Uncommon Value:

The Investment Performance of Contrarian Funds

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Abstract

This paper studies the investment behavior and performance of contrarian mutual funds, as well as the performance of stocks widely held and traded by such funds over the 1994 to 2006 period. We define a "contrarian fund" as a fund that trades in a direction opposite to mutual fund "herds" much more frequently than the average fund. We find that contrarian funds tend to persist in trading against the herd over time, and that they outperform herding funds by more than 2.6% per year, both before and after fund expenses. We further find that a value-weighted portfolio of stocks widely held by contrarian funds (relative to herding funds) outperform stocks least widely held by contrarian funds over the following four quarters by more than 5%, adjusted for the stock characteristics. Finally, we investigate whether contrarian funds outperform simply because they provide liquidity to herding funds, or whether they possess superior information on stock fundamentals. We find some evidence that at least part of the superior returns of contrarian funds derives from their superior information, relative to herding funds—contrarian funds avoid holding stocks with worsening profitability much more successfully than herding funds.

The popular media has long excoriated equity mutual fund managers for their tendency to trade together in a "herd-like" manner, with little regard for fundamental stock values.[1] Indeed, academic studies seem to reinforce this impression by documenting several regularities in stock trades by fund managers. For instance, it is well-known that equity funds collectively chase past winning stocks, as well as favoring glamour stocks (e.g., Grinblatt, Titman, and Wermers, 1995; Falkenstein, 1996).

While much empirical research has investigated trades of institutional investors that herd or use common strategies, little is known about the strategies and performance of contrarian investors.[2] Among U.S. equity mutual funds, it is interesting that few fund managers with herd-like behavior stand out with sustained investment success. Indeed, star managers such as Peter Lynch or Bill Miller usually implement quite unique stock picking strategies, some of which involve investing as contrarians, i.e., investing differently from the crowd.[3] Interestingly, contrarian behavior among stock analysts also seems to be rewarded: Clement and Tse (2005) show that bold forecasts are more accurate predictors of company earnings than herding forecasts. Such observations naturally lead to some questions: If herding systematically hurts performance, as indicated by Brown, Wei, and Wermers (2007) and Puckett and Yan (2007), does being contrarian systematically help?[4] And, if so, do

[1] For instance, Louis Rukeyser of *Wall $treet Week* once stated that, as opposed to individual investors: "They (large investors) buy the same stocks at the same time and sell the same stocks at the same time."
[2] For example, Grinblatt, Titman, and Wermers (1995) analyze the relationship between positive-feedback trading, herding, and mutual fund performance. Other papers that document herding by mutual funds include Nofsinger and Sias (1999), Wermers (1999), and Sias (2004).
[3] Bill Miller, a well-known contrarian and value-oriented investor who manages the Legg Mason Value Trust fund, holds the record of beating the S&P 500 index for 15 consecutive years (although his winning streak ended in 2006).
[4] Brown, Wei, and Wermers (2007) and Puckett and Yan (2007) document, over the past several years, sharp return reversals following mutual fund herding trades. That is, buy trades by large herds of funds are followed by negative abnormal returns, while sell trades are followed by positive abnormal returns during the following year.

contrarian funds derive their performance simply by trading against underperforming herding funds, or do they follow more successful strategies than herds?

In this paper, we address these questions by analyzing the investment behavior and performance of contrarian mutual funds. At the theoretical level, the performance of contrarian funds depends on the economic rationale for their contrarian behavior.[5] One possibility is that contrarian investors may trade on private information that is very different from conventional wisdom, while another is that they profit simply by countering the behavioral tendencies of the crowd (providing liquidity to herding mutual funds). In both cases, we would expect contrarian funds to outperform herding funds. Alternatively, contrarian investors may be those who are overconfident about their private signals or abilities (Daniel, Hirshleifer, and Subrahmanyan, 1998). In this case, we would expect contrarian investors to underperform.

Since most studies indicate that the average U.S. domestic equity mutual fund underperforms its benchmarks, net of fees (e.g., Carhart, 1997), it would be unusual to find outperformance among funds that tend to systematically invest with the crowd. Indeed, Brown, Wei, and Wermers (2007) and Puckett and Yan (2007) find evidence consistent with herding funds underperforming their benchmarks. However, since funds that invest against the crowd are, by definition, in the minority, such funds could potentially outperform their benchmarks.

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[5] While we know of no theory of contrarian investing, there is a large literature on herding behavior. Specifically, investors may herd because they (1) unintentionally trade together by following common informative signals on stock values (Hirshleifer, Subrahmanyam, and Titman, 1994), perhaps due to reputational concerns (Froot, Scharfstein, and Stein, 1992); (2) intentionally mimic each other due to reputational concerns (Scharfstein and Stein, 1990) or because they infer information from each other's trades (Bikhchandani, Hirshleifer, and Welch, 1992), or (3) unintentionally trade together due to common stock preferences (Falkenstein, 1996).

Our study first investigates whether contrarian funds systematically outperform other funds, and, if so, the source of this outperformance. A challenging issue is the empirical identification of contrarian funds. It is tempting to define a contrarian fund as one that intensely employs a particular well-formulated quantitative contrarian strategy, or a group of such strategies, such as buying stocks with low returns and selling stocks with high returns. However, there is a distinction between the quantitative strategies documented in academic studies (which use publicly available information to generate return-predictive signals across a large number of stocks) and the fundamental analysis employed by the majority of mutual funds (which likely produces private information on a relatively small subset of stocks).[6]

Accordingly, we uniquely identify contrarian funds, not based on any particular set of strategies, but based on their tendency to trade against the crowd. Our method is very simple: we measure the "contrarianness" of a mutual fund by measuring the degree to which the fund trades against herds; funds with a high contrarian index frequently trade against the herd—especially when large numbers of funds are herding—while funds with a low contrarian index are those who frequently trade with the herd. Specifically, we employ the LSV (1992) measure of the intensity of herding in an individual stock, conditioned on whether more funds are buying or selling that stock during a particular quarter (relative to the average stock during the same quarter). Then, we calculate the contrarian index of a fund (*CON4*) by measuring (on a portfolio-weighted basis) the tendency of the fund to trade in the opposite direction from the

[6] Also, such an approach may not be successful in identifying outperforming contrarian funds. For example, Houge and Loughran (2006) report that value funds do not outperform growth funds. They infer that trading costs and various investment restrictions faced by mutual funds have substantially limited the benefit from trading on the value anomaly – a valid concern when selecting contrarian funds based on other quantitative strategies as well.

LSV herding measure over a four-quarter period. For instance, if most mutual funds are buying IBM and selling Cisco during 2001, then a fund that is selling IBM and buying Cisco (with no other trades) during that year would exhibit a high contrarian measure.

We apply our contrarian measure to analyze all actively managed U.S. domestic equity mutual funds over the 1994 to 2006 period. First, using *CON4*, we identify, at the end of each calendar quarter, the quintile of funds that are most contrarian. These funds tend to be larger, older, and employ lower-turnover strategies than other funds, characteristics that are consistent with an ability to provide liquidity to herding funds. Also, contrarian funds prefer stocks with slightly larger market capitalization, significantly higher book-to-market (B/M) ratio, and significantly lower past returns, compared to other funds. Thus, contrarian funds tend to hold past losers, stocks that generally underperform, and value stocks, which generally outperform. We also find that contrarian funds persist in their contrarian strategies—funds in the most contrarian quintile continue to employ contrarian strategies more strongly than the average fund during at least the following eight calendar quarters. This suggests that contrarian funds do not simply trade against herds by chance, but systematically take the opposite position of herds either deliberately or through their uniquely different strategies.

