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Assessing sentiment timing ability and mutual fund manager skill

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Abstract

We develop a method that can statistically identify fund managers that exhibit selectivity in their trades, and find that occurrences of good and bad selectivity exceed random expectation. Mutual funds exhibit selectivity by tilting their portfolios towards the better performing stocks when they buy (sell) stocks with high sentiment betas preceding an increase (decrease) in investor sentiment. Conversely, funds that incorrectly time investor sentiment exhibit bad stock selection, explaining the above random incidence of this behavior. Our method can distinguish skill from fortuitous stock selection, and provides a practical tool for evaluating the performance of fund managers.

JEL Classification: G2, G11, G14, G23

Keywords: Mutual fund, selectivity, investor sentiment, skill

Assessing sentiment timing ability and mutual fund manager skill

1. Introduction

In an efficient market, stocks would be correctly priced and mutual fund managers would only exhibit superior performances by chance. However, Baker and Wurgler (2006, 2007) show that stocks are mispriced according to their sentiment beta and the prevailing level of investor sentiment. In an effort to improve their performance, fund managers could use stock sentiment betas to assist in the selection of stocks in two ways. First, they might attempt to identify underpriced stocks to buy and overpriced stocks to sell. Second, they might attempt to time investor sentiment by buying (selling) high (low) sentiment beta stocks before an increase in sentiment, and conduct the opposite trades prior to a decrease.

An analogous decomposition of stock selectivity[1] is proposed by Cremers and Petajisto (2009) who use the proxy 'Active Share' for selection of mispriced stocks and the proxy 'tracking error variance' for factor timing. However, both proxies measure selectivity only as a deviation from a benchmark portfolio albeit across different dimensions. We contribute to the literature by developing a method that can identify selectivity, both good and bad, on a fund-by-fund basis in any calendar quarter. Moreover, our procedure involves a more direct measure of market timing using Baker and Wurgler's (2007) indexes of investor sentiment.

[1] We use the term 'selectivity' to refer to a fund's record of selecting stocks that exhibit better performances in the following quarter, that may have arisen from picking mispriced stocks, timing the market or luck. We distinguish "selectivity" from "skill", and reserve the latter to describe the stock selection ability of particular fund managers that exhibit *persistent* selectivity. Previous studies use the term 'selectivity' and 'skill' interchangeably.

Evaluating the stock selection skills of mutual fund managers is complicated by the selection of appropriate performance benchmarks, and extricating performance attributable to their trades from the impact of the extant portfolio. Moreover, allowance must be made for the constraints that a fund's style objectives, trading costs and portfolio diversification considerations place on a manager's trades. To accommodate these issues, we discern selection ability (selectivity) by observing an increased weighting of higher ranking stocks and decreased weighting of lower ranking stocks, rather than looking for major portfolio changes or the acquisition of stocks that yield stellar performances.[2] The ranking of a stock in each fund's portfolio is determined by the stock's return performance in the subsequent quarter. More specifically, we develop a two-step procedure. In the first step, we identify fund-quarters in which mutual funds that conduct trades, that with statistical significance, exhibit good or bad selectivity. In the second step, we identify funds that exhibit selectivity over multiple quarters more frequently than randomly expected, and classify the managers as skilful. Our contribution is therefore extended to provide an innovative, objective and practical procedure for evaluating individual fund managers.

Using our method, we find that occurrences of both good and bad selectivity exceed random expectation. We also show that mutual funds that time investor sentiment by trading to alter their portfolio's sentiment beta ahead of changes in investor sentiment can more commonly exhibit selectivity (good or bad). More funds that buy (sell) high (low) sentiment beta stocks, thereby increasing the sentiment beta of their portfolio, exhibit good selectivity if sentiment subsequently increases. A higher proportion of funds that do the opposite prior to a decrease in sentiment also

[2] The goal of tilting a fund's portfolio towards better performing stocks is to *improve* fund performance. However, performance itself is an opaque measure of selectivity as several other factors also contribute to fund performance. Our measure of selectivity is more direct since it focuses on the performance of the stocks funds trade.

exhibit good selectivity. We also find that bad selectivity is more prevalent amongst fund-quarters that exhibit perverse timing. Perverse timing may be the consequence of mutual funds incorrectly predicting the direction of the change in investor sentiment but use their prediction to alter the sentiment beta of their portfolio.

The elevated incidence of good stock selection might be attributed to the fulfillment of a goal; however, managers would not aim to pursue bad stock selection. Rather, a more plausible explanation for the incidence of systematically poor stock selection, which exceeds the incidence expected from 'bad luck', is an incorrect prediction resulting in perverse timing of sentiment.

The paper proceeds as follows. In Section 2 we discuss the salient literature and develop our hypotheses. In Section 3 we discuss the data and overview the methodology. Section 4 details the procedure for identifying selective trades and considers the interaction of selectivity and investor sentiment. In Section 5 we present the procedure to distinguish selectivity attributable to skill from luck, while Section 6 concludes the study.

2. Investor Sentiment and Market Timing

Baker and Wurgler (2007) develop a monthly sentiment index, and show that following a month of high investor sentiment, speculative stocks exhibit lower average returns relative to safe, easy to arbitrage stocks.[3] This result is reversed in the month after investor sentiment is low. They reason that the attributes that make stocks speculative also cause them to be more difficult to value and arbitrage, and may be captured by the stock's sentiment beta or the co-movement of its price with an index of sentiment changes. Antoniou, Doukas and

[3] Baker and Wurgler (2006), Glushkov (2006) and Duan, Hu and McLean (2009) also find stock prices deviate more from intrinsic value depending on the attributes of the stocks.

Subrahmanyam (2011) also consider time variation related to investor sentiment and find greater momentum profits during high sentiment periods, and attribute this to greater mispricing of stocks during periods of optimism. During periods of pessimism, momentum profits become insignificant.

It is apparent from the literature that some stocks become mispriced, and that the level of mispricing varies according to the level of investor sentiment. When sentiment is high, mutual fund managers would be more likely to demonstrate their stock selection ability and achieve the aim of buying stocks that are underpriced and selling stocks that are overpriced. The testable implication is that more funds will exhibit selectivity when investor sentiment is high. We refer to this as the mispricing hypothesis.

The level of investor sentiment is associated with mispricing, but changes to investor sentiment may also affect stock prices. Following Baker and Wurgler's (2007) reasoning that a stock's sentiment beta captures its relative price response to changes in investor sentiment, fund managers that believe they can predict changes in sentiment may be motivated to trade stocks according to their expectations. That is, they may attempt to time the market with respect to investor sentiment. Cremers and Petajisto (2009) examine market timing by fund managers but use tracking error variance as a proxy. They reason that a fund that generally holds the constituents of a benchmark index but concentrates the weighting on specific sectors, incurs systematic risk relative to the index, and generates a higher tracking error variance. Such funds are motivated by bets on market conditions favorable to that sector, which, in turn, may be affected by investor sentiment. However, Cremers and Petajisto (2009) do not distinguish funds that successfully time the market from those that make unsuccessful factor bets. Accordingly, losses from the latter may cancel the profits earned by the successful timers obscuring the relation between tracking error variance and returns.

Early attempts such as Treynor and Mazuy (1966) to detect market timing focused on a squared relation between fund returns and those of the benchmark portfolio. More recently, Elton, Gruber and Blake (2011) and Ferson and Mo (2012) use the holdings of fund portfolios to determine market timing. Elton, Gruber and Blake (2011) compute unconditional fund betas from the weighted average of the stock betas in the portfolio, and discern timing from changes in this beta and benchmark returns in the following month. Ferson and Mo (2012) determine the covariance of portfolio weights with benchmark returns, and identify market timing as a contribution to fund excess returns (alphas). However, in these studies, the focus on fund returns rather than the returns of the stocks the funds trade, provides an indirect indication of selectivity, and therefore market timing. We substitute sentiment beta for the unconditional beta used by Elton, Gruber and Blake (2011) but with the application of the procedure from Cullen, Gasbarro, Monroe and Zumwalt (2012), we can determine, in any quarter, which of these adjustments are statistically significant. By relating these adjustments to subsequent changes in investor sentiment[4], we can detect timing, and draw inferences about how timing affects selectivity without the need to consider fund returns.

