Selectivity, Style, Sentiment and Skill in Mutual Fund Trades

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Abstract

Fund managers can only exhibit selectivity through purchasing (selling) stocks that appreciate (depreciate) more frequently than expected from random occurrence, if stocks are incorrectly priced. We develop a method that can statistically identify fund managers that exhibit net, buy, and sell selectivity in their trades, as well as distinguish manager skill from fortuitous stock selection. Stock investor sentiment betas are calculated from the recently developed investor sentiment index, and used to indicate stock mispricing. We find that superior stock selection is concentrated in funds that hold high sentiment beta stocks; the major constituent of funds with the aggressive growth objective.

JEL Classification: G2, G11, G14, G23

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1. Introduction

Mutual fund boards of directors have a fiduciary duty to act in the best interest of the funds' shareholders. This includes monitoring fund manager's performance and deciding which managers to engage or dismiss. Managers with prior superior performance will argue that they possess stock selection ability, while poorly performing managers will attribute their performance to bad luck. Dispute over the selection of an appropriate benchmark thwarts the assessment of comparative performance. In addition, academics have grappled with extricating performance attributable to the trades that managers initiate, from the impact of the extant portfolio.[1]

Further complicating the assessment is the recognition that managers must consider the fund's style objectives, and are constrained by trading costs and portfolio diversification considerations when choosing their trades. Accordingly, selection ability needs to be determined by observing an increased weighting of favored stocks and decreased weighting of less favorable stocks rather than looking for major portfolio changes or the acquisition of stocks that yield stellar performances.

The ability of a fund manager to outperform in selecting stocks depends on whether the stocks are mispriced. Baker and Wurgler (2006, 2007) argue that stocks prone to mispricing tend to be difficult to arbitrage or value and are sensitive to investor sentiment. The stock's investor sentiment beta is a measure of this sensitivity. Accordingly, stocks with higher sentiment betas

[1] According to Kothari and Warner (2001), the decision to trade a stock is also more likely to reflect information about its investment potential than the decision to hold the stock.

offer managers greater opportunity to exhibit their skills. We extend the literature by using investor sentiment betas to examine selectivity in mutual funds.

Similar to Grinblatt and Titman (1993), we employ a procedure that can examine stock selection by fund managers that simultaneously focuses on the fund's trades and avoids the need for benchmarks. However, 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. Since this (net) selectivity may arise from identifying stocks to buy that become superior performers, or from selling stocks that subsequently underperform, we also examine buy selectivity, and sell selectivity. Our method is not confounded by style restrictions that constrain the universe of stocks from which managers can select, nor the performance of the extant portfolio.[2] In addition, by considering the investor sentiment betas of the stocks that funds trade, that are we are able to discern the source of varying selection ability across fund investment objectives. We calculate investor sentiment betas for each stock from the investor sentiment index recently developed by Baker and Wurgler (2007).

We find that slightly higher than random proportions of funds exhibit good and perverse net selectivity. However, more managers buy stocks that appreciate, and fewer managers purchase stocks that subsequently underperform. Aggressive growth funds exhibit the highest proportion of good net selection, buy selection and sell selection, and avoid buying poorly performing stocks. These funds tend to be in the highest sentiment beta pentile. Poor net and sell selectivity is observed in the Growth and Income funds, possibly because managers are less able to identify overpriced stocks among the lower sentiment beta stocks these funds tend to hold. Finally, our

[2] Howard and Callahan (2005) suggest that a style constrained portfolio limits stocks available for selection and, by implication, impedes selectivity.

method enables boards of directors to attribute a manager's stock selection performance to either skill or luck by examining their stock selection over time.

The paper proceeds as follows. In Section 2 we discuss the salient literature and in Section 3 discuss the data and methodology. Section 4 provides the empirical results while Section 5 concludes the study.