We next investigate the performance of contrarian funds. We find that the most contrarian quintile outperforms the least contrarian quintile (i.e., those funds that tend to herd) by over 2.6% per year, using the four-factor Carhart (1997) model—both before and after expenses. However, it is important to control for price momentum, as contrarian funds systematically trade against recent price movements (selling past winners and buying past losers). For instance, contrarian funds exhibit roughly the same performance as herding funds, based upon their unadjusted returns or their Fama and French (1993) three-factor alphas.

Given the superior performance of contrarian funds, we explore the potential sources of their alphas. First, if contrarian funds derive their performance entirely by providing liquidity to herding funds, we would expect their performance to be higher when mutual fund herds lead to severe dollar trade imbalances so that price-pressure effects are greatest. Therefore, we employ the measure *Dratio* (defined, for a given stock during a given quarter, as the difference between total dollar buys and sells, divided by the sum of buys and sells by all domestic equity mutual funds) as a proxy for the demand for liquidity by herding mutual funds. We then use this stock-level *Dratio* to construct a "dollar trade imbalance" based fund-level contrarian index, $*CON4* (as compared to the prior-mentioned LSV measure "count-based" fund contrarian index, *CON4*).

Although funds with the highest $*CON4* values (those funds providing liquidity) continue to outperform, the performance spread between these funds and funds with the lowest $*CON4* values (those funds demanding liquidity) is smaller than that between funds with high and low *CON4* scores. Since we find the dollar-weighted measure, $*CON4*, to have weaker explanatory power for the profit of contrarian funds, contrarian funds do not produce superior returns simply by providing liquidity to herds.

Second, contrarian funds may outperform herding funds because they have different performance-related characteristics. For instance, contrarian funds exhibit lower levels of turnover than other funds (as noted previously), which likely leads to lower trading costs. Accordingly, at the end of each calendar quarter, we regress the four-factor alpha on several fund characteristics, including the above-mentioned contrarian index, *CON4*, as well as variables that capture fund size, age, expenses, turnover, and past flows, and the tendency of funds to trade on momentum or to trade illiquid stocks. Although other fund characteristics, such as the tendency to trade illiquid stocks, significantly predict four-factor alphas of funds, *CON4* remains a significant (and positive) predictor of alphas.

Finally, we investigate whether the superior performance of contrarian funds translates into a successful stock-picking strategy. To accomplish this, we create a stock-level measure of contrarian trading to determine whether stocks held predominantly by contrarian funds outperform those held mainly by herding funds. We find that, although stocks most heavily held by contrarian funds do not outperform stocks most heavily held by herding funds in terms of unadjusted returns, they show significantly higher characteristic-adjusted returns, using the Daniel, Grinblatt, Titman, and Wermers (1997; DGTW) benchmarks. Specifically, a zero cost strategy that buys the (value-weighted) quintile of stocks with the highest contrarian scores and sells the quintile with the lowest contrarian scores earns a DGTW-adjusted alpha of over 1.6% during the following quarter. Moreover, this strategy continues to outperform during quarters +2 through +4 by more than 4%.

We find that contrarian stocks continue to outperform even after we control for the portion of their returns that can be explained by herding, which again confirms that the superior returns of contrarian-traded stocks are not simply due to the reversals of stocks traded by herds. Lastly, low contrarian score stocks not only earn inferior abnormal returns, they also show significant deterioration in their operating performance, as indicated by negative changes in their industry-adjusted ROAs during quarters +2 through +4. However, stocks with a high contrarian score exhibit almost no deterioration in their ROAs, which indicates that contrarian funds are able to identify stocks with poor fundamentals. Overall, the evidence suggests that contrarian funds do not merely profit from liquidity provision, but also appear to have better information on stock fundamentals than the majority of mutual funds.

We note that our study is consistent with Wang and Zheng (2008), who find that hedge funds that follow distinctive strategies outperform. However, Gupta-Mukherjee (2008) identifies mutual funds that deviate from their peers, and (unlike our paper) finds that deviating funds underperform.[7,8] Finally, the evidence in our paper is consistent with Da, Gao and Jagannathan (2007) that mutual fund managers can profit from both informed trading and liquidity provision.

In Section I, we describe our data and method of identifying contrarian (and herding) funds. In Section II, we compare the characteristics of these two types of funds. Section III examines the performance of contrarian funds. Section IV further explores the sources of contrarian performance. Finally, Section V concludes the paper.

I. Data and Methodology

A. Mutual Fund Sample

Our sample of mutual funds includes those that exist in both the Thomson Financial CDA/Spectrum mutual fund holdings data and the CRSP mutual fund data during the period 1994 to 2006. Funds in these two datasets are matched via the MFLINKS file (available from Wharton Research Data Services, WRDS). Since our focus is on actively managed U.S. domestic equity funds, we exclude index funds, international funds, municipal bond funds, "bond and preferred" funds, and metals funds. The Thomson Financial data provide quarterly "snapshots" of portfolio holdings for all U.S.-based mutual funds; further information on

[7] Our results do not rely on defining a particular peer group for a fund; we use the entire mutual fund universe as the "peer group." We believe that this is a more powerful approach to measuring contrarian investing behavior, as many funds do not belong to a pure peer group (such as funds that hold both value and growth stocks).
[8] One possible explanation for the difference in findings is that funds whose holdings deviate a lot from the consensus include both contrarian funds and extreme herding funds.

these data is available from WRDS. We infer mutual fund trades from quarterly changes of portfolio holdings for each fund, adjusting for splits and stock dividends. For funds not reporting at the end of a given quarter, we carry forward (for a maximum of one quarter) their most recent holdings to calculate trades during the following quarter.

Information on fund net returns, flows, size, age, expense, and other characteristics is obtained from the CRSP mutual fund data. Multiple share classes of a fund in the CRSP data are combined into a single fund (value-weighted, using total net asset values of each share class at the beginning of each month) before matching with the Thomson Financial data. To be included in the final sample for a given calendar quarter, we require each fund to have more than $10 million in total net assets and have at least 10 reported stock holdings at the end of the current and prior quarters. These screens are imposed to reduce the potential noise in reported holdings.

B. Construction of Contrarian Fund Index

We define contrarian funds as those that tend to trade against mutual fund herds. To construct a quantitative measure of contrarian trading, we implement the following steps:

First, we construct a stock-level herding measure, following Lakonishok, Shleifer, and Vishny (1992):

$$HM_{i,t} = | p_{i,t} - \overline{p}_{i,t} | - E(| p_{i,t} - \overline{p}_{i,t} |) \tag{1}$$

where $p_{i,t}$ is the proportion of mutual funds buying stock i, out of all funds trading stock i during quarter t. $\overline{p}_{i,t}$, a proxy for the expected value of $p_{i,t}$, is the mean of $p_{i,t}$ over all stocks traded by the funds during quarter t. E($|p_{i,t}$ - $\overline{p}_{i,t}|$) is an adjustment factor, which equals the expected value of $| p_{i,t} - \overline{p}_{i,t} |$ under the null of no herding (Lakonishok et al, 1992). Similar to Wermers (1999) and Brown, Wei, and Wermers (2007), we require a stock to be traded by at least five funds during a given quarter, in computing the measure of Equation (1), to construct a meaningful measure of fund herding.[9] We also exclude stocks that are newly issued within the prior four quarters, as funds are likely to acquire such a new issue simultaneously simply because it represents a new part of the market portfolio.