Cullen, Gasbarro, Monroe and Zumwalt (2012) demonstrate that mutual fund portfolios with high (low) weighted averages of stock sentiment betas experience better performance when investor sentiment increases (decreases). Moreover, they find that mutual funds conduct trades to

[4] Massa and Yadav (2012) specifically consider investor sentiment, however, only consider timing to the extent that they consider fund manager preferences for holding stocks that react contrary to the level of investor sentiment; or exhibit “sentiment contrarian behavior”.

alter their sentiment beta, raising the likelihood that funds will make such adjustments in an attempt to time predicted changes in investor sentiment. That is, fund managers may attempt to time investor sentiment by trading stocks according to their expected performance in the predicted market conditions, and in doing so alter their portfolio's sentiment beta. If they are successful in their prediction, and increase (decrease) their sentiment beta ahead of an increase (decrease) in investor sentiment, more funds would exhibit good selectivity. If their predictions are unsuccessful, more would exhibit poor selectivity. We refer to this as the sentiment prediction hypothesis.

To test this hypothesis, we exploit the procedure in Cullen, Gasbarro, Monroe and Zumwalt (2012) that can determine, with statistical significance, funds that trade to alter their sentiment beta in any quarter. We relate the changes funds make to their sentiment beta to subsequent changes in sentiment measured ex-post using Baker and Wurgler's (2007) sentiment changes index. This link provides a direct measure of market timing, which we use to identify funds that successfully and unsuccessfully time investor sentiment, and as a consequence examine the sentiment prediction hypothesis.

3. Data description and methodology

3.1. *Data description*

We obtain the quarterly stock holdings of all US equity mutual funds in the Thomson Financial Services Ltd database between 1991 and 2005. We infer transactions from changes to the holdings, while allowing for stock capitalization changes. Monthly stock price and return data are obtained from Center for Research in Security Prices (CRSP) and are used to calculate quarterly excess returns before these are combined with the holdings data.[5] We calculate stock sentiment betas using the Baker and Wurgler (2007) monthly change in investor sentiment index.[6]

3.2. *Overview of Method*

We consider whether mutual funds exhibit selectivity by examining the stocks they chose to trade in one period, and whether fund managers display skill in stock selection by examining fund selectivity over multiple periods. Funds are deemed to exhibit good selectivity if they increase (decrease) the weighting of stocks that subsequently become superior (inferior) performers. Initially, we rank stocks based on their (ex-post) performance after a calendar quarter in which a mutual fund conducts its trades. These rankings are used to assign each fund's stocks to several "performance" buckets. We then use regression analysis to determine which funds correctly select stocks by acquiring future better performers and/or disposing of future poorer performers, and which funds exhibit perverse selectivity by buying future poor performers and/or selling future better performers.[7]

[5] We restrict our sample to funds with average equity holdings exceeding 80% and average cash holdings below 10% of fund assets to ensure that our data covers most of the changes to a mutual fund's portfolio. Additionally, we must be able to replicate within 10% of the value of the fund's net tangible assets by using the stock holdings data and assuming start-of-quarter prices for the stock for it to remain in our sample.

[6] We use the sentiment index based on the first principal components of six non-orthogonalized sentiment proxies that is made available on Jeffrey Wurgler's website at http:www.stern.nyu.edu/~jwurgler. These index series finished in 2005, until recently, and our study concludes accordingly.

[7] Elton, Gruber, Blake, Krasny and Ozelge (2010) caution against the use of quarterly mutual fund holdings since approximately 20% of the within-quarter transactions are omitted. We recognize this limitation but balance sample

To examine the possibility that selectivity may relate to how funds adjust their sentiment beta ahead of anticipated changes in sentiment, we require stock sentiment betas. We calculate these by employing the procedure traditionally used to generate market betas, but use Baker and Wurgler's (2007) non-orthogonalized monthly sentiment changes index in place of market return. Fund portfolio holdings are then ranked according to the stocks' sentiment betas, and preferences in trading are identified using the same procedure used to gauge selectivity. Once determined, we relate the preferences funds exhibit in trading stocks according to sentiment betas to their trades that exhibit selectivity. Next, we consider the effect of Cremers and Petajisto's (2009) definition of stock-picking versus timing behavior on our relation between timing and selectivity, and finally identify fund managers that exhibit skill in their stock selection.

3.3 Descriptive statistics

Our sample contains 2173 distinct mutual funds, and 27,349 fund-quarters that meet our selection and data quality criteria. Panel A of Table 1 shows the distribution of fund market capitalization and number of stocks in each fund. The skewed distributions reflect a few very large funds, and a small number of funds holding a large number of stocks. Panel B documents the number of funds for which we are able to calculate selectivity betas that are represented in our dataset for various numbers of calendar quarters over the fifteen years between 1991 and 2005.

[Table 1]

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size with frequency of observation. For example, Elton, Gruber, Blake, Krasny and Ozelge (2010) have 215 funds and 6432 fund-months in the period 1994 – 2005, compared to our study with 2173 funds and 27,349 fund-quarters in the period 1991 – 2005.

4. Selectivity and Sentiment

4.1. Identifying selectivity in trades

Evaluating the stock selection skill of a fund manager by focusing on fund performance is confounded by the appropriateness of the benchmark and the impact of the extant portfolio.[8] To avoid these complications, Grinblatt and Titman (1993) and Chen, Jegadeesh, and Wermers (2000) employ methods that avoid the use of benchmarks and focus on the trades of fund managers. However, while they are able to conclude that selectivity exists in mutual funds, their methods do not permit statistical identification of particular funds that are selective in a particular quarter.

Grinblatt and Titman (1993) use quarterly holdings to create zero-investment portfolios that consist of the assets in the funds' portfolios reported at the start of each period held long, while shorting the assets held in the previous period. Since the portfolio has zero investment, any return will reveal selectivity, but a number of fund quarters need to be examined before it is possible to conclude statistical significance of this return. Chen, Jegadeesh, and Wermers (2000) also focus on fund trades to assess stock selection ability, but only as an aggregate of trades across mutual funds. Stocks are ranked according to the level of trading by mutual funds and those more commonly bought by mutual funds have significantly higher returns than those sold.

[8] For example, Carhart (1997) finds that persistence of fund performance can be largely explained by price momentum in the stocks that a fund holds. Persistence is also partly explained by factors such as portfolio turnover and costs per transaction (for funds holding less-liquid stocks), which increase costs and reduce net performance.

The level of mutual fund trading in a stock is determined from the change to the aggregate proportion of fund ownership of a stock from one period to the next.

Similar to Grinblatt and Titman (1993) and Chen, Jegadeesh, and Wermers (2000), our procedure examines stock selection by fund managers by focusing on mutual fund trades.[9] However, unlike these studies, our method is able to test with statistical confidence whether managers exhibit superior stock selection in any calendar quarter on a fund-by-fund basis.

An alternative measure of stock selectivity is provided by Cremers and Petajisto (2009). They measure selectivity by the deviation of a fund's portfolio from an index, and refer to this as "Active Share". Lower commonality with the index indicates that managers are engaging in stock selection. However, their method concentrates on stock holdings and ignores the trades managers conduct. Another measure of deviation from benchmark portfolios using the R-square of fund returns is proposed by Amihud and Goyenko (2013). Neither measure distinguishes good from bad stock selection, and are less direct than the procedure we employ.

In our procedure, the stocks held by each mutual fund at the start of each calendar quarter are ranked according to their performance over the three months following the end of the quarter. Adapting the method in Cullen, Gasbarro and Monroe (2010), we assign the performance ranked stocks to twenty equal-value buckets. We derive a measure of each bucket's future return performance by value-weighting the performance (Bucket_Performance) of each stock in the bucket. Bucket_Performance is used as the independent variable in our regression. Like Cullen, Gasbarro and Monroe (2010), we use "TradeValue", the value of stocks in each bucket in a

[9] We acknowledge that the decision to hold a stock affects a fund's performance. However, as Kothari and Warner (2001) point out, the decision to trade a stock is also more likely to reflect information about its investment potential than the decision to hold the stock.

fund's portfolio that are *traded* during a quarter, as the dependent variable. Stock purchases are assigned a positive value, and sales a negative value. The regressions that we perform for each of the 27,349 fund-quarters are therefore:

$$\text{TradeValue}_j = \alpha + \beta \text{Bucket\_Performance}_j + \varepsilon_j \qquad (1)$$

where:

$$\text{TradeValue}_j \equiv \sum_{i=1}^{n} \text{Value stock}_i \text{ traded;}$$

$$\text{Bucket\_Performance}_j \equiv \sum_{i=1}^{n} (\text{Performance}_i \times \frac{\text{Value stock}_i \text{ held}}{\sum_{i=1}^{n} \text{Value stock}_i \text{ held}});$$

$$\text{Value stock}_i \text{ traded} = \text{value of stock i traded during quarter t;}$$

$$\text{Value stock}_i \text{ held} = \text{value of stock i held at the start of quarter t;}$$

$$\text{Performance}_i = \text{Performance of stock i in quarter t} + 1\text{; and}$$

$$\text{n} = \text{number of stocks in bucket j.}$$

Significantly negative or positive coefficients on "Bucket_Performance" identify funds where trading is selective with respect to future stock performance. We refer to these coefficients as selectivity trade betas, with a positive beta indicating that in a fund-quarter, the stocks with high future returns are being purchased, while stocks with poor future returns are being sold. Conversely, a negative selectivity trade beta identifies portfolio adjustments that are systematically perverse. This follows since, by construction, there was no initial relation between the value of stock in bucket$_j$ and the buckets' future performance. The statistical significance of the number of selectivity trade betas arising from the repeat regressions is established by comparison with critical values from the cumulative binomial distribution.