2. Literature review

Grinblatt and Titman (1993) use quarterly holdings to measure the ability of fund managers to select stocks with superior performance. This is achieved by creating a zero-investment portfolio that consists of the assets in the fund's portfolio reported at the start of each period held long, while shorting the assets held in the previous period. This procedure focuses on the trades conducted during the period and eliminates the confounding effect of momentum.[3] Since the portfolio has zero investment, any return will reveal selectivity. The average performance for the entire sample of 274 funds is close to zero when a one-quarter period is used, but is 1.9% per annum when the period is one year. When partitioned into fund type, aggressive growth funds have average abnormal performance of 3.4% per annum and growth funds of 2.1% per annum.

Similar to Grinblatt and Titman (1993), Chen, Jegadeesh, and Wermers (2000) focus on mutual fund trades rather than holdings to assess stock selection ability. However, unlike

[3] 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.

Grinblatt and Titman (1993), who consider selectivity on a fund-by-fund basis, Chen, Jegadeesh, and Wermers (2000) only consider selectivity in aggregate mutual fund trades. 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. 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. This applies to large, small, value and growth stocks. Growth funds can select stocks that outperform benchmarks, but income funds are on average, unable to do so. Active fund managers appear to possess only marginally superior stock selection ability.

Chen, Jegadeesh, and Wermers (2000) also find that when funds that were previously better performers purchase stocks, these stocks marginally outperform those purchased by funds that previously underperformed. This suggests that funds may have limited ability to repeat the selection of better performing stocks. Most of the persistence in fund performance, however, is attributed to their extant stock holdings since those of better performing funds significantly outperform those of poorly performing funds.

Using bootstrap techniques, Kosowski, Timmermann, Wermers and White (2006) find that the best and worst performing mutual funds exhibit stock selection ability, and that their performances are not entirely due to luck. Superior performances reflect managerial selection ability rather than lower expenses, while inferior performances result from expenses rather than selection ability. However, selection ability varies according to fund style. Income fund managers do not exhibit selective ability, unlike managers in growth funds, which are able to generate persistent superior returns.

Cuthbertson, Nitzche and O'Sullivan (2008) employ a similar methodology to Kosowski, Timmermann, Wermers and White (2006) to differentiate manager skill from luck using UK funds. They find that less than 10% of funds exhibit stock picking ability and show that relatively few funds achieve superior performance through skill alone. Furthermore, this superior performance is not persistent, whereas poor performance is not attributed to bad luck and is persistent. Fama and French (2009) argue that the Kosowski, Timmermann, Wermers and White (2006) and Cuthbertson, Nitzche and O'Sullivan (2008) results may be attributed to the particular bootstrapping technique they employ. Using a variation on the bootstrapping procedure, they find no evidence that fund managers possess selection skill.

Mutual fund managers may show stock selection ability where the stocks have particular attributes. Baker and Wurgler (2006) create an annual sentiment index to examine the impact of investor sentiment on stock returns. They find that stocks become relatively overvalued when market sentiment is high, and when the stocks have low capitalization and profitability, and high volatility and growth. Therefore, in response to market sentiment, prices may deviate more from intrinsic value depending on the attributes of the stocks. Glushkov (2006) addresses this issue by augmenting the Fama and French 3-factor model with the Pastor and Stambaugh (2003) liquidity factor and a sentiment index to compute 'sentiment betas' for individual stocks. He finds that stocks with greater sensitivity to investor sentiment have characteristics similar to those identified by Baker and Wurgler (2006) as being associated with mispricing.

Baker and Wurgler (2007) develop a monthly sentiment index, and show that following a month of high investor sentiment, speculative stocks that are difficult to arbitrage exhibit lower average returns relative to safe, easy to arbitrage stocks. 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. Accordingly, these stocks are more sensitive to investor sentiment.

Duan, Hu and McLean (2009) focus on stocks with high idiosyncratic volatility. They use a procedure similar to Chen, Jegadeesh, and Wermers (2000) and find that managers are able to select stocks when they possess this characteristic. They reason that this follows because such stocks may have greater mispricing because arbitrage is more costly or because information is more asymmetric. However, while not discounting the existence of superior selection ability by some fund managers, they note that as an average, the ability of managers to select from these stocks has decreased over time.