Further, we classify a stock as a ``buy-herd" stock if $p_{i,t} > \overline{p}_{i,t}$ (i.e., if the proportion of mutual fund buys is higher than average for that quarter). Similarly, stocks with $p_{i,t} < \overline{p}_{i,t}$ are classified as ``sell-herd" stocks. The conditional buy-herding (BHM_{it}) and sell-herding (SHM_{it}) measures are calculated as the following:

$$BHM_{i,t} = HM_{i,t} \mid p_{i,t} > \overline{p}_{i,t} \tag{2}$$

$$SHM_{i,t} = HM_{i,t} \mid p_{i,t} < \overline{p}_{i,t} \tag{3}$$

We rank all ``buy-herd" stocks into quintiles by their buy-herding measure, and assign ranks of one through five to the quintiles. This rank measure, $RBHM_{it}$, equals five for stocks most heavily bought by mutual fund herds, according to Equation (2). Similarly, we rank all ``sell-herd" stocks into quintiles by their SHM_{it}, and the quintile with rank $RSHM_{it}$ equals five are stocks most heavily sold by herds, according to Equation (3). This nonparametric ranking number reduces the influence of outlier stock-quarters, i.e., those with extreme buy- or sell-

[9] For example, this measure, computed for a stock-quarter traded by only one fund (regardless of whether it is a buy or a sell), would be positive, indicating herding.

herding.[10] In addition, it allows us to aggregate buy-herding and sell-herding trades of each fund to construct its contrarian index.

Next, since the LSV herding measure captures the tendency for a group of funds to trade a stock in the same direction (controlling for expected same-direction trading that occurs by random chance), we consider a fund as making a contrarian trade if it purchases a sell-herding stock or sells a buy-herding stock. Specifically, for each trade of stock *i* made by fund *j* during quarter *t*, we construct a signed contrarian measure, CM_{ijt}, that equals $RBHM_{it}$ if the fund sells a ``buy-herd" stock, or $RSHM_{it}$ if it buys a ``sell-herd" stock. Conversely, $\mathrm{CM}_{ijt} = -RBHM_{it}$ if the fund buys a ``buy-herd" stock and $\mathrm{CM}_{ijt} = -RSHM_{it}$ if it sells a ``sell-herd" stock. Essentially, CM_{ijt}, captures the extent to which a fund's trade of a given stock is on the opposite side vs. the same side of herds.

Finally, we create a fund-level contrarian index, CON_{jt}, as the weighted average of CM_{ijt} across all trades by fund *j* during quarter *t*, with the weight being the absolute change of stock *i*'s weight in fund *j*. That is,

$$CON_{jt} = \sum_{i=1}^{N} \omega_{ijt} CM_{ijt} \tag{4}$$

where ω_{ijt} is defined as

$$\omega_{ijt} = \frac{\left| v_{ij,t} - v_{ij,t-1} \right| / V_{j,t}}{\sum_{i=1}^{N} \left| v_{ij,t} - v_{ij,t-1} \right| / V_{j,t}} \tag{5}$$

[10] Our results are not materially different if we construct the contrarian index based upon each stock's raw herding measure.

with $v_{ij,t}$ being stock i's dollar value in fund j at the end of quarter t, $V_{j,t}$ being fund j's total value at the same date, and N being the total number of stocks traded by the fund. Therefore, the weight on a given stock's contrarian measure, CM_{ijt}, will be greater if the fund changes its holdings more dramatically, relative to other stocks.

Although the contrarian index is constructed based upon the concurrent herding measure of individual stocks, contrarian funds that wish to trade in the opposite direction of the herd can only observe the actual portfolio holdings of other funds with a lag. However, they may base their trading decisions on other sources of information. First, contrarian managers may be able to infer the overall market sentiment by vigilantly observing public signals, such as analyst recommendation revisions, trading volume, and bid and ask spreads.[11] Moreover, brokers may ``tip" preferred fund managers with information on their other clients' actions or on upcoming analyst recommendation revisions.[12]

Note that a fund may have a high contrarian index simply by random chance. Therefore, we use the rolling average of a fund's contrarian index during the most recent four quarters to classify contrarian funds,

$$CON4_{j,t} = \frac{1}{4}\sum_{k=0}^{3} CON_{j,t-k} \ . \qquad (6)$$

Defining a fund's contrarian index using a long enough sequence of trades also ensures that the measure does not merely reflect occasional deviation from the herd due to temporary

[11] For instance, Brown, Wei, and Wermers (2007) find that mutual fund herds follow analyst recommendation revisions, making this a useful public signal of trading direction for the majority of funds.
[12] Interestingly, Irvine, Lipson, and Puckett (2006) find evidence consistent with brokerage firms leaking information several days prior to the release of their analysts' initial buy and strong buy recommendations for stocks.

liquidity driven transactions. Throughout the remaining of the paper, we use *CON4* as the fund-level contrarian index, unless otherwise noted.

Table 1 reports summary statistics for the contrarian index and other fund characteristics. Note that while the median fund size is about $280 millions in terms of total net assets, the mean fund size is much higher. This suggests that there exist some very large funds, especially when we consider the total net asset value across all of their share classes. Both the mean and the median of the contrarian index are about -0.75. This is not surprising, given that trades made by the majority of the funds are considered as herding trades (and thus assigned a negative *CM*) by construction. In addition, the cross-sectional standard deviation of the contrarian index is 0.71, which suggests that it has significant dispersion relative to its mean.

II. Contrarian Funds

A. Characteristics of Contrarian Funds

For a trade to take place there have to be both a buyer and a seller -- that is, it cannot be the case that all investors in the market are herds. Since contrarian funds trade differently from their peers by definition, it is interesting to see whether their behavior is intentional. For example, it is possible that a fund chooses to sell certain stocks while other funds are buying them because it has been hit by an idiosyncratic redemption shock. In this case, a contrarian fund this period may become a herding fund next period. To see whether these two types of funds are fundamentally different, we first examine whether there exist systematic differences between herding funds and contrarian funds in terms of their characteristics.

Each quarter, we sort funds into contrarian quintiles based upon their contrarian indexes (*CON4*) and calculate the average contrarian index value, size, expense ratio, turnover, age, and flows. In addition, to see how the investment choices of contrarian funds differ from those of other funds, we also calculate the average size, book-to-market (BM) and momentum quintile ranks of fund portfolios.

Table 2 suggests that contrarian funds are generally larger, as measured by their average total net asset value. They are also older and have a lower turnover ratio, compared with funds that herd. These characteristics are consistent with their ability to provide liquidity to herding funds. In terms of the preference of their holdings, while contrarian funds hold stocks with slightly larger market capitalization, they have a very strong tendency to invest in stocks with a high book-to-market (BM) ratio and low past returns, according to the average size, BM and momentum quintile ranks of their holdings. Thus, contrarian funds tend to hold past losers and value stocks. This finding is consistent with Wermers (1999) and Brown, Wei and Wermers (2007), who find that mutual fund herds engage in positive feedback trading and strongly sell past loser stocks. Ex-ante, some of these characteristics of contrarian funds, including large fund size and holding liquid stocks and past losers, are unfavorable factors for fund performance. However, higher book-to-market stocks are favorable factors for performance.

Overall, there is very little difference between herding and contrarian funds in terms of their unadjusted returns. Given that stocks held by these two types of funds have distinctively different characteristics, we will take a closer look at their performance later, after adjusting for differences in characteristics of their portfolios.

B. Persistence of Contrarian Indexes

Extant studies have shown that financial analysts and fund managers exhibit herding behavior either because of informational cascades or correlated information arrival (e.g., Bikhchandani, Hirshleifer, and Welch, 1992; and Hirshleifer, Subrahmanyam, and Titman, 1994) because they have career concerns (e.g., Froot, Scharfstein, and Stein, 1992; and Scharfstein and Stein, 1990) or because they share common preferences for certain types of stocks (e.g., Falkenstein, 1996). If a group of investors herd together because they receive correlated information, it is unlikely that any other fund would intentionally trade against them. In such cases, the identity of contrarians is likely to be random. On the other hand, if herding is due to non-informational reasons such as career concerns, more sophisticated investors may either intentionally trade against a herd to take advantage of the temporary mispricing from the price pressure of the herding trade, or they may unintentionally trade against a herd when their private information indicates they should do so. In either of these cases, there may exist persistent contrarians. Therefore, in Table 3 we examine whether the identity of contrarian funds is persistent.