We perform the preceding analysis with three variations. In the first, we calculate "TradeValue$_j$" by including both the buy and sell trades in a quarter, and refer to the coefficient in Equation (1) as the “net” selectivity trade beta. In the second, we include only the buy trades, while in the third we include only sell trades. We refer to the latter regression coefficients as “buy” selectivity and “sell” selectivity trade betas respectively. By separating trades into buys and sells, we can obtain an insight into whether fund managers make the correct selection with respect to the stocks they buy, and those they sell, additional to whether they make the correct combined (net) selection of stocks to trade.

In summary, we use equation (1), to perform 27,349 univariate linear regressions to identify fund-quarters where there is a relation between future stock performance and proportion of stocks traded by a fund. A statistically positive net selectivity trade beta indicates that adjustments to a fund’s portfolio during a quarter are consistent with fund managers exhibiting selectivity by acquiring stocks that are destined to become the better performers, while disposing of stocks that are subsequently the poorer performers. A negative net selectivity trade beta identifies funds with perverse selectivity, where managers purchase stocks that subsequently underperform, or sell stocks that subsequently outperform, or both.

Panel A of Table 2 reports the pooled count for net selectivity, buy selectivity and sell selectivity over the fifteen-year period for the 10 percent significance level (two-tailed). Using the binomial distribution, we are able to determine that the frequency of both positive and negative net selectivity trade betas exceed that expected by random occurrence with 99 percent statistical confidence. The frequency of positive betas (9.5%) suggests that some fund managers are able to identify the correct stocks to buy and sell (good selectivity). However, the higher than random incidences of negative betas (9.3%) indicate that some managers have a propensity to trade stocks imprudently (bad selectivity). It should be noted that while we find that 9.5 percent of funds exhibit good selectivity, 5 percent are expected to do so randomly. Therefore, we are able to say, with statistical confidence, that some fund managers exhibit skill in stock selection, but are unable to say which funds that exhibit selectivity did so from skill.[10]

Examination of selectivity with respect to stocks purchased (buy selectivity) and stocks sold (sell selectivity) separately, reveals incidences of good and bad selectivity that are largely similar to the incidences for net selectivity. However, relative to bad buy selectivity (7.7%), the frequency of good buy selectivity (9.0%) is marginally higher (Z=5.52).[11] Relative to good sell selectivity (8.5%), the frequency of bad sell selectivity (9.5%) is higher (Z=3.82). These results suggest that more managers are able to correctly select stocks to buy, but more make errors in selling stocks that subsequently outperform those they retain.

[Table 2]

4.2. Identifying sentiment-based trades

We use Baker and Wurgler's (2007) non-orthogonalized monthly "sentiment changes" index to calculate sentiment betas for each stock. This index is used as the independent variable in a time-series regression analogous to that used for calculating the traditional market beta. As with the market beta, the stock's returns over the previous 60 months[12] are used as the dependent variable. Having determined stock sentiment betas, we adapt the procedure that uses Equation (1) in the previous section to determine whether a fund's trades exhibit preference for stocks according to their sentiment beta, in a particular quarter. The adaption involves ranking stocks

[10] We propose a method to distinguish skill from luck in Section 5.

[11] Statistical significance of this difference is established using the Z-test for dependent proportions. Throughout the discussion that follows we cite Z-statistics for differences in dependent proportions, or for the difference in a proportion from its expected (e.g. full time-series) value as appropriate.

[12] We eliminate stocks without a minimum of 12 months of returns.

held and acquired by a fund, by the stocks' sentiment betas rather than by the stock's future performances. Equation (1) is altered by replacing "performance" by "sentiment beta", while "Bucket_Performance" is replaced by "Bucket_Sentiment_Beta". As before, 27,349 regressions are performed, one for each fund-quarter, and those with statistically significant "sentiment beta trade betas" are identified. A positive sentiment beta trade beta indicates that adjustments to a fund's portfolio during a quarter are consistent with fund managers acquiring high sentiment beta stocks and/or selling low sentiment beta stocks. A negative sentiment beta trade beta shows that managers are reducing the weighted average sentiment beta of their stock portfolio by doing the opposite.

Panel B shows the proportions of negative and positive sentiment trade betas are both significantly greater than the expected 5 percent random occurrence. This shows that at various times, funds conduct trades designed to either increase or decrease the sentiment beta of their portfolio.

4.3. Selectivity as investor sentiment changes

Investor sentiment varies over time. If the mispricing of stocks varies according to the level of investor sentiment, then the opportunity for mutual funds to exhibit selectivity should be greatest when sentiment is high, and mispricing is greatest. (The mispricing hypothesis.) Alternatively, if fund managers attempt to predict investor sentiment and trade stocks according to their expected performance, higher levels of good and bad selectivity would be observed prior to large increases or decreases in sentiment. More funds that make successful predictions would exhibit good selectivity whereas more that make unsuccessful predictions would exhibit poor selectivity. (The sentiment prediction hypothesis). Moreover, if investor sentiment is meanreverting, then more funds that decrease (increase) their sentiment beta when investor sentiment is high (low), would exhibit better selectivity. More funds that make the opposite adjustments would exhibit poor selectivity.

We measure the level of investor sentiment by averaging Baker and Wurgler's (2007) monthly sentiment index at the start of each month during the calendar quarter that we examine fund trades. To measure the change in investor sentiment over the quarter following the trading period, we average the monthly values of Baker and Wurgler's (2007) sentiment changes index during this quarter. We rank fund-quarters using the average sentiment index and allocate fund-quarters to approximate quintiles, and then repeat this process using the average sentiment changes index. For each quintile, the percentage of net, buy, and sell selectivity trade betas that are significantly positive or negative are shown in Table 3.

[Table 3]

Quintile 5 in Panel A of Table 3 contains fund-quarters from the intervals in which investor sentiment was highest. Inconsistent with the mispricing hypothesis, when investor sentiment is high, the proportion of funds exhibiting bad selectivity (12.4%) statistically exceeds the proportion exhibiting good selectivity (9.1%, Z=5.29). Moreover, the proportion of funds exhibiting bad selectivity in this quintile statistically exceeds the proportion exhibiting bad selectivity (9.3%, Z=7.92) for the full time-series in Table 2. It is also apparent that the elevated proportion of funds exhibiting bad selectivity arises both from funds incorrectly choosing stocks to buy (10.4%) and incorrectly choosing stocks to sell (11.1%). When sentiment is low, quintile 1 shows the proportion of funds exhibiting good selection (8.1%) marginally exceeds the proportion exhibiting bad selection (7.2%, Z=1.70). However, both are marginally below the proportions (9.3%, Z=3.53 and 9.5%, Z=5.34) for the full time-series in Table 2. From the components of net selectivity it is apparent, that as a group, mutual funds find it easier to avoid buying the wrong stocks, but more difficult to identify the correct stocks to sell. When sentiment is low, statistically fewer funds (4.9%, Z=9.02) incorrectly choose stocks to buy, while the reduced good selectivity arises from statistically fewer funds (5.5%, Z=8.33) able to identify the correct stocks to sell.

When actual changes in investor sentiment that are identified ex-post are considered, the pattern of good buy selectivity and bad sell selectivity identified in quintile 1 of Panel A is repeated in intervals of extreme sentiment increase in quintile 5 of Panel B. Buy selectivity is greatest, featuring reduced bad selectivity (5.4%) and elevated good selectivity (13.5%). Both proportions differ significantly from the proportions for the full time-series in Table 2 (7.7%, Z=6.33 and 9.0%, Z=11.53 respectively), and from each other (Z=13.90). Sell selectivity is least, with reduced good (7.2%) and elevated bad (12.7%) selectivity. Notably, the reverse is observed in quintile 1 for extreme sentiment decreases. Buy selectivity is least, showing elevated bad selectivity (13.5%) and reduced good selectivity (7.7%), while sell selectivity is greatest showing reduced bad selectivity (8.5%) and elevated good selectivity (12.7%). The proportions of good and bad selectivity differ statistically (Z=9.31 and Z=6.72) for each of buy and sell selectivity, and from the proportions in Table 2 (Z=15.95, Z=3.33, Z=2.50 and Z=11.04). Both buy and sell selectivity contribute to the overall measure of net selectivity, and the elevated instances of both bad and good net selectivity preceding the largest sentiment increases or decreases. We interpret these findings as indicating that preceding an increase in investor sentiment, as a group, funds find it easier to identify which stocks to buy, but more difficult to choose the right stocks to sell. Conversely, preceding a decrease, funds find it easier to identify the correct stocks sell, but more difficult to choose the right ones to buy.

