standards, and public enforcement	Cross-sectional	La Porta et al. 2006
Mutual Fund Industry Age (years)	Mutual fund industry development	Number of years since the first open-end fund was sold in the country	Time-series	Ferreira et al. 2012
Mutual Fund Industry Proportion	Mutual fund industry development	Relative mutual fund industry size, which is total equity assets under management divided by equity market size	Time-series	World Development Indicators (WDI) database; EFAMA Asset Management Report

CONCLUSION

This dissertation participates into the study stream of mutual fund industry by investigating the relation between managerial skills possessed by mutual fund managers and fund performance, and it contributes to the literature by investigating the validity and efficiency of fund manager’s skills under different market states, finding the essential elements of fund manager’s stock picking skills, and exploring the research of mutual fund managerial skills to other countries. Given the important role of mutual fund industry to the financial markets, the findings of this dissertation show values for further academic research and industry implications.

VITA

FENG DONG

Old Dominion University
Strome College of Business
Department of Finance
Constant Hall, Suite 2111
Norfolk, VA 23529

E-mail: fdong@odu.edu
Tel: 614-736-0605
http://orgs.odu.edu/badsa/fdong.html

RESEARCH INTERESTS

Institutional Investor Activity, Behavioral Finance, Empirical Asset Pricing

TEACHING INTERESTS

Investments, Corporate Finance, International Finance

EDUCATION

Old Dominion University, Strome College of Business August, 2017
PhD degree in Finance (*Proposal Defended*)

- Minor in International Business

The Ohio State University, Fisher College of Business June, 2012
Specialized Masters Degree in Finance

- Tracks in Corporate Finance and Investment

Oklahoma City University, Meinders School of Business May, 2011
Bachelor of Science in Business

- Majors: Finance & Economics

PUBLICATIONS

Shen, J., Najand M., Dong, F, & He, W. (2017). News and Social Media Emotions in the Commodity Market. *Review of Behavior Finance*, forthcoming

Chen, Y., Dong, F., & Chen, H. (2016). Business Process and Information Security: A Cross-Listing Perspective. *Journal of Industrial Integration and Management*, 1(2)

CONFERENCE PAPERS

Dong, F., & Doukas, J. (October 2017). "Does Corporate Managerial Ability Matter for Fund Managers?" Financial Management Association Annual Meeting (FMA 2017), Boston

Mallon, M., Guldiken, O., Benischke, M., Dong, F., & Nguyen, T. (July 2017). "Foreign Subsidiary Performance in Emerging Markets: An Institutional Perspective" Academy of International Business Annual Meeting (AIB 2017), Dubai, United Arab Emirates

Shen, J., Dong, F., & He, W. (November 2016). "Emotion at Work on Big Data Analytics: Using Media-Based Emotion for Predicting Commodity Price." International Conference on Behavioral, Economic, and Socio-Cultural Computing (BESC2016), Duke University, Durham, North Carolina

Chen, Y., Dong, F., Chen, H., & Xu, L. (August 2016). "Can Cross-Listing Mitigate the Impact of an Information Security Breach Announcement on a Firm's Values?" In IOP Conference Series: Materials Science and Engineering

HONORS AND AWARDS

- Research Assistantship 2013-17
- PhD scholarship 2013-17
- Outstanding Finance PhD Student Award 2016
- Treasury of Business Administration Doctoral Student Association 2014
- Professor's Award in Finance 2011
- Third Place Undergraduate Winner, *Donald W. Reynolds Governor's Cup--Oklahoma's Statewide Collegiate Business Plan Competition* 2011
- Graduated Cum Laude 2011
- President's Honor Roll 2010
- Dean's Honor Roll 2010
- President of Chinese Students and Scholars' Association 2009

TEACHING EXPERIENCE

- Instructor, *FIN323 Introductory Financial Management* Fall 2016
  Average Teaching Evaluation: 4.9/5.0 (Department Mean 4.2/5.0)
- Teaching Assistant, *MBA641 Investing in the Stock Market* Spring 2017
- Teaching Assistant, *FIN220 Wall Street 101* Spring 2017
- Teaching Assistant, *MBA641 Investing in the Stock Market* Fall 2016
- Teaching Assistant, *FIN220 Wall Street 101* Fall 2016
- Teaching Assistant, *FIN497 Option Valuation & Trading Strategies* Summer 2016
- Teaching Assistant, *FIN220 Wall Street 101* Summer 2016
- Teaching Assistant, *FIN220 Wall Street 101* Spring 2016
- Teaching Assistant, *FIN220 Wall Street 101* Spring 2015
- Teaching Assistant, *MBA695 Stock Market* Spring 2015

BUSINESS EXPERIENCE

- **Research Assistant** 2014-current, Norfolk, VA
  The Gregory A. Lumsden Bloomberg Trading Room and Research Lab
- **Financial Advisor** 2012-2013, Garden City, NY
  Matrix Partners Network
- **Equity Trader** 2012, New York City, NY
  WTS Proprietary Trading Group LLC
- **Project Member** 2012, Columbus, OH
  State Teachers Retirement System (STRS)
- **Chief Financial Officer** 2011- 2012, Oklahoma City, OK
  Quorum Company
- **Finance Intern** 2010, Yantai, China
  Bank of China, Ltd. Yantai Branch

SKILLS

Programming: SAS, Stata, Eviews, MS Office, Gretl
Databases: CRSP, Compustat, ExecuComp, Bloomberg (*BESS, BMC certified*), CapitalIQ, WRDS, LexisNexis, Morningstar, Thomson ONE
Languages: English (fluent), Mandarin Chinese (native)

ACADEMIC MEMBERSHIPS

- American Finance Association (AFA)
- European Financial Management Association (EFMA)
- Financial Management Association (FMA)

REFERENCES

***Prof.* JOHN A. DOUKAS** (*PhD Committee Chair*)
European Financial Management (EFM) Managing Editor
Professor of Finance & Eminent Scholar
W. B. Spong, Jr., Chair in Finance
Department of Finance
Strome College of Business
Old Dominion University
Constant Hall, Suite 2080
Norfolk, VA 23529-0222, USA
Research Associate
Judge Business School
Cambridge University, UK
Tel: 757-683-5521 Fax: 757-683-5639
Email: jdoukas@odu.edu

***Prof.* MOHAMMAD NAJAND**
Professor of Finance
Finance Department Chair
Department of Finance
Strome College of Business
Old Dominion University
Constant Hall, Suite 2125
Norfolk, VA 23529-0222, USA
Tel: 757-683-3509
Email: mnajand@odu.edu

***Prof.* DAVID D. SELOVER**
Professor of Economics
Department of Economics
Strome College of Business
Old Dominion University
Constant Hall, Suite 2036
Norfolk, VA 23529-0222, USA
Tel: 757-683-3541
Email: dselover@odu.edu

ANDREW H. COHEN
Manager/Senior Lecturer
Gregory A. Lumsden Trading Room & Research Lab
Strome College of Business
Old Dominion University
Constant Hall, Suite 2002
Norfolk, VA 23529-0222, USA
Tel: 757-683-7004
Email: acohen@odu.edu