Each quarter, we group funds into quintiles, based on their contrarian indexes (*CON4*). We then track the average contrarian index of these portfolios during each of the eight subsequent quarters. Table 2 presents both the four-quarter rolling contrarian measure (*CON4*) and the non-overlapping measure (*CON1*) during the eight quarters following the portfolio formation quarter. The results indicate that funds in the top contrarian quintile continue to have significantly higher contrarian indexes than funds in the bottom contrarian quintile during each of the following eight quarters. While it is not surprising that *CON4* is persistent during the first four post-formation quarters due to its overlapping nature, it is notable that it remains persistent during Qtr+5 to Qtr+8. Furthermore, the average non-overlapping contrarian index (i.e., *CON1)* also shows strong persistence during the subsequent eight quarters. This suggests that a fund's tendency to trade against herds is a very stable characteristic. Since the identity of contrarian funds is highly persistent, the evidence is consistent with the existence of contrarians that either trade against the herd intentionally or systematically trade on superior private information.

III. Performance of Contrarian Funds

A. Fama-French Three-Factor Measure and Carhart Four-Factor Measure

When contrarians take the opposite side of fund herds when they trade, it is possible that they have obtained private information that is not available to their peers. This private information should lead to superior performance, relative to other funds. In addition, empirical studies provide evidence that many contrarian investment strategies generate abnormal profits, such as those based on short-term return reversals (Lo and McKinlay, 1998), long-run return reversals (DeBondt and Thaler, 1985), and the value anomaly (Fama and French, 1992 and Lakonishok, Shleifer, and Vishny, 1994). Although it is tempting to jump from such stock-level evidence to the conclusion that contrarian funds should outperform, contrarian strategies often involve long time horizons, trading small stocks (with large trading costs), and betting against potentially profitable price momentum. Therefore, it is not clear whether a fund would profit from simply engaging in these quantitative trading strategies.

Da, Gao and Jaganathan (2007) argue that a mutual fund's stock selection ability can be decomposed into informed trading and liquidity provision. Therefore, even if contrarian funds do not possess private information, they can still outperform herds from their capacity as liquidity providers because they may benefit from the temporary mispricing generated by herds (e.g., Brown, Wei and Wermers, 2007). In this section, we examine the relation between the degree to which a fund employs contrarian strategies and the fund's performance.

Specifically, we sort all mutual funds into quintile portfolios according to their contrarian indexes at the end of each quarter, and then compute the equally weighted return of each portfolio of funds during the following quarter. To evaluate the abnormal performance investors are able to capture, we consider both before- and after-expense performance of these portfolios. To contrast the performance of contrarian and herding funds, we also form a zero-investment portfolio that is long the portfolio with the highest contrarian index (group 5) and short the portfolio with the lowest index (group 1). The advantage of this portfolio approach, as opposed to a fund-by-fund regression analysis, is that we can include funds that only have a very short performance history. To estimate the risk adjusted performance of these portfolios, we use both the Fama-French (1993) three-factor model and the Carhart (1997) four-factor model. The following time series regressions are performed for each fund quintile:

$$R_t - R_{ft} = \alpha + \beta^{MKT} MKT_t + \beta^{SML} SML_t + \beta^{HML} HML_t + e_t \tag{7}$$

$$R_t - R_{ft} = \alpha + \beta^{MKT} MKT_t + \beta^{SML} SML_t + \beta^{HML} HML_t + \beta^{MOM} MOM_t + e_t \tag{8}$$

where R_t is monthly net return to a fund quintile, both before and after fund expenses. To compute R_t, funds in each quintile are equal-weighted, rebalanced monthly, and the quintiles are ranked at the beginning of every calendar quarter. R_{ft} is the monthly riskfree rate, proxied by the yield of Treasury bills with one-month maturity. MKT_t is the market return in excess of the risk free rate, where the market return is proxied by the CRSP value-weighted index return. SMB_t, HML_t, and MOM_t are size, book-to-market, and momentum factors, respectively[13]. Note that it is essential to adjust for momentum in stock returns when evaluating the performance of our contrarian portfolios. Since mutual fund herding is especially strong for stocks with extreme past returns, as shown in Grinblatt, Titman and Wermers (1995) and Wermers (1999), contrarian funds tend to buy past losers and sell past winners when they trade against herds. Therefore, controlling for stock momentum can help better detect contrarian managers that possess true skills beyond mechanically trading against stock momentum.

Panels A and B of Table 4 present the results for before- and after-expense performance, respectively. First, before we adjust fund performance for risk factors and characteristic-based benchmarks, unadjusted returns of funds monotonically increase with their contrarian indexes, although the difference between group 5 and group 1 is not statistically significant. Second, note that there is a consistent pattern on factor loadings of contrarian portfolios. Relative to herding funds (Quintile 1), contrarian funds (Quintile 5) tend to have significantly lower exposure to the size (SMB) and momentum factors, and significantly higher exposure to the value factor (HML). This is consistent with the information presented in Table 2, which is based upon the characteristics of their holdings: contrarian funds tend to hold large stocks, value stocks, and past losers.

Under the Fama-French three-factor model, the monthly pre-expense alpha for the contrarian funds (Quintile 5) is 3.7 bps, vs. -0.9 bps for the herding funds (Quintile 1). The

[13] We obtain data on R_f, MKT, SMB, HML, and MOM from Ken French's website: http://mba.tuck.dartmouth.edu/pages/faculty/ken.french.

difference, at 4.7 bps, is positive, but statistically insignificant. The difference in the after-expense three-factor alpha between contrarian and herding funds is also insignificant. Recall that in Table 2 we document several characteristics of contrarian funds that are, ex ante, unfavorable to fund performance, such as larger fund size, a preference for past losers and large stocks. Thus, it is somewhat surprising that contrarian funds do not underperform herding funds based upon either unadjusted returns or Fama-French three-factor alphas. Moreover, contrarian funds significantly outperform, once we control for momentum trading under the Carhart (1997) four-factor model, before or after fund expenses. Specifically, contrarian funds significantly outperform herding funds by about 2.63% a year based upon their after-expense four-factor alphas.

B. The Performance of Contrarian Funds With an Alternative Measure of Contrarian Index

The LSV herding measure is a count based measure that focuses on the number of funds trading in the same direction rather than the size of buys versus sells. That is, the greater the relative number of funds trading in the same direction, the greater is BHM or SHM. An alternative approach to measure herding is to examine the dollar trade imbalance *Dratio*:

$$Dratio_{i,t} = \frac{\$\mathrm{buys}_{i,t} - \$\mathrm{sells}_{i,t}}{\$\mathrm{buys}_{i,t} + \$\mathrm{sells}_{i,t}} \qquad (9)$$

where $\$\mathrm{buys}_{i,t}$ ($\$\mathrm{sells}_{i,t}$) is calculated as the total number of shares of stock *i* purchased (sold) during quarter *t* by all mutual funds, multiplied by the average of the beginning and end of quarter prices during quarter *t*. Essentially, *Dratio* measures the aggregate net purchase of stock *i* during quarter *t* by all mutual funds that trade it.

Compared with *Dratio*, which may be driven by the actions of a small number of very large funds that systematically implement large trades, the LSV herding measure is more "democratic," in that it better captures the aggregate view shared by the majority of the mutual funds. If funds that trade against herds perform better because they have private information that is not available to other funds, then their performance should be more related to the contrarian index constructed based upon the LSV herding measure. On the other hand, if their abnormal performance comes entirely from their ability to provide liquidity to herds when there is sizable trade imbalance, it should be better explained by the contrarian index constructed with *Dratio*.