4.4. Selectivity by changing fund sentiment betas to time investor sentiment

The preceding analysis indicates that, as a group, mutual fund selectivity is not enhanced when sentiment is high. Therefore, as a group, mutual fund selectivity does not conform to the mispricing hypothesis. However, there is some evidence that selectivity, good and bad, varies according to investor sentiment changes over the calendar quarter following stock selection (the trading period), particularly when the components buy and sell selectivity is examined. To further explore the sentiment prediction hypothesis, we consider the subset of mutual funds that either increase or decrease their sentiment beta during the trading period to assess the prevalence of good and bad selectivity in these groups.

A stock's sentiment beta indicates a stock's price response to changing investor sentiment. On average, when investor sentiment increases, stocks with high sentiment betas outperform low sentiment beta stocks. Conversely, when investor sentiment decreases, on average, stocks with low sentiment betas outperform high sentiment beta stocks. If funds attempt to predict sentiment and trade accordingly, those that buy (sell) stocks with high sentiment betas and/or sell (buy) stocks with low sentiment betas ahead of increasing sentiment would more commonly exhibit good (bad) selectivity. Alternatively, funds that buy (sell) stocks with low sentiment betas and/or sell (buy) stocks with high sentiment betas ahead of decreasing sentiment would more commonly exhibit good (bad) selectivity. These permutations are summarized in Figure 1.

[Figure 1]

We identify funds that, with statistical significance, trade to decrease or increase their sentiment beta, and for various market conditions (sentiment tertiles) cross-tabulate the proportion we identify as exhibiting bad or good selectivity in Table 4. In Panel A, the market conditions are the tertiles of BW07's sentiment changes index in the calendar quarter following trading, and in Panel B, the market conditions are the average of the start-of-month values of BW07's sentiment index over the trading period. Only the highest and lowest tertiles are reported. Consistent with Figure 1, Panel A of Table 4 shows that more funds that decrease their sentiment beta ahead of falling investor sentiment exhibit good net selectivity (24.3%) and fewer exhibit bad selectivity (4.9%). These proportions are significantly different from each other (Z=12.14), and respectively above (Z=15.93) and below (Z=4.78) the corresponding proportions for the full time-series in Table 2. Of the funds that increase their sentiment beta ahead of rising investor sentiment, significantly more (Z=11.35) exhibit good net selectivity (21.3%), and less exhibit bad selectivity (5.4%). Also consistent with Figure 1, of the funds that alter their sentiment beta in the opposite direction to the subsequent change in investor sentiment, there is an increased incidence of bad selectivity and decreased incidence of good selectivity.

[Table 4]

Examination of buy and sell selectivity in Panel A of Table 4 shows that sell selectivity, bad and good drives net selectivity when funds trade to reduce their sentiment beta, while good and bad buy selectivity drives net selectivity when funds trade to increase their sentiment beta. It follows that selectivity relates most strongly to the trades that involve high sentiment beta stocks. That is, and as Figure 1 demonstrates, where sentiment beta is decreased by selling high sentiment beta stocks, and increased by buy buying high sentiment beta stocks.

The above results support the sentiment prediction hypothesis to the extent that of the funds that trade to alter their sentiment beta in the same direction as the subsequent change in investor sentiment, more exhibit good selectivity. However, the *actual* change in investor sentiment is only known ex-post, and it remains unclear whether selectivity relates to trading to alter a fund's sentiment beta according to the level of sentiment *during* the calendar quarter that trading occurs. Panel B of Table 4 displays a similar pattern of buy and sell selectivity to that in Panel A where the sentiment tertile 'rise' is replaced with 'low' and 'fall' is replaced with 'high'. Net selectivity also follows the same pattern except where sentiment beta is decreased during a low sentiment period and is not associated with elevated bad selection as is the case with sell selectivity. Although the differences between the proportions of funds exhibiting good or bad selectivity are not as marked in Panel B as in Panel A, it remains the case that, compared to the full sample in Table 2, statistically more funds that buy high sentiment beta stocks when sentiment is low (13.3%, Z=4.97) or sell high sentiment stocks when sentiment is high (15.7%, Z=8.34) exhibit greater selectivity. We conclude that, consistent with the sentiment prediction hypothesis, mutual funds *could* improve their selectivity by conducting trades based on stock sentiment betas given the level of investor sentiment when they trade. However, while some funds conduct the appropriate sentiment based trades, other funds are either over-optimistic or over-pessimistic and adjust their sentiment beta in the wrong direction to benefit.

We further examine the relation between selectivity, trading to alter sentiment beta and investor sentiment by performing the following logistic regression:

$$\begin{aligned}\mathrm{SelectivityTradeBeta}_{jt} = {} & a_0 + b_1\mathrm{SentimentTradeBeta}_{jt} \times \mathrm{L13mSI}_t + b_2\mathrm{SentimentTradeBeta}_{jt} \times \mathrm{SChI}_t \\ & + b_3\mathrm{SentimentTradeBeta}_{jt} \times \mathrm{SChI}_{t+1} + \varepsilon_{jt}\end{aligned} \quad (2)$$

where $\mathrm{SelectivityTradeBeta}_{jt}$ are the signed statistically significant 'β' coefficients estimated using equation (1) for each fund j in quarter t when stocks are ranked on prior performance, $\mathrm{SentimentTradeBeta}_{jt}$ are the signed statistically significant 'β' coefficients when stocks are ranked on stock sentiment beta, L13mSI is the one-month lagged moving three-month average of

BW07 non-orthogonalized monthly investor sentiment index and $SChI_{t-1}$ are the three-month averages of BW07 non-orthogonalized monthly investor sentiment changes index.

Model (1) in Table 5 shows the parameter estimates for equation (2) when we include only the information about investor sentiment that is available at the time funds conduct their trades. SentimentTradeBeta takes on the value of 1 if, with statistical significance, a fund trades to increase its sentiment beta, and -1 if it trades to decrease its sentiment beta. Accordingly, we interpret the statistically negative coefficient b_1 as confirming the result in Panel B of Table 4, that increasing (decreasing) sentiment beta when sentiment is low (high) improves selectivity. The significantly positive coefficient b_2 indicates that increasing (decreasing) sentiment beta while sentiment is increasing (decreasing) also improves selectivity. The model correctly predicts 65.3 percent of instances that we observe good and bad selectivity, with pseudo r-squares of 3.5% and 4.7%.

[Table 5]

Model (2) demonstrates that selectivity is very strongly dependent on whether a fund trades to increase or decrease its sentiment beta ahead of a change in investor sentiment. Consistent with Model (1), the coefficient b_2 remains statistically positive, and consistent with Panel A of Table 4, the coefficient b_3 is also statistically positive. The model correctly predicts 76.4 percent of instances that we observe good and bad selectivity, with pseudo r-squares of 31.5% and 42%. Therefore, funds would be able to improve the likelihood of exhibiting good selectivity if they can predict a decrease in investor sentiment and reduce their sentiment beta in anticipation, or can predict an increase, and increase their sentiment beta.

We have shown that the proportion of funds that exhibit bad or good selectivity exceeds random expectation. Of the funds we identify as exhibiting good (bad) selectivity some will have done so by good (bad) luck, and some by skill (perverse skill). We have also shown that the proportions also depend on how fund trades adjust their sentiment beta ahead of changes in investor sentiment. However, the actual changes in sentiment are only known ex-post, and it remains ambiguous whether funds correctly (incorrectly) adjust their sentiment beta from skill (perverse skill) in predicting investor sentiment. We consider the question of luck or skill in Section 5.

4.5. Selectivity, Active Share and tracking error variance.

According to Cremers and Petajisto (2009), managers can only outperform their benchmarks by deviating from them, by either attempting to identify mispriced stocks, or from making factor bets. They proxy attempts to identify mispriced stocks with "Active Share" and factor bets by tracking error variance. In this context, timing investor sentiment may be viewed as a factor bet. However, Cremers and Petajisto (2009) find that higher fund returns are more associated with Active Share than with tracking error variance, whereas the evidence presented in the previous section suggests that selectivity is primarily related to market timing. However, as we are able to distinguish good from bad stock selection and identify market timing directly, we partition the results from Tables 3 and 4 into the four quadrants of high and low Active Share and high and low tracking error variance to reconcile these findings.