Zhang (2009) finds that some mutual fund managers can identify underpriced stocks that are subject to selling pressure by other funds that experience substantial redemptions. These fund managers can earn a significant abnormal return by acquiring the stocks and holding them until selling pressure is reduced. Unfortunately, this methodology is restricted to funds that identify stocks with the particular attribute of being fire-sold, however it suggests that less-liquid stocks may be more prone to mispricing.

We extend the literature by using investor sentiment betas to examine selectivity in mutual funds. Stocks with high investor sentiment betas have characteristics that are associated with them being difficult to arbitrage or have subjective valuations, and accordingly more prone to mispricing. Mutual fund managers that trade high sentiment beta stocks may be better placed to demonstrate their stock selection skills and this may also explain superior selection evident in growth funds.

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.[4] We calculate stock sentiment betas using the Baker and Wurgler (2007) monthly change in sentiment index[5].

3.2. *Method*

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 better future performers and/or disposing of poorer future performers, and which funds exhibit perverse selectivity by buying poor future performers and/or selling better future performers.[6] Finally, we calculate the investor sentiment beta for each stock

[4] 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.

[5] 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. Accordingly, our study concludes in 2005 corresponding to the index availability.

[6] 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 size with frequency of observation. For example, Elton, Gruber, Blake, Krasny and Ozelge (2010) have 215 funds

in a fund’s portfolio at the start of a trading quarter, and weight these by the stocks proportionate value. This weighted average sentiment beta is used to partition fund-quarters into sentiment beta pentiles.

3.2.1. Assignment to performance buckets and regression analysis

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 then assign the performance ranked stocks to twenty equal-value buckets. Analogously, we derive a measure of each bucket’s future return performance by value-weighting the performance (Performance_Bucket) of each stock in the bucket. We use Performance_Bucket 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 fund’s portfolio that were *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 27,594 fund-quarters are therefore:

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

where:

and 6432 fund-months in the period 1994 – 2005, compared to our study with 2173 funds and 27,594 fund-quarters in the period 1991 – 2005.

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

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

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

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

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

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

Significantly negative or positive coefficients on "Performance_Bucket" identify funds where trading is selective with respect to future stock performance. We refer to these coefficients as selectivity 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 beta identifies portfolio adjustments that are systematically perverse. This follows since, by construction, there was no initial relation between the value of stock in a Performance_Bucket and the buckets' future performance. The statistical significance of the number of selectivity 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 beta. In the second, we include only the buy trades, while in the third we include only sell trades. We refer to the regression coefficients as "buy" selectivity and "sell" selectivity 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.

3.2.2. Calculating stock and portfolio investor sentiment betas

We use the monthly "change in sentiment" index of Baker and Wurgler (2007) to calculate investor 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[7] are used as the independent variable.

The investor sentiment betas of the stocks in a fund's portfolio at the start of a trading quarter, are weighted according to the stock's proportionate value, to obtain the portfolio's sentiment beta. We refer to these as fund-quarter sentiment betas (FQSBeta). By ranking and partitioning our data into FQSBeta pentiles, we are able to compare stock selectivity in funds according to the sentiment betas of the stocks they hold.

4. Results

4.1 Descriptive statistics

Our sample contains 2,173 distinct mutual funds, and 27,594 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

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

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]

4.2. Identifying selectivity in trades

Using equation (1), we perform 27,594 univariate linear regressions to determine if there is a relation between future stock performance and proportion of stocks traded by a fund during a calendar quarter. Each regression is for one fund-quarter, and fund-quarters with statistically significant net selectivity betas are identified. A positive net selectivity 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 beta identifies funds with perverse selectivity, where managers purchase stocks which subsequently underperform, or sell stocks which subsequently outperform, or both. We repeat this procedure to determine whether funds exhibit selectivity only with respect to the stocks they buy, in the first instance, and then with respect to those they sell.