To measure the size of aggregate dollar trade imbalances, each quarter we first sort all stocks into quintiles based upon their *Dratio*. This is done separately for stocks with a positive versus negative *Dratio*. We then consider a trade as contrarian if the fund purchases (sells) a stock with negative (positive) *Dratio* and assign it a rank ranging from 1 to 5 depending on the stock's *Dratio* quintile portfolio assignment. Similarly, we assign a trade the negative of the stock's *Dratio* rank if it is in the same direction as the dollar trade imbalance. Finally, *$CON* is calculated as the average contrarian measure across all stock trades during the quarter, weighted by the standardized absolute dollar trade value (see Equation (5)). Similar to the construction of *CON4*, $*CON4* is the rolling average of *$CON* during the four quarters prior to the current quarter.

Table 5 presents the performance of fund quintiles formed on this alternative contrarian index (*$CON4*). Here we observe a similar pattern: contrarian funds outperform herding funds in both their before- and after-expense performance. Again, the difference between herding funds and contrarian funds is highly significant based upon their Carhart four-factor alphas. However, the alphas of contrarian funds, relative to herding funds, are actually smaller when they are based upon the aggregate order imbalance (Table 5) than when they are based upon the count of funds trading in the same direction (Table 4). This evidence is not consistent with the hypothesis that the profits of contrarian funds come entirely from their passive trading against herds. Contrarian funds, therefore, generate abnormal returns, relative to herding funds, at least partially based on superior private information.

C. The Persistence of Contrarian Fund Performance

While we have documented that contrarian funds outperform herding funds, it is not clear whether investors would actually benefit from investing with them. Since investors may not be able to infer the trades of contrarian funds until they observe fund holdings in their quarterly filings with SEC, average investors would not be able to replicate the portfolios of contrarian funds if contrarian profits are short-lived or there is delay in accessing the holdings information of these funds. Therefore, we examine the persistence of contrarian fund performance by increasing the lag between the formation of contrarian fund portfolios and the measuring of their returns.

Table 6 reports the monthly Carhart four-factor alpha of the zero investment portfolio that longs the portfolio of funds with the highest contrarian index and shorts the portfolio of funds with the lowest contrarian index during each of the four quarters after portfolio formation. The result indicates that this investment strategy continues to deliver significantly positive abnormal returns when we allow for additional delays in implementing it. Furthermore, there is no indication that the return differential between contrarian funds and herding funds declines with the length of the lag between the disclosure of their holdings and the formation of the zero-cost portfolio. Specifically, while contrarian funds outperform herding funds by about 2.6% (annualized) during the quarter immediately following the disclosure of their holdings (Qtr+1), the spread between these two groups of funds remains as high as 2.43% three quarters later (Qtr+4). This evidence suggests that a feasible and profitable strategy is available to investors who simply obtain access to funds' quarterly filings with the SEC within at least 12 months after the date of the portfolio holdings.

D. Multivariate Analysis of Contrarian Fund Performance

In previous sections, we have shown that contrarian funds significantly outperform herding funds based on their Carhart four-factor alphas, and that their superior performance persists for at least four quarters. While the portfolio approach we have adopted so far does not require individual funds to have a long history of returns in order for their risk-adjusted performance to be measured, it aggregates information about individual funds' contrarian investment strategies by assuming that all funds in the same contrarian portfolio are similar. For instance, forming portfolios of funds ignores differences in fund size and tendency to hold illiquid stocks, both of which are related to fund performance. In addition, perhaps the superior alphas of contrarian funds is at least partially due to their tendency to exhibit lower turnover and to trade larger stocks, relative to herding funds—characteristics that are consistent with lower trading costs.

To account for the impact of these various fund holding and trading characteristics on performance, we examine, in Table 7, the cross-sectional performance of contrarian funds in a multivariate setting. Specifically, each quarter, we compute the abnormal return of a fund as the difference between its realized returns and expected returns under the Carhart four-factor model. We estimate factor loadings using three years' of past monthly returns of the fund to estimate the expected returns during a particular quarter. Compared with the portfolio approach we employed in previous sections, the rolling estimation allows for time variation in the factor loadings of individual funds. Finally, we implement a panel regression of four-factor adjusted returns on the contrarian index (*CON4*), controlling for lagged fund characteristics.

In addition to controlling for fund characteristics, including fund size, age, expense ratio, turnover, and past fund flows, we also control for some potential common trading strategies of contrarian funds. Since Wermers (1999) and Sias (2004) show that mutual fund herding is more pronounced among small stocks, it is conceivable that contrarian funds profit simply by providing liquidity to herding funds because small stocks tend to be less liquid. If passive liquidity provision is the main source of contrarian profits, then we should see the explanatory power of contrarian index subsumed by the extent at which contrarian funds trade illiquid stocks. Therefore, we create an illiquidity trading index that is calculated in a way similar to the contrarian index. Using the exchange-specific percentile rank of Amihud (2001) illiquidity ratio of individual stocks, the illiquidity trading index of a fund is defined as the weighted average Amihud illiquidity ranks across all stock trades the fund makes during the quarter, with the weight being the portfolio value standardized absolute dollar value of each trade (see Equation (5)). Finally, since previous studies on mutual fund herding show that herds are strongly influenced by past stock returns, we also control for negative feedback trading strategies. Specifically, we create a momentum trading index by calculating the weighted average returns in the past twelve months of all stocks traded by the fund, with the weight being the signed dollar amount of the trade standardized by the total value of the fund portfolio. Essentially, the more a fund purchases (sells) stocks with greater (smaller) past returns, the higher would be the momentum trading index. Again, we measure the illiquidity trading index and momentum trading index as the average over the most recent four quarters.

In Table 7, we regress the quarterly abnormal return of each mutual fund on the lagged contrarian index, illiquidity trading index, momentum trading index and the other prior-mentioned fund characteristics. We also include quarter dummies to control for time fixed-effects, and use logged fund size and age to reduce the influence of outliers. All standard errors are adjusted for clustering by funds. Table 7 indicates that funds do earn abnormal performance by trading illiquid stocks, as indicated by the significantly positive coefficient on the illiquidity trading index. However, funds with a greater momentum trading index actually realize lower abnormal returns. This is probably unsurprising, given that we measure abnormal performance based upon funds' Carhart four-factor alphas, which explicitly account for stock momentum. Furthermore, the result suggests that a simple price contrarian strategy would not generate the same profit that contrarian funds earn. Most interestingly, Table 7 shows that the effect of the contrarian index on fund performance remains significantly positive in all settings. The sign and magnitude of the coefficient on the contrarian index is consistent with our earlier findings. Specifically, an increase in the contrarian index by 0.75 (corresponding to about one standard deviation) increases the quarterly abnormal return of a mutual fund by about 15 basis points (0.1983*0.75 = 0.1487), or 0.6% per year.

IV. Contrarian Score and Cross-Section of Stock Returns

The evidence so far indicates that contrarian funds embrace past losers in their portfolio holdings and trades, but manage to outperform herding funds after controlling for the impact of price momentum. A possible explanation for this is that contrarian funds have superior stockpicking ability; in particular, they have the ability to pick stocks that are past losers, but that outperform the average past losing stock. In this section, we further investigate this hypothesis, and shift our analysis from the fund level to the individual stock level, using an approach developed by Wermers, Yao, and Zhao (2007). A salient feature of this approach is that it makes use of information from all funds, rather than focusing on merely a small subset of funds (e.g., the top or bottom quintile of funds).