Accordingly, in Table 6A, we partition fund-quarters of significant selectivity trade betas into the four quadrants of high and low Active Share and high and low tracking error variance using data made available on Antti Petajisto's website at www.petjisto.net/data.html. In Panel A, we sort by Active Share then by tracking error variance, and in Panel B we do the reverse. We find that fund-quarters with high Active Share and low tracking error variance, classified by

Cremers and Petajisto (2009) as 'diversified stock pickers', do not exhibit elevated levels of selectivity, good or bad, in either panel. However, fund-quarters with low Active Share and high tracking error variance classified as 'factor bets', exhibit higher incidences of both good and bad selectivity. This pattern is observed with respect to net, buy, and sell selectivity, and is also apparent in Table 6B when the traditional measure of tracking error variance used by Chevalier and Ellison (1997) is employed. These results are consistent with tracking error variance being a proxy for factor timing, with the higher incidence of bad selectivity being explained by failed factor bets. However, our results do not support the contention that greater deviation from the composition of index portfolios is, in itself, a proxy for stock selection ability.

[Table 6A and 6B]

We repeat the analysis presented in Table 4 in which we examine the relation between trading to alter a fund's sentiment beta and the market conditions of high or low investor sentiment, and increasing or decreasing sentiment. In this instance, we partition the sample into quadrants of high or low Active Share, and high or low tracking error variance, and present these results in Table 7A. For Panels A to D we create the quadrants by first sorting by Active Share, and then tracking error variance, while in Panels E to H we do the reverse. In Cremers and Petajisto's (2009) parlance, Panels B and F are 'diversified stock pickers', while Panels C and G are 'factor timers'. The pattern predicted in Figure 1 and observed in Panel A of Table 4, where funds that trade to increase (decrease) their sentiment beta exhibit good (bad) selectivity if investor sentiment subsequently increases and the reverse when sentiment decreases, is observed in columns 2-5 of all panels of Table 7A. Notably, the pattern is most pronounced for funds with low Active Share and high tracking error variance, the factor timers. Diversified stock pickers, with high Active Share and low tracking error variance, exhibit a less pronounced relation between selectivity and the interaction of trading that alters sentiment beta with investor sentiment. However, it is apparent that even “diversified stock pickers” appear to time the market. This result confirms the findings in Tables 6A and 6B that both good and bad selectivity is greater for funds with high tracking error variance, and that, consistent with factor timing behavior, the source of this increased incidence is trading to alter fund sentiment betas. Curiously, for ‘closet indexers’ with low Active Share and low tracking error variance, the number of funds exhibiting poor selectivity when they increase their sentiment beta ahead of a fall in sentiment, is elevated.

[Table 7A]

Columns 6-9 of Table 7A show that when sentiment is high, poor selectivity is the hallmark of funds with low Active Share when they trade to increase their sentiment beta. For the ‘closet indexers’ with both low Active Share and low tracking error variance, more than 45 percent of funds tilt their portfolio towards stocks that subsequently underperform. This result suggests strongly that even ‘closet indexers’ engage in market timing, but as a group are generally unsuccessful. However, from the number of fund-quarters in column 7 it appears that the tracking error variances obtained from Antti Petajisto’s website may be correlated with investor sentiment. A greater number of fund-quarters are classified as having low (high) tracking error variance when investor sentiment is low (high). It is possible that this result arises because Cremers and Petajisto (2009) measure tracking error variance as the variance of the residuals from a regression of fund returns on the benchmark index. The regression uses the relatively short interval of 6-months of daily returns, which may fall largely into periods of high or low investor sentiment. It is likely that the benchmark index correlates with investor sentiment, and as a consequence produces an association between the variance of the regression residuals and investor sentiment. Moreover, as Petajisto (2010) cautions, if fund managers time the market by holding cash, for example, this may increase tracking error variance without affecting the regression residuals.

Table 7B repeats the analysis shown in Table 7A but uses Chevalier and Ellison's (1997) measure of tracking error variance. The results are largely similar, but with two notable exceptions. First, the number of fund-quarters (column 7) falling into high or low sentiment periods is more balanced, and second, the frequency of poor selectivity exhibited by 'closet indexers', that increase their sentiment beta ahead of a fall, or when sentiment is high, is not elevated to the same degree. Accordingly, we conclude that successful and unsuccessful timing of investor sentiment is a pervasive characteristic of fund management, albeit more prevalent in funds with higher tracking error variances.

[Table 7B]

5. Distinguishing skill from luck

In any given quarter, a fund may exhibit superior stock selection by chance rather than skill. However, skill may be identified if superior selection is persistent. Grinblatt and Titman (1993) and Carhart (1997) examined persistence using return performance as the measure of selection ability. This measure has limitations arising from the choice of benchmarks and effect of the extant portfolio that are the focus studies by Daniel, Grinblatt, Titman and Wermers (1997) and Chen, Jegadeesh, and Wermers (2000). Nonetheless, the use of performance as the measurement of selectivity requires the creation of portfolios of funds to increase the power of the statistical tests[13] before out-performance can be concluded. Consequently, these studies principally base their conclusions on portfolios rather than individual funds. Moreover, as previously argued, while improved performance is the objective of good stock selection, performance[14] alone is an indirect measure of selectivity. In contrast, our measure is not only direct, but it statistically identifies selectivity fund-by-fund, and the persistence in this selectivity can therefore be used fund-by-fund to distinguish, with statistical confidence, skill from luck.

We interpret the fund-quarters with significantly positive selectivity betas as exhibiting good stock selection. However, as a consequence of our 90 percent (2-tailed) confidence requirement, funds executing purely random trades would exhibit good (or bad) stock selection with a 5 percent probability. If the board of directors' goal is to reward skillful managers and dismiss poor managers, it is necessary to distinguish luck from skill. We obtain statistical separation of skill from luck by considering a fund manager's selectivity performance over several quarters, and using the cumulative binomial probability distribution with a 99 percent confidence interval. For a particular fund, we conclude that a manager has skill by using the number of quarters as the number of trials, the number of quarters in which a fund exhibits selectivity (has a statistically positive selectivity beta) as the number of successes, and 5 percent as the probability of a successful outcome. This 5 percent probability arises from the earlier regressions that identified the selection betas with 90 percent confidence.

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[13] The statistical significance of performance is addressed using bootstrapping techniques in studies by Kosowski, Timmermann, Wermers and White (2006) Cuthbertson, Nitzche and O'Sullivan (2008) and Fama and French (2010).

[14] In separate tests, we confirm that, on average, funds that exhibit good selectivity outperform those our measure classifies as exhibiting bad selectivity. However, there is substantial overlap on these distributions.

Panels A and B of Table 8 show the number of funds that we classify as exhibiting good (bad) skill from repeated positive (negative) selectivity. In Panel A, various ranges of the number of quarters a fund enters our dataset correspond to the minimum number of quarters that a fund in that range must exhibit (net) selectivity to be considered skillful. Because our dataset holds fewer funds with longer records, the number of funds varies accordingly. For example, in our dataset, 557 funds have between 4 and 9 (inclusive) quarters of data, and the cumulative binomial probability distribution requires a minimum of 2 quarters of positive stock selection before we classify 83 funds as having good stock selection skill. In aggregate, 1697 funds in our dataset appear four or more times, and we class 255 (228) as having good (bad) net stock selection skill. Similar to the final row in Panel A, in Panel B we report the number of funds exhibiting bad or good stock selection skill, but consider net, buy and sell selectivity.

[Table 8]

The analyses we report in Panels A and B of Table 8 allows us to identify 255 funds as having good stock selection ability, with 99 percent statistical confidence. However, for our method to be practically useful for evaluating a fund manager's stock selection skill, a suitable evaluation period may be one calendar year. Consistent with the preceding discussion, to classify a fund manager as skillful, an evaluation period of four quarters requires a fund to exhibit selectivity two or more times. Accordingly, in Panel C we identify 3034 fund-years where funds have four consecutive quarters of data that comprise a calendar year. Note that some funds may have more than one calendar year of data, while some funds will not have four contiguous quarters of data that comprise a calendar year. We observe 131 fund-years where we can, with 99 percent statistical confidence, conclude that the fund managers have stock (net) selection skill. Of further interest, we report that over our 15-year sample period, we identify two funds that demonstrate good selection skill in three calendar years and another five in two calendar years. Fourteen funds demonstrate bad selection skill over two calendar years, and two over three years.