Table 2 reports the pooled count for net selectivity, buy selectivity and sell selectivity over the fifteen-year period for the 10% significance level (two-tailed). Using the binomial distribution, we are able to determine that the frequency of both positive and negative net selectivity betas exceed that expected by random occurrence with 99% statistical confidence. The frequency of positive betas suggests that some fund managers are able to identify the correct stocks to buy and sell. However, the higher than random incidences of negative betas indicate that some managers have a propensity to trade the wrong stocks. On examination of the buy selectivity betas, the higher than random frequency of positive betas indicates that some managers correctly identify which stocks to buy, while the reduced incidence of negative betas indicates that managers are able to avoid purchasing the stocks that subsequently underperform. However, with respect to the stocks fund managers sell, a different story emerges. Fund managers appear unable to identify which stocks to sell, as indicated by the statistically random frequency of positive sell selectivity betas. The higher incidence of negative sell selectivity betas indicates a tendency for funds to sell stocks that subsequently outperform the stocks they retain, and possibly drives the higher incidence of negative net selectivity betas.

[Table 2]

Table 3 reports the selectivity beta by fund investment objective, i.e. Growth and income, Growth, and Aggressive growth. The results are consistent with previous studies where evidence of superior selection is more prominent in the Aggressive growth category of funds. We find that these funds more commonly exhibit statistically positive net selection, buy selection, and sell selection. In addition, they avoid buying stocks which subsequently underperform. Growth and income funds do not exhibit positive selectivity more frequently than random expectation. Furthermore, they are unable to avoid selling stocks that subsequently become superior performers, and, therefore, exhibit a higher incidence of negative net selectivity.

[Table 3]

4.3. Investor sentiment, style and selectivity

Our expectation is that the investor sentiment beta of the stocks funds trade may affect the fund’s selection ability. To investigate whether fund investment styles are related to the sentiment betas of the stocks they hold, we crosstabulate investment style by fund-quarter sentiment beta pentile. Based on the results reported in Table 4, it is apparent that Growth and income funds have 85% of their stocks in the lowest three sentiment beta pentiles. Growth funds exhibit a more balanced spread with approximately equal proportions, while most Aggressive growth funds are in the highest sentiment beta pentile.

[Table 4]

Table 5 reports the proportions of negative and positive net, buy, and sell selectivity betas in each fund-quarter sentiment beta pentile. The funds that, on average, hold stocks with the highest sentiment betas are contained in pentile 5. The incidence of net selectivity betas observed in Table 2 is reflected in the lowest three sentiment beta pentiles in Table 5, however, funds with high sentiment stocks appear better able to avoid poor selection, while a greater than random proportion continue to exhibit good selection. This is consistent with our expectation that higher sentiment beta stocks are less likely to be efficiently priced and, therefore, present greater opportunity for managers to demonstrate selection skills. Good selectivity, represented by a reduced incidence of negative selection betas and an increased incidence of positive selection betas, is more apparent in the high sentiment pentiles, for both buy and sell selectivity, relative to the lower sentiment pentiles. Notably, poor sell selectivity is primarily restricted to the lower three sentiment pentiles. Again, this is consistent with our expectation that managers are less able to identify mispricing in stocks with lower sentiment betas.

[Table 5]

Superior stock selection is only possible when stocks are mispriced. A high sentiment beta is indicative of potential mispricing of a stock. Our analysis has shown that funds that hold higher sentiment beta stocks exhibit better selectivity. This is consistent with the finding that

Aggressive Growth funds exhibit better selectivity because these funds predominantly hold stocks with high sentiment betas, which are more likely to be mispriced.

4.4. Distinguishing 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% (2-tailed) confidence requirement, funds executing purely random trades would exhibit good (or bad) stock selection with a 5% probability. If the board of director's 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 manager's selectivity performance over several quarters, and using the cumulative binomial probability distribution. For a particular fund, we ascertain the confidence interval with which 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% as the probability of a successful outcome. This 5% probability arises from the earlier regressions that identified the selection betas with 90% confidence.