A. Contrarian Score for Stocks

Since contrarian funds seem to have better stock-picking abilities than herding funds, the degree to which a stock is owned by contrarian, rather than herding, funds should reflect information about the stock's future performance. Therefore, we aggregate information across funds to extract the information content of fund holdings, and construct a contrarian score for each stock held by sample funds in a given quarter. Following Wermers, Yao, and Zhao (2007), the contrarian score for a stock is defined as:

$$\alpha_{it} = \frac{\sum_{j=1}^{M} \omega_{ijt-1} CON4_{jt-1}}{\sum_{j=1}^{M} \omega_{ijt-1}}$$

where M is the number of funds holding the stock and ω_{ijt} denotes the weight of stock *i* in fund *j* during quarter *t*. Intuitively, the contrarian score of a stock is a weighted average of the fund contrarian indexes, with weights proportional to the portfolio weights of funds on the stock. If a stock is more heavily owned by contrarian funds relative to herding funds, its contrarian score is higher. In addition, if a stock is owned by only 10 contrarian funds, it will have a lower score than a stock that is owned by 20 contrarian funds. Therefore, both the size and the commonality of the “bet” on a stock, by contrarian funds, are counted.

B. Contrarian Score and Stock Returns

The contrarian score captures return-predictive information contrarian funds possess in generating superior performance (after controlling for price momentum). To evaluate its return-predictive power, we first use the sorted portfolio approach. Specifically, at the beginning of each calendar quarter during the sample period, we classify sample stocks into quintiles based on the contrarian score. The stocks in our analysis are those used in constructing the fund-level contrarian index (Section II.A). Further, to avoid market microstructure issues in measuring returns and to make it possible to take short positions, we require that the stock price at the end of the formation quarter be no less than $5. Finally, because Wermers, Yao, and Zhao (2007) show that the weighted average alpha approach performs better with more funds holding the stock, we only include stocks that are held by at least 10 funds at the end of the formation quarter.

We form both equal-weighted and value-weighted portfolios within each contrarian-score quintile. The portfolios are held during the next four quarters after portfolio formation, and rebalanced at the end of each quarter. To evaluate portfolio performance we examine both the unadjusted returns and the characteristic-adjusted returns of Daniel, Grinblatt, Titman, and Wermers (DGTW, 1997). For the latter, we reconstitute DGTW size, book-to-market ratio, and momentum characteristic benchmarks at the end of each quarter, which better controls for changing stock characteristics and fund strategies (such as momentum) that depend on rapidly changing characteristics.

Table 8 reports the results. For the equal-weighted portfolios, the average unadjusted returns to the portfolio with the highest contrarian scores are 4.29, 4.26, 4.22, and 4.47 percent during the next four quarters, respectively; the corresponding characteristic-adjusted returns are 0.50, 0.34, 0.30, and 0.30 percent. The return spreads between the highest and lowest contrarian score quintile stocks are 1.17, 1.73, 2.09, and 2.05 percent (unadjusted returns) and 1.05, 1.16, 1.15, and 0.95 percent (characteristic-adjusted returns). These are economically large return differences. The *t*-statistics for these differences are significantly positive for the unadjusted return spread of Q3 and Q4, and for the characteristic-adjusted return spreads during all four quarters. In addition, the value-weighted portfolios produce similar return patterns. These results suggest that stocks with high contrarian scores outperform stocks with low contrarian scores after we control for momentum and other stock characteristics.

C. Source of Superior Performance: Liquidity Provision or Fundamental Information?

Why do stocks with high contrarian scores outperform? As a related question, is there an economic explanation for the stockpicking ability of contrarian funds? Note that contrarian funds are often (but not necessarily always) the counterparty of herds. Stocks with high contrarian scores are those heavily held by contrarian funds, which, by definition, tend to purchase and hold stocks that are sold by herding funds. Brown, Wei, and Wermers (2007) show that mutual funds' herding behavior creates a temporary price pressure effect. Specifically, stocks heavily bought by funds tend to outperform those heavily sold by funds for a short period of one or two quarters, and, during subsequently quarters, the pattern is reversed. It is possible that the contrarian funds simply take advantage of such temporary mispricing by trading against herds. In this case, the superior performance of contrarian funds can essentially be viewed as compensation for providing liquidity to the market. On the other hand, if contrarian funds also profit from their private information, contrarian stocks should continue to outperform herding stocks even after we account for the return reversals caused by herds.

To investigate the sources of contrarian profit, we perform the following Fama-MacBeth regressions. The dependent variable is the DGTW characteristic-adjusted return during each of the four quarters after portfolio formation (Qtr+1 to Qtr+4). The main explanatory variable is the contrarian score of individual stocks. The control variables include stock-level herding indexes (Adjherd) during the past four quarters (Qtr -4 to Qtr-1). Adjherd is a transformation of the buy-herding measure (BHM) and sell-herding measure (SHM) defined in Section II.A. For buy-herding stocks, we rank their buy-herding measure BHM into quintiles, and assign them a value ranging from 1 to 5, with 5 for stocks in the highest buy-herding quintile. We rank sell-herding stocks similarly. However, we assign them a herding measure ranging from -5 to -1 with -5 for the highest sell-herding quintile (stocks sold most heavily by herds). Note that the contrarian score measures the tendency of contrarian funds to heavily hold a given stock-quarter in common, while Adjherd measures the tendency of funds to trade in the same direction (herd) in that stock-quarter. While the herd may be comprised of different funds than the funds from which the contrarian score is derived, they need not be.

The regression is performed each quarter, and the time series averages of the estimated coefficients and the corresponding Fama-MacBeth *t*-statistics are reported in Table 9. When we use the contrarian score as the only explanatory variable, without controlling for herding, the coefficient for the contrarian score is significantly positive during all four quarters (Qtr+1 to Qtr+4). When the herding indexes for the past four quarters are included as control variables, the coefficients for the contrarian score become smaller, but are still significantly positive.[14] The result suggests that about 1/3 of the return-predictive information contained in the contrarian score is related to the price pressure effect of aggregate mutual fund herding. However, liquidity provision cannot fully explain the stock picking ability of contrarian funds.

Given that the return-predictive power of the contrarian score is not completely due to the price pressure effect caused by aggregate fund herding, we examine whether the additional stock picking information produced by contrarian funds is related to a firm's fundamentals, such as future operating performance. More precisely, our hypothesis is that contrarian funds selectively trade against herds—the stocks they pick are not the average stock being heavily sold by herds or an average past loser; rather, they are ones with greater improvement of operating performance in the future—which explains their higher future returns.

To examine this hypothesis, we look at the change of operating performance of stocks across the contrarian score quintiles. The operating performance measure we use is the industry-adjusted return on assets, which is defined as the return on assets (ROA) in excess of the average ROA for its affiliated industry.[15] Since we have both equal-weighted and value-weighted contrarian score portfolios, we compute average industry-adjusted ROA using both equal weights and value weights. We compute ROA for a future quarter (e.g., Qtr+1) by the net income reported during that quarter, divided by the total assets at the beginning of that quarter. The announcement dates are from the quarterly Compustat file. If the announcement

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[14] As an additional note, the coefficients for herding indexes are all negative, even when Q1 stock return are the dependent variable. In contrast, Brown, Wei, and Wermers (2007) find, using sorted portfolios, that the stocks more heavily bought by herds have higher returns during the immediate next quarter (Q1), and the stocks more heavily sold by herds have lower returns during Q1. This discrepancy is caused by the control of herding measures in all four quarters post portfolio formation. Essentially, the persistence of fund herding delays the return reversal process.

[15] We classify stocks into industry groups according to their two-digit SIC codes.

date is missing, we assume that the announcement takes place two months after the fiscal quarter end.

The results are shown in Table 10. Stocks with higher contrarian scores tend to have greater changes of industry-adjusted ROAs during all four future quarters. For equal-weighted portfolios, the differences in the change of adjusted ROA between the top and bottom contrarian score quintiles are 0.04, 0.16, 0.22, and 0.18 percent during Qtr+1 to Qtr+4, respectively.[16] The differences are statistically significant for Qtr+2 to Qtr+4. For value-weighted portfolios, the top-bottom differences in the change of adjusted ROA are 0.02, 0.14, 0.24, and 0.14 percent, from Qtr+1 to Qtr+4, respectively. The differences are also statistically significant for Qtr+2 to Qtr+4.