6. Conclusion

By examining changes to mutual fund portfolio holdings, we are able to statistically identify funds that, in a calendar quarter, realign their portfolios by buying the stocks that later became better performers while selling stocks that became poorer performers. We refer to this realignment as good selectivity, and find that it is achieved by more funds than would be expected from random occurrence. However, in a similar number of fund-quarters, funds exhibit bad selectivity. Unlike good selectivity that may be rationalized as the outcome of trades by skilled managers focused on improving a fund's return performance, bad selectivity is unlikely to be an objective. Moreover, bad luck can only partially explain the prevalence of funds that exhibit bad selectivity in the stocks they trade.

The sensitivity of a stock's returns to changing investor sentiment affects the stock's relative performance. On average, stocks with high sentiment betas perform relatively better (worse) when investor sentiment increases (decreases). This raises the possibility that the elevated incidences of good and bad selectivity may relate to the differing abilities of funds to predict changes in investor sentiment. Funds that trade stocks to effect an appropriate change in their portfolio's sentiment beta ahead of a change in sentiment would exhibit better selectivity. In traditional parlance, this may be described as "timing" market sentiment. Consistent with the sentiment prediction hypothesis, we find that a larger proportion of funds that buy stocks with high sentiment betas exhibit good selectivity when they do so ahead of an increase in investor sentiment. Ahead of a decrease, more funds that sell high sentiment beta stocks exhibit good selectivity. Funds that conduct the opposite trades in high sentiment beta stocks exhibit bad selectivity.

Selectivity that stems from timing investor sentiment is possible if funds can predict changes in sentiment. However, we also find that selectivity is demonstrated by funds that make sentiment based trades according on the level and change in investor sentiment at the time the trades are being executed. In support of the mispricing hypothesis, an increased proportion exhibit good selectivity when funds sell high sentiment beta stocks when sentiment is high, and buy high sentiment stocks when sentiment is low. In addition, more exhibit good selectivity when the fund's sentiment beta is adjusted in the same direction as the contemporaneous change in investor sentiment. That is, the likelihood of a fund executing trades that tilt the portfolio towards stocks that become the better performers is improved if the trades are based on sentiment beta, and information about investor sentiment that is available at the time of the trades.

We consider the Cremers and Petajisto (2009) attributes of active share as a proxy for stock picking and tracking error variance as a proxy for factor timing. Their focus on deviations from benchmark portfolios precludes identification of good and bad selectivity or timing, which our method is able to discern. Our results suggest that fund managers attempt to time investor sentiment, with varying success, irrespective of the Cremers and Petajisto (2009) divisions. However, we find support for their conjecture that tracking error variances proxies market timing from the elevated incidence of timing behaviour in this group.

When we examine a fund's trading behavior over time, we can distinguish genuine stock selection skill from fortuitous selection of the correct stocks to buy or sell. We use this to develop a practical method to evaluate, with 99 percent statistical confidence, the stock selection ability of a particular fund manager. We conclude that mutual fund managers can improve their selectivity by timing investor sentiment, particularly if they are skilled.

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Trading period (t)			Appraisal period (t+1)	
High Sbeta stocks	Low Sbeta stocks	Sbeta trade	SChI	Apparent selectivity
Buy	Sell	Increase	Increase (+)	Good
Sell	Buy	Decrease		Bad
Buy	Sell	Increase	Decrease (-)	Bad
Sell	Buy	Decrease		Good

Figure 1. Summary of how selectivity reflects trades that change sentiment beta prior to changes in investor sentiment.

The figure shows how the change in investor sentiment (SChI) during the appraisal period differentially affects the apparent selectivity of mutual funds that have traded to alter their sentiment beta (Sbeta) in the preceeding period. For example, the first row shows that during the trading period, funds that either buy high sentiment beta stocks, sell low sentiment beta stocks, or both, increase their sentiment beta (positive SentimentTradeBeta) such that if in the subsequent period investor sentiment increases, they will appear to have tilted their portfolio towards the better performing stocks (positive NetSelectivityTradeBeta).

Table 1

Descriptive statistics, 1991 to 2005

Panel A. Fund descriptive statistics	Mean	Median	Standard Deviation
Number of fund-quarters	27,349		
Number of funds	2173		
Market capitalization ($ million)	1043	234	3840
Number of stocks in portfolio	154	93	239
Fund-quarter sentiment beta	0.0199	0.0172	0.0159

Panel B. Funds with selectivity betas calculated over time						
Number of quarters	<4	4 - 7	8 - 11	12 - 19	20 - 39	40+
Count of funds	467	398	292	497	483	36

Fund-quarter sentiment betas are a weighted average of the stock sentiment betas held by a fund at the start of a quarter. Selectivity betas are the coefficients (β) from repeated regressions of $\text{TradeValue}_j = \alpha + \beta \text{ Bucket\_Performance}_j + \varepsilon_j$.

Panel B presents the number of funds with associated number of quarters that permit this regression. For example, a fund with six quarters of data will be counted in cell headed ‘4 – 7’.

Table 2
Significant selectivity betas, 1991 to 2005

	N	Binomial CV Range		Trade Betas			
				Negative		Positive	
		Min	Max	Count	Percent	Count	Percent
Panel A Selectivity Trade Betas							
Net	27,349	1283	1452	2530	9.3%	2588	9.5%
Buy	27,349	1283	1452	2095	7.7%	2468	9.0%
Sell	27,349	1283	1452	2594	9.5%	2326	8.5%
Panel B Sentiment Trade Betas							
Sentiment Trade Beta	27,349	1283	1452	2717	9.9%	3645	13.3%

The number of statistically significant selectivity betas is generated from linear regressions of: $\text{TradeValue}_j = \alpha + \beta \text{ Bucket\_Performance}_j + \varepsilon_j$ where:

$$\text{TradeValue}_j \equiv \sum_{i=1}^{n} \text{Value stock}_i \text{ traded;}$$

$$\text{Bucket\_Performance}_j \equiv \sum_{i=1}^{n} (\text{Performance}_i \times \frac{\text{Value stock}_i \text{ held}}{\sum_{i=1}^{n} \text{Value stock}_i \text{ held}});$$

$$\text{Value stock}_i \text{ traded} = \text{value of stock i traded during quarter t;}$$

$$\text{Value stock}_i \text{ held} = \text{value of stock i held at the start of quarter t;}$$

$$\text{Performance}_i = \text{Performance of stock i in quarter } t+1 \text{; and}$$

$$n = \text{ number of stocks in bucket j.}$$

The number of statistically significant sentiment trade betas is generated from the same formulas, however in place of “Performance”, “Sentiment_beta” is substituted. Cumulative binomial distribution critical values (Bin CV) reflect a 1 percent probability that a lower (Min) or greater (Max) count occurs by chance. All percentages are significance at the 1 percent level.

Table 3

Time-series variation of significant selectivity betas, 1991 to 2005

		Net Selectivity		Buy Selectivity		Sell Selectivity	
Quintile	N	Negative	Positive	Negative	Positive	Negative	Positive
Panel A Average sentiment index quintile							
1 Low	5452	7.2%	8.1%	4.9%	9.5%	9.9%	5.5%
2	5588	8.7%	9.0%	5.4%	9.9%	10.7%	6.5%
3	5712	9.8%	10.0%	10.0%	7.0%	7.3%	11.4%
4	5097	8.1%	11.2%	7.6%	10.2%	8.4%	10.1%
5 High	5500	12.4%	9.1%	10.4%	8.6%	11.1%	9.0%
Panel B Change sentiment index quintile							
1 Decrease	5492	12.8%	11.2%	13.5%	7.7%	8.5%	12.7%
2	5414	9.3%	7.6%	7.6%	7.4%	9.5%	8.4%
3	5529	7.1%	8.3%	5.9%	8.2%	8.0%	7.0%
4	5539	7.7%	8.6%	5.9%	8.7%	8.8%	7.3%
5 Increase	5375	9.3%	11.6%	5.4%	13.5%	12.7%	7.2%

Fund-quarters are ranked by the average of the three start-of-month values of the sentiment index (Panel A) during, and sentiment changes index (Panel B) following the quarters that we examine fund trades, before the time-series are partitioned and fund-quarters allocated to quintiles. For each quintile, the proportion of selectivity betas generated from the regression $\text{TradeValue}_j = \alpha + \beta \text{ Bucket\_Performance}_j + \varepsilon_j$ for each fund-quarter that are statistically negative or positive is calculated. Trade value is the value, in each performance bucket j, of the net, buy and sell trades during a quarter. The cumulative binomial distribution is used to determine which proportions are statistically different from the 5 percent expected as a random occurrence.