Table 6 shows, for various levels of statistical confidence, the number of funds that we classify as exhibiting skill from repeated good (bad) net selection. This information is repeated for three different minimum numbers of quarters over which we establish a fund's selectivity performance. Because our dataset holds fewer funds with longer records, the number of funds varies accordingly. Suppose for example, it was considered that 80% confidence that a manager's good net selection was due to skill rather than luck was sufficient, then, if we require a minimum record of eight quarters, 568 out of 1308 funds, or 43% of managers would be considered skillful.[8] Before considering a manager for dismissal on the other hand, it may be prudent to be at least 99% confident that their net selectivity performance was not due to bad luck, and accordingly, a maximum of 63 or less than 5% would face dismissal. Similar qualitative results are found for buy and sell selectivity.

[Table 6]

5. Conclusion

We statistically identify net selectivity by examining fund-by-fund whether managers realign their portfolios by buying the stocks that became better performers while selling those that became poorer performers. Net selectivity is subdivided into buy selectivity where managers buy stocks that appreciate, and sell selectivity where they sell stocks that subsequently underperform. From a net selectivity perspective, we find that more managers than expected from random occurrence exhibit both good selectivity and poor selectivity. However, by

[8] In our earlier analysis, we used a 90% (2-tailed) confidence interval to statistically identify funds exhibiting selectivity. In doing so, we simultaneously denied some skilled managers the classification of 'selective', and set a low probability that an unskilled manager is classified as 'selective'. Because of this low probability (5%), a relatively long assessment period (number of trials) is required before a second instance of being 'selective' (number of successes) is necessary for the manager to maintain the classification of 'skillful' (with 80% statistical confidence). To produce a practical management appraisal tool which applies the principle that repeated selectivity will identify skill, a lower confidence requirement for 'selectivity' is suggested. For example, if 60% (instead of 90%) is used, although the probability of a random trade being misclassified as 'selective' increases to 20%, a shorter assessment period is required before a manager must exhibit multiple instances of 'selectivity' to be classified as 'skillful'.

considering the components of selectivity, we show that more managers buy stocks that appreciate, and fewer managers purchase stocks that subsequently underperform. Poor selectivity is primarily driven by poor choice of stocks to sell.

We add to the literature by reasoning that selectivity should be more prevalent when fund managers trade stocks that are more sensitive to investor sentiment and, therefore, less efficiently priced. Using the Baker and Wurgler (2007) investor sentiment index, we calculate stock sentiment betas, which we average for each fund's holdings. The higher the fund's weighted average sentiment beta at the start of a quarter, the more likely it is that the stocks it trades will be mispriced. Consistent with this expectation, more funds in the highest sentiment beta pentile are characterised by statistically significant good stock net selection and good sell selection, while they avoid buying stocks that subsequently underperform. The higher incidence of poor sell selectivity observed in the full sample is driven exclusively by the lower sentiment pentiles in which managers are less able to identify overpriced stocks.

Mutual funds follow an expressed investment objective. We focus on growth and income, growth, and aggressive growth and relate these objectives to the investor sentiment beta of the stocks they hold. Growth and income funds hold stocks that principally have low sentiment betas, while the stock holdings of aggressive growth funds are dominated by high sentiment beta stocks. Growth funds hold an even spread of sentiment beta stocks. We find that aggressive growth funds consistently exhibit the highest proportion of good net selection, buy selection and sell selection, and avoid buying poorly performing stocks.

We are able to identify individual funds that exhibit selection ability, and distinguish those with genuine selection skill from those that fortuitously selected the correct stocks, when we examine their trading behavior over time. Using various confidence intervals, we can assess whether it is appropriate to reward the selection skill of a fund manager, or alternatively whether these managers should be asked to justify their imprudent stock selection.

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Table 1
Descriptive statistics, 1991 to 2005

Panel A. Fund descriptive statistics

	Mean	Median	Standard Deviation
Number of fund-quarters	27,594		
Number of funds			
Full sample	2,173		
Aggressive growth	169		
Growth	1,265		
Growth and income	364		
Market capitalization ($ million)	1,043	234	3,840
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 $\mathrm{TradeValue}_j = \alpha + \beta\, \mathrm{P}\mathit{erformance}\_\mathrm{Bucket}_j + \varepsilon_j$. 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

Selectivity	N	Binomial CV Range		Selectivity Beta			
				Negative		Positive	
		Min	Max	Count	Percent	Count	Percent
Net	27,594	1295	1464	1567	5.7%***	1689	6.1%***
Buy				1228	4.5%***	1518	5.5%***
Sell				1635	5.9%***	1417	5.1%

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

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

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

Value stock_i traded = value of stock i traded (net, buy, or sell) during quarter t;

Value stock_i held = value of stock i held at the start of quarter t; and

n = number of stocks in Performance_Bucket j.