Overall, the evidence suggests two possible sources of contrarian funds' stock picking ability. Contrarian funds take advantage of the temporary mispricing created by the herding behavior of mutual funds as a whole; at the same time, they have the ability to predict future operating performance of stocks.

V. Conclusion

Domestic-equity mutual fund managers tend to exhibit commonality in their trades, that is, they tend to "herd" in their stock purchases and sales. Further, stocks with large levels of mutual fund herding exhibit large return reversals during the following year. A minority of domestic-equity mutual funds resist the temptation to herd in their stock trades—we call such funds "contrarian funds."

[16] The cross-sectional distribution of ROA is highly skewed. As a result, the industry-adjusted ROA tends to be negative.

In this paper, we investigate the behavior and performance of contrarian funds during 1994-2006, as well as the performance of stocks widely held and traded by such funds. First, we examine the portfolio holdings and trades of funds to identify contrarian funds using an index that measures the tendency of a fund to trade against the crowd (i.e., against the majority of mutual funds). This index is shown to be highly persistent for at least eight quarters. We then compare the performance of contrarian funds with herding funds and find that contrarian funds significantly outperform herding funds based upon their Carhart (1997) four-factor alphas. Specifically, contrarian funds significantly outperform herding funds by about 2.63% a year, net of expenses. This superior performance cannot be explained by their fund characteristics and their trading of illiquid stocks and momentum stocks.

Next, we build a stock-level contrarian score, which measures the tendency of contrarian funds to hold a given stock during a given calendar quarter. We find that stocks in the highest contrarian score portfolio outperform stocks in the lowest contrarian index portfolio by 1.66% per quarter during the quarter following the portfolio formation quarter. In addition, the superior returns of the highest contrarian score portfolio persist for four quarters after portfolio formation. Finally, we show that the return predictability of the contrarian score is not only related to the temporary mispricing caused by herds, it also reflects contrarian funds' ability to predict stock fundamentals.

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Table 1: Summary Statistics

This table reports summary statistics for the sample of actively managed US equity mutual funds from 1994 to 2006. Each quarter, we calculate the cross-sectional mean, median, standard deviation, 25th and 75th percentile values of funds' total net asset value, total expenses, annual turnover, quarterly flows, age, raw quarterly returns, and contrarian index. Time-series averages of these summary statistics are reported.

	Mean	Median	Std Dev	25th	75th
Fund Size	1099	280	2148	84	973
Total Exp.	0.0130	0.0124	0.0046	0.0100	0.0154
Turnover	0.9023	0.6847	0.8346	0.3627	1.1714
Flows	0.0163	-0.0045	0.1018	-0.0375	0.0437
Fund Age	14.9452	9.5192	14.9217	5.3846	18.2981
Raw Return	0.0289	0.0272	0.0528	-0.0012	0.0574
CON4	-0.7408	-0.7712	0.7176	-1.1685	-0.3464

Table 2: Characteristics of Contrarian Funds

This table examines the characteristics of contrarian funds. Each quarter, we group funds into quintile portfolios and calculate their average total net asset value (TNA), total expenses, turnover ratio, age, fund flows, raw quarterly returns and average size, B/M and momentum ranks of their stock holdings. Time-series averages of the contrarian index and fund characteristics of each quintile portfolio are reported. The difference in these variables between contrarian funds (quintile 5) and herding funds (quintile 1) and t-statistics calculated with Newey-West robust standard errors are also reported.

Contrarian Quintiles	CON4	Fund Size	Total Exp. (%)	Turnover (%)	Flow	Fund Age	Raw Ret (%)	Size Rank	B/M Rank	Mom Rank	Illiquidity Rank
1	-1.6726	887	1.3401	90.4370	2.0131	14.0981	2.8975	4.3121	2.3203	3.1853	10.3373
2	-1.0866	1031	1.3056	99.3530	1.4413	15.2007	2.8747	4.3901	2.4536	3.1122	10.1218
3	-0.7716	1122	1.2789	94.9080	1.3036	14.9914	2.8805	4.4422	2.5844	3.0075	9.8734
4	-0.4391	1163	1.2672	86.3670	1.3943	15.2082	2.8498	4.4738	2.7099	2.9002	9.8371
5	0.2651	1293	1.2995	67.6900	1.9726	15.2269	2.9521	4.4827	2.8591	2.7636	10.1741
5-1	1.9377	406	-0.0406	-22.7470	-0.0004	1.1288	0.0546	0.1706	0.5388	-0.4217	-0.1632
	(74.32)[a]	(3.42)[a]	(-2.66)[b]	(-7.10)[a]	(-0.05)	(2.89)[a]	(0.10)	(2.64)[b]	(14.84)	(-17.07)	(-0.19)

Table 3: Persistence of Contrarian Index

In each quarter, we rank funds into quintiles based on their contrarian indexes (*CON4*). Funds with the lowest contrarian indexes (herding funds) are in Quintile 1 and funds with the highest (contrarian funds) are in Quintile 5. We then track funds in each quintile and report their average contrarian indexes (*CON4* in Panel A and *CON* in Panel B) for the following eight quarters. We also report the difference of contrarian indexes between the top (Q5) and the bottom (Q5) fund quintiles, as well as the corresponding t-statistics (in parentheses) computed with Newey-West robust standard errors.

Panel A: Average *CON4* in the subsequent eight quarters

Contrarian	Low	2	3	4	High	High-Low
Qtr+1	-1.5257	-1.0433	-0.7663	-0.4748	0.1102	1.6359
						(66.55) [a]
Qtr +2	-1.3803	-0.9921	-0.7614	-0.5094	-0.0416	1.3387
						(56.02) [a]
Qtr +3	-1.2277	-0.9435	-0.7512	-0.5492	-0.1937	1.0340
						(42.89) [a]
Qtr +4	-1.0700	-0.8919	-0.7384	-0.5963	-0.3497	0.7204
						(26.46) [a]
Qtr +5	-1.0492	-0.8832	-0.7388	-0.6001	-0.3574	0.6919
						(24.21) [a]
Qtr +6	-1.0285	-0.8786	-0.7402	-0.6059	-0.3635	0.6651
						(20.53) [a]
Qtr +7	-1.0070	-0.8738	-0.7422	-0.6088	-0.3777	0.6292
						(18.70) [a]
Qtr +8	-0.9888	-0.8685	-0.7441	-0.6058	-0.3910	0.5978
						(18.37) [a]

Panel B: Average *CON* in the subsequent eight quarters

Contrarian	Low	2	3	4	High	High-Low
Qtr+1	-1.1048	-0.9095	-0.7460	-0.5936	-0.3149	0.7899
						(23.50) [a]
Qtr +2	-1.0915	-0.8869	-0.7453	-0.5868	-0.3348	0.7567
						(24.53) [a]
Qtr +3	-1.0601	-0.8911	-0.7339	-0.5894	-0.3401	0.7200
						(21.43) [a]
Qtr +4	-1.0386	-0.8932	-0.7338	-0.6125	-0.3383	0.7003
						(19.64) [a]
Qtr +5	-1.0214	-0.8716	-0.7561	-0.6075	-0.3513	0.6701
						(16.07) [a]
Qtr +6	-1.0166	-0.8606	-0.7511	-0.6124	-0.3676	0.6489
						(15.43) [a]
Qtr +7	-0.9732	-0.8713	-0.7368	-0.6126	-0.3958	0.5775
						(14.36) [a]
Qtr +8	-0.9689	-0.8630	-0.7386	-0.5970	-0.3937	0.5752
						(16.15) [a]

Table 4: Performance of Contrarian Funds

Each quarter we sort funds into quintile portfolios based upon their contrarian indexes. We then estimate the performance of each contrarian fund portfolio using Fama-French (1993) three-factor model and Carhart (1997) four-factor model. Panel A reports results for fund returns measured before expense while Panel B reports results for fund returns measured after expense. Alpha is expressed in percentage per month. We also report the performance of the zero cost portfolio that buys quintile 5 funds and sells quintile 1 funds. t-statistics calculated with Newey-West robust standard errors are in parentheses.