Table 4

Time-series variation of significant selectivity betas, 1991 to 2005

Sentiment Trade Beta	Sentiment Tertile	N	Net Selectivity Negative	Net Selectivity Positive	Buy Selectivity Negative	Buy Selectivity Positive	Sell Selectivity Negative	Sell Selectivity Positive
Panel A Change sentiment index tertile								
Decrease	Rise	883	18.3%	3.9%	7.5%	5.0%	19.3%	5.3%
Decrease	Fall	996	4.9%	24.3%	5.5%	15.8%	5.5%	20.5%
Increase	Rise	1232	5.4%	21.3%	5.0%	21.8%	6.9%	9.7%
Increase	Fall	1375	28.8%	3.6%	26.8%	4.4%	13.7%	5.3%
Panel B Sentiment index tertile								
Decrease	Low	778	7.5%	8.2%	4.1%	6.8%	12.5%	7.7%
Decrease	High	1044	11.7%	15.9%	6.1%	10.2%	11.5%	15.7%
Increase	Low	1094	6.1%	10.5%	6.6%	13.3%	7.7%	6.6%
Increase	High	1371	23.0%	9.7%	20.2%	9.4%	13.0%	6.1%

Fund-quarters are ranked by change sentiment index (Panel A) following, and average sentiment index (Panel B) during, the quarters that we examine fund trades, before the time-series are partitioned and we identify fund-quarters in the highest and lowest tertiles. Within each tertile, we identify fund-quarters where funds have (with statistical significance) traded to decrease or increase their sentiment beta. Within each of the four sub-groups in each of Panels A and B, the proportion of selectivity betas generated from the regression $\text{TradeValue}_j = \alpha + \beta\ \text{Bucket\_Performance}_j + \varepsilon_j$ for each fund-quarter that are statistically negative or positive is calculated. Trade value is the value, in each performance bucket j, of the net, buy and sell trades during a quarter. The cumulative binomial distribution is used to determine which proportions are statistically different from the 5 percent expected as a random occurrence.

Table 5

Selectivity Trade Beta

The table presents the logistic regression:

$$\text{SelectivityTradeBeta}_{jt} = a_0 + b_1\text{SentimentTradeBeta}_{jt} \times \text{L13mSI}_t + b_2\text{SentimentTradeBeta}_{jt} \times \text{SChI}_t + b_3\text{SentimentTradeBeta}_{jt} \times \text{SChI}_{t+1} + \varepsilon_{jt}$$

where $\text{SelectivityTradeBeta}_{jt}$ are the signed statistically significant 'β' coefficients estimated using equation (1) for each fund j in period t when stocks are ranked on prior performance, $\text{SentimentTradeBeta}_{jt}$ are the signed statistically significant 'β' coefficients when stocks are ranked on stock sentiment beta, L13mSI is the one-month lagged moving three-month average of BW07 non-orthogonalized monthly investor sentiment index and SChI_{t-1} are the three-month averages of BW07 non-orthogonalized monthly investor sentiment changes index. The p-values are in parentheses.

	Model			
	(1)		(2)	
Intercept	-0.041		-0.091	
	(0.421)		(0.151)	
Sentiment Trade Beta $_{jt}$ x L13mSI_t	-0.288		0.154	
	(0.000)		(0.121)	
Sentiment Trade Beta $_{jt}$ x SChI_t	0.370		0.586	
	(0.000)		(0.000)	
Sentiment Trade Beta $_{jt}$ x SChI_{t+1}			2.692	
			(0.000)	
Predicted	Bad	Good	Bad	Good
Observed Bad Selectivity	591	234	666	159
Observed Good Selectivity	322	453	150	625
Percent correct	65.3		76.4	
Cox & Snell R^2	0.035		0.315	
Nagelkerke R^2	0.047		0.420	

Table 6A

Significant selectivity betas by active share and tracking error variance, 1991 to 2005

			Net selectivity		Buy selectivity		Sell selectivity	
Active	TEV	N	Negative	Positive	Negative	Positive	Negative	Positive
Panel A Sort by Active Share then by tracking error variance								
Low	Low	4720	9.9%	7.8%	7.5%	9.0%	10.8%	6.4%
High	Low	4619	7.7%	8.9%	7.3%	8.6%	8.0%	7.5%
Low	High	4712	11.2%	10.8%	8.8%	9.6%	10.1%	9.7%
High	High	4612	9.1%	10.4%	8.2%	9.0%	9.4%	7.0%
Panel B Sort by tracking error variance then by Active Share								
Low	Low	4658	10.3%	8.4%	7.6%	9.2%	11.2%	6.9%
High	Low	4675	8.1%	8.7%	7.1%	8.7%	8.8%	7.5%
Low	High	4665	11.2%	10.4%	9.1%	9.6%	9.5%	10.4%
High	High	4665	8.4%	9.3%	7.9%	8.7%	8.8%	9.1%

The proportion of selectivity betas generated from ‘N’ repeat linear regressions of $\text{TradeValue}_j = \alpha + \beta\ \text{Bucket\_Performance}_j + \varepsilon_j$ that are statistically negative or positive. Trade value is the value, in each bucket j, of the net, buy and sell trades during a quarter. The cumulative binomial distribution is used to determine which proportions are statistically different from the 5 percent expected as a random occurrence. All percentages are significance at the 1 percent level.

Table 6B
Significant selectivity betas by active share and traditional tracking error variance, 1991 to 2005

			Net selectivity		Buy selectivity		Sell selectivity	
Active	TEV	N	Negative	Positive	Negative	Positive	Negative	Positive
Panel A Sort by Active Share then by tracking error variance								
Low	Low	3926	8.8%	9.3%	6.7%	9.9%	8.9%	7.8%
High	Low	4543	8.6%	8.7%	7..0%	8.2%	8.7%	7.5%
Low	High	3926	11.1%	9.5%	7.5%	8.9%	10.6%	8.6%
High	High	4543	8.9%	10.2%	7.9%	9.1%	8.8%	9.8%
Panel B Sort by tracking error variance then by Active Share								
Low	Low	4240	8.8%	8.6%	6.3%	9.6%	9.7%	7.1%
High	Low	4229	8.2%	8.9%	7.1%	8.4%	9.4%	7.4%
Low	High	4237	11.1%	10.5%	8.0%	8.9%	9.8%	9.9%
High	High	4232	8.0%	9.6%	7.9%	9.0%	8.3%	9.1%

The proportion of selectivity betas generated from 'N' repeat linear regressions of $\text{TradeValue}_j = \alpha + \beta \text{ Bucket\_Performance}_j + \varepsilon_j$ that are statistically negative or positive. Trade value is the value, in each bucket j, of the net, buy and sell trades during a quarter. The cumulative binomial distribution is used to determine which proportions are statistically different from the 5% expected as a random occurrence. All percentages are significance at the 1 percent level.

Table 7A
Time-series variation of significant net selectivity betas by Active Share and tracking error variance, 1991 to 2005

	Change sentiment index tertile					Sentiment index tertile		
Sentiment Trade Beta	Sentiment Change Index	N	Negative	Positive	Average Sentiment Index	N	Negative	Positive
Panel A. Low Active Share then Low Tracking Error Variance.								
Decrease	Rise	100	18.0%	2.0%	Low	199	6.5%	4.5%
Decrease	Fall	88	5.7%	19.3%	High	64	18.8%	10.9%
Increase	Rise	206	6.8%	22.8%	Low	272	7.4%	10.3%
Increase	Fall	215	41.4%	2.3%	High	144	47.6%	11.3%
Panel B High Active Share then Low Tracking Error Variance.								
Decrease	Rise	111	7.2%	5.4%	Low	167	4.2%	8.4%
Decrease	Fall	89	3.4%	22.5%	High	75	2.7%	9.3%
Increase	Rise	188	11.9%	18.9%	Low	277	4.7%	10.5%
Increase	Fall	166	16.3%	6.6%	High	122	7.4%	15.6%
Panel C Low Active Share then High Tracking Error Variance.								
Decrease	Rise	202	22.2%	2.5%	Low	90	8.9%	15.6%
Decrease	Fall	255	3.5%	27.8%	High	314	11.8%	17.8%
Increase	Rise	229	3.9%	28.8%	Low	135	4.4%	10.4%
Increase	Fall	357	33.9%	2.5%	High	390	27.7%	9.0%
Panel D. High Active Share then High Tracking Error Variance.								
Decrease	Rise	186	21.5%	4.3%	Low	69	4.3%	10.1%
Decrease	Fall	235	4.7%	23.0%	High	277	14.4%	16.6%
Increase	Rise	220	6.8%	20.0%	Low	84	7.1%	3.6%
Increase	Fall	246	25.6%	4.5%	High	294	18.0%	11.2%
Panel E. Low Tracking Error Variance then Low Active Share.								
Decrease	Rise	131	24.4%	3.1%	Low	186	8.1%	7.0%
Decrease	Fall	120	3.3%	25.8%	High	102	23.5%	16.7%
Increase	Rise	230	6.5%	23.0%	Low	234	7.3%	9.8%
Increase	Fall	263	41.4%	3.0%	High	203	45.9%	12.3%
Panel F. Low Tracking Error Variance then High Active Share.								
Decrease	Rise	105	9.5%	3.8%	Low	184	4.9%	8.7%
Decrease	Fall	77	5.2%	15.6%	High	72	4.2%	8.3%
Increase	Rise	156	5.1%	17.3%	Low	296	6.1%	10.1%
Increase	Fall	135	11.9%	8.1%	High	105	10.5%	17.1%
Panel G. High Tracking Error Variance then Low Active Share.								
Decrease	Rise	224	20.5%	4.5%	Low	60	5.0%	15.0%
Decrease	Fall	277	2.9%	30.0%	High	360	11.1%	17.2%
Increase	Rise	239	4.6%	28.5%	Low	116	3.4%	11.2%
Increase	Fall	358	34.4%	3.4%	High	400	36.1%	14.5%