Cumulative binomial distribution critical values (Bin CV) reflect a 1% probability that a lower (Min) or greater (Max) count occurs by chance.
*** indicates significance at the 1 percent level.

Table 3
Significant selectivity betas by fund investment objective, 1991 to 2005

Investment objective	N	Net selectivity Negative	Net selectivity Positive	Buy selectivity Negative	Buy selectivity Positive	Sell selectivity Negative	Sell selectivity Positive
Growth & income	5670	6.5%***	5.6%	4.9%	5.2%	6.6%***	4.9%
Growth	16,948	5.5%***	6.3%***	4.4%***	5.6%***	5.8%***	5.1%
Aggressive growth	2320	4.7%	7.2%***	4.3%*	6.0%**	5.3%	6.4%***

The proportion of selectivity betas generated from 'N' repeat linear regressions of $\text{TradeValue}_j = \alpha + \beta\,\text{Performance\_Bucket}_j + \varepsilon_j$ that are statistically negative or positive. The cumulative binomial distribution is used to determine which proportions are statistically different from the 5% expected as a random occurrence.

***, ** and * indicates significance at the 1, 5 and 10 percent levels respectively.

Table 4
Investment style by fund-quarter sentiment beta, 1991 to 2005

	Fund investment objective					
FQSBeta pentile	Growth and income		Growth		Aggressive growth	
1	2042	36.0%	2981	17.6%	90	3.9%
2	1608	28.4%	3267	19.3%	146	6.3%
3	1147	20.2%	3550	20.9%	272	11.7%
4	734	12.9%	3643	21.5%	524	22.6%
5	139	2.5%	3507	20.7%	1288	55.5%
Total	5670	100%	16,948	100%	2320	100%

FQSBeta denotes fund-quarter investor sentiment beta. This table presents a crosstabulation of fund investment objective by FQSBeta pentiles.

Table 5
Significant selectivity betas by fund-quarter sentiment beta, 1991 to 2005

FQSBeta pentile	N	Net Selectivity Negative	Net Selectivity Positive	Buy Selectivity Negative	Buy Selectivity Positive	Sell Selectivity Negative	Sell Selectivity Positive
1	5518	6.2%***	6.3%***	4.8%	5.2%	5.7%***	5.4%
2	5519	6.1%***	5.8%***	4.4%	5.6%	7.2%***	4.8%
3	5519	5.8%***	5.7%***	4.7%	5.3%	6.4%***	4.7%
4	5519	5.1%	6.4%***	4.7%	6.3%***	5.2%	5.1%
5	5519	5.1%	6.5%***	3.7%***	5.1%	5.2%	5.7%***

FQSBeta denotes fund-quarter investor sentiment beta. The proportion of selectivity betas generated from 'N' repeat linear regressions of $\text{TradeValue}_j = \alpha + \beta\, \text{Performance\_Bucket}_j + \varepsilon_j$ that are statistically negative or positive. The cumulative binomial distribution is used to determine which proportions are statistically different from the 5% expected as a random occurrence.

***, ** and * indicates significance at the 1, 5 and 10 percent levels respectively.

Table 6
Funds with skillful stock selection over multiple calendar quarters, 1991 to 2005

Minimum quarters	N	Confidence Interval	Skillful Net Selectivity Bad	Good
4	1706	80%	709	774
		90%	433	489
		95%	290	319
		99%	72	91
8	1308	80%	515	568
		90%	321	371
		95%	178	201
		99%	63	76
12	1016	80%	407	439
		90%	236	267
		95%	150	167
		99%	49	58

The number of funds where managers exhibit bad or good skill in performing net selectivity in trading stocks over repeat trading quarters, with various levels of statistical confidence.