Panel H. High Tracking Error Variance then High Active Share.								
Decrease	Rise	139	17.3%	2.2%	Low	95	4.2%	6.3%
Decrease	Fall	193	6.2%	18.7%	High	196	12.2%	15.8%
Increase	Rise	218	6.4%	18.3%	Low	122	4.9%	6.6%
Increase	Fall	228	22.8%	2.2%	High	242	12.8%	12.0%

Fund-quarters are partitioned first by high or low Active Share then by high or low Tracking error variance in Panels A to D, and second by Tracking error variance then Active Share in Panels E to H. Fund-quarters are ranked by change sentiment index following, and average sentiment index during, the quarters that we examine fund trades, before the time-series are partitioned and we identify fund-quarters in the highest and lowest tertiles. Within each tertile, we identify fund-quarters where funds have (with statistical significance) traded to decrease or increase their sentiment beta. Within each of the four sub-groups, the proportion of selectivity betas generated from the regression $\text{TradeValue}_j = \alpha + \beta\,\text{Bucket\_Performance}_j + \varepsilon_j$ for each fund-quarter that are statistically negative or positive is calculated. Trade value is the value, in each bucket j, of the net trades during a quarter. The cumulative binomial distribution is used to determine which proportions are statistically different from the 5% expected as a random occurrence.

Table 7B

Time-series variation of significant net selectivity betas by Active Share and traditional tracking error variance, 1991 to 2005

	Change sentiment index tertile					Sentiment index tertile		
Sentiment Trade Beta	Sentiment Change Index	N	Negative	Positive	Average Sentiment Index	N	Negative	Positive
Panel A. Low Active Share then Low Tracking Error Variance.								
Decrease	Rise	103	11.7%	1.0%	Low	94	10.6%	5.3%
Decrease	Fall	104	2.9%	11.5%	High	98	7.1%	8.2%
Increase	Rise	171	5.3%	19.9%	Low	161	5.6%	11.8%
Increase	Fall	170	19.4%	5.9%	High	128	18.8%	6.3%
Panel B High Active Share then Low Tracking Error Variance.								
Decrease	Rise	126	9.5%	5.6%	Low	97	3.1%	7.2%
Decrease	Fall	102	2.9%	13.7%	High	114	7.0%	8.8%
Increase	Rise	225	7.6%	16.9%	Low	146	2.7%	13.7%
Increase	Fall	152	12.5%	5.9%	High	175	7.4%	10.3%
Panel C Low Active Share then High Tracking Error Variance.								
Decrease	Rise	159	26.4%	1.3%	Low	137	9.5%	9.5%
Decrease	Fall	172	5.2%	27.3%	High	208	16.8%	16.8%
Increase	Rise	168	3.6%	29.8%	Low	184	5.4%	10.9%
Increase	Fall	243	35.0%	1.2%	High	260	27.7%	9.2%
Panel D. High Active Share then High Tracking Error Variance.								
Decrease	Rise	162	21.0%	3.7%	Low	133	5.3%	8.3%
Decrease	Fall	188	4.8%	23.8%	High	210	15.2%	17.6%
Increase	Rise	181	3.3%	20.4%	Low	200	5%	8.0%
Increase	Fall	239	24.3%	4.6%	High	227	18.5%	13.2%
Panel E. Low Tracking Error Variance then Low Active Share.								
Decrease	Rise	118	16.1%	0.8%	Low	125	7.2%	5.7%
Decrease	Fall	116	0.9%	14.7%	High	112	12.5%	11.6%
Increase	Rise	180	4.4%	22.2%	Low	197	6.1%	11.2%
Increase	Fall	200	23.0%	5.0%	High	153	22.8%	5.9%
Panel F. Low Tracking Error Variance then High Active Share.								
Decrease	Rise	119	10.9%	4.2%	Low	79	8.9%	14.9%
Decrease	Fall	91	6.6%	14.3%	High	109	7.3%	7.3%
Increase	Rise	206	7.3%	16.0%	Low	132	0.8%	16.7%
Increase	Fall	141	13.5%	6.4%	High	157	7%	8.9%
Panel G. High Tracking Error Variance then Low Active Share.								
Decrease	Rise	189	25.9%	4.5%	Low	135	8.9%	10.4%
Decrease	Fall	200	4.5%	29.0%	High	244	16.8%	16.4%
Increase	Rise	192	4.2%	26.0%	Low	175	5.7%	9.1%
Increase	Fall	269	33.8%	3.0%	High	300	26.3%	10.0%

Panel H. High Tracking Error Variance then High Active Share.								
Decrease	Rise	124	15.3%	3.2%	Low	122	4.1%	5.7%
Decrease	Fall	159	5.0%	18.9%	High	165	11.5%	17.6%
Increase	Rise	167	4.2%	21.6%	Low	187	5.3%	8%
Increase	Fall	194	20.1%	3.1%	High	180	14.4%	15.0%

Fund-quarters are partitioned first by high or low Active Share then by high or low Tracking error variance in Panels A to D, and second by Tracking error variance then Active Share in Panels E to H. Fund-quarters are ranked by change sentiment index following, and average sentiment index during, the quarters that we examine fund trades, before the time-series are partitioned and we identify fund-quarters in the highest and lowest tertiles. Within each tertile, we identify fund-quarters where funds have (with statistical significance) traded to decrease or increase their sentiment beta. Within each of the four sub-groups, the proportion of selectivity betas generated from the regression $\text{TradeValue}_j = \alpha + \beta\,\text{Bucket\_Performance}_j + \varepsilon_j$ for each fund-quarter that are statistically negative or positive is calculated. Trade value is the value, in each bucket j, of the net trades during a quarter. The cumulative binomial distribution is used to determine which proportions are statistically different from the 5% expected as a random occurrence.

Table 8
Selectivity over multiple calendar quarters, 1991 to 2005

Selectivity type	Critical value (99% conf.)	Number of observation quarters	N	Selectivity Skill Bad	Good
Panel A. Funds exhibiting selectivity in multiple quarters by number of observation quarters					
Net	2	4 – 9	557	61	83
	3	10 – 17	508	66	60
	4	18 – 26	406	57	71
	5	27 – 37	179	34	33
	6	38 – 48	44	10	7
	7	49 – 60	3	0	1
	2 – 7	4 – 60	1697	228	255
Panel B. Funds exhibiting net, buy and sell selectivity in multiple quarters					
Net	2 – 7	4 – 60	1697	228	255
Buy	2 – 7	4 – 60	1697	164	199
Sell	2 – 7	4 – 60	1697	243	176
Panel C. Fund-calendar years with net, buy and sell selectivity in two or more quarters					
Net	2	4	3034	189	131
Buy	2	4	3034	147	109
Sell	2	4	3034	160	126

Panel A shows the number of funds that exhibit bad and good skill at being selective. The number of quarters a fund appears in our dataset is used to separate funds before they are grouped using the minimum number of quarters (critical values) required for them to be classed as skilled. The critical values corresponding to 99% confidence are obtained from the cumulative binomial probability distribution using the number of quarters as the number of observations, the number of quarters the fund exhibits negative or positive selectivity as the number of successes, and the probability (5%) that a fund is incorrectly classed as selective (negative or positive) as the probability of a success. Panel B reports the number of funds that exhibit bad or good skill with 99% confidence where the number of quarters the fund appears in our dataset ranges from 4 to 56. Skill is the ability of the fund to exhibit net, buy or sell selectivity. Panel C shows the number of fund-calendar years that funds exhibit bad or good skill at making negative or positive selectivity, respectively, with 99% confidence, for net, buy and sell selectivity. In all panels, N is the total number of funds or fund-calendar years in each category.