Panel A: Before-Expense Performance

Model	**Raw Ret**	**Fama-French Three-Factor Model**				**Carhart Four-Factor Model**				
Quintile	(%)	α(%)	RMRF	SMB	HML	α(%)	RMRF	SMB	HML	UMD
1—Low	0.9740	-0.0093	0.9987	0.2514	-0.0303	-0.0872	1.0277	0.2340	-0.0151	0.0762
	(2.59)	(-0.12)	(51.16)	(10.49)	(-1.07)	(-1.17)	(52.88)	(8.30)	(-0.62)	(3.25)
2	1.0092	0.0254	0.9751	0.2118	0.0221	-0.0332	0.9969	0.1986	0.0335	0.0574
	(2.86)	(0.38)	(64.53)	(10.23)	(0.78)	(-0.49)	(62.08)	(10.01)	(1.39)	(2.78)
3	1.0314	0.0252	0.9753	0.1715	0.0907	-0.0009	0.9850	0.1657	0.0958	0.0255
	(3.07)	(0.49)	(91.66)	(10.39)	(3.13)	(-0.02)	(65.27)	(10.06)	(3.39)	(1.26)
4	1.0647	0.0404	0.9718	0.1228	0.1579	0.0651	0.9626	0.1283	0.1531	-0.0242
	(3.32)	(0.79)	(84.66)	(5.63)	(5.68)	(1.14)	(69.07)	(7.46)	(4.92)	(-1.37)
5—High	1.0778	0.0373	0.9561	0.0954	0.2300	0.1299	0.9217	0.1162	0.2119	-0.0906
	(3.50)	(0.58)	(57.20)	(2.67)	(6.34)	(2.03)	(49.32)	(5.22)	(4.84)	(-3.60)
High-Low	0.1038	0.0466	-0.0427	-0.1560	0.2603	0.2171	-0.1060	-0.1178	0.2269	-0.1668
	0.71	(0.47)	(-1.54)	(-4.02) [a]	(6.93) [a]	(3.39) [a]	(-5.46) [a]	(-4.07) [a]	(5.46) [a]	(-11.35) [a]

Panel B: After-Expense Performance

Model	Fama-French Three Factor Model				Carhart Four Factor Model				
Quintile	α(%)	RMRF	SMB	HML	α(%)	RMRF	SMB	HML	UMD
1—Low	-0.1216	0.9988	0.2513	-0.0304	-0.1996	1.0278	0.2338	-0.0151	0.0764
	(-1.62)	(51.19)	(10.48)	(-1.07)	(-2.68)	(52.93)	(8.30)	(-0.62)	(3.26)
2	-0.0837	0.9751	0.2116	0.0219	-0.1425	0.9970	0.1984	0.0334	0.0575
	(-1.26)	(64.55)	(10.21)	(0.77)	(-2.10)	(62.09)	(10.00)	(1.38)	(2.78)
3	-0.0820	0.9754	0.1713	0.0904	-0.1081	0.9851	0.1654	0.0955	0.0256
	(-1.60)	(91.62)	(10.38)	(3.12)	(-1.89)	(65.30)	(10.04)	(3.38)	(1.27)
4	-0.0659	0.9718	0.1224	0.1575	-0.0413	0.9627	0.1280	0.1527	-0.0241
	(-1.29)	(84.42)	(5.62)	(5.67)	(-0.72)	(68.97)	(7.45)	(4.91)	(-1.36)
5—High	-0.0729	0.9561	0.0951	0.2299	0.0195	0.9218	0.1158	0.2118	-0.0904
	(-1.13)	(57.25)	(2.67)	(6.34)	(0.31)	(49.39)	(5.21)	(4.85)	(-3.60)
High-Low	0.0487	-0.0427	-0.1561	0.2603	0.2191	-0.1060	-0.1179	0.2270	-0.1668
	(0.49)	(-1.54)	(-4.02) [a]	(6.93) [a]	(3.43) [a]	(-5.46) [a]	(-4.08) [a]	(5.47) [a]	(-11.36) [a]

Table 5: Performance of Contrarian Funds Defined By Alternative Contrarian Measure

Each quarter we sort funds into quintile portfolios based upon their tendency to trade against stocks with high absolute dollar trade imbalance (*Dratio*). We then estimate the performance of each contrarian fund portfolio using Fama-French (1993) three-factor model and Carhart (1997) four-factor model. Panel A reports results for fund returns measured before expense while Panel B reports results for fund returns measured after expense. Alpha is expressed in percentage per month. We also report the performance of the zero cost portfolio that buys quintile 5 funds and sells quintile 1 funds. t-statistics calculated with Newey-West robust standard errors are in parentheses

Panel A: Before-Expense Performance

Model	**Fama-French Three Factor Model**				**Carhart Four Factor Model**				
Quintile	α(%)	RMRF	SMB	HML	α(%)	RMRF	SMB	HML	UMD
1—Low	0.0254	0.9672	0.2703	-0.0018	-0.0358	0.9900	0.2566	0.0102	0.0599
	(0.35)	(63.73)	(12.38)	(-0.06)	(-0.52)	(54.29)	(12.38)	(0.44)	(2.82)
2	-0.0045	1.0053	0.2214	0.0392	-0.0536	1.0235	0.2104	0.0488	0.0480
	(-0.08)	(64.35)	(11.07)	(1.26)	(-0.82)	(54.01)	(9.47)	(1.67)	(2.14)
3	0.0145	0.9942	0.1599	0.0935	0.0055	0.9976	0.1579	0.0953	0.0088
	(0.28)	(80.64)	(6.32)	(3.57)	(0.08)	(61.19)	(6.51)	(3.62)	(0.37)
4	0.0237	0.9779	0.1267	0.1337	0.0390	0.9722	0.1301	0.1307	-0.0150
	(0.46)	(77.50)	(5.39)	(4.84)	(0.66)	(63.78)	(6.59)	(4.38)	(-0.79)
5—High	0.0583	0.9324	0.0747	0.2067	0.1175	0.9105	0.0880	0.1951	-0.0579
	(1.01)	(62.32)	(2.83)	(6.24)	(1.97)	(51.31)	(4.80)	(5.04)	(-2.82)
High-Low	0.0329	-0.0348	-0.1956	0.2084	0.1532	-0.0795	-0.1687	0.1849	-0.1178
	(0.38)	(-1.48)	(-5.44) [a]	(6.16) [a]	(2.47) [b]	(-3.50) [a]	(-6.34) [a]	(5.64) [a]	(-9.07) [a]

Panel B: After-Expense Performance

Model	**Fama-French Three Factor Model**				**Carhart Four Factor Model**				
Quintile	α(%)	RMRF	SMB	HML	α(%)	RMRF	SMB	HML	UMD
1—Low	-0.0795	0.9673	0.2700	-0.0019	-0.1408	0.9901	0.2563	0.0101	0.0600
	(-1.10)	(63.67)	(12.36)	(-0.07)	(-2.04)	(54.28)	(12.37)	(0.43)	(2.83)
2	-0.1132	1.0053	0.2211	0.0388	-0.1624	1.0235	0.2101	0.0484	0.0481
	(-1.87)	(64.36)	(11.06)	(1.25)	(-2.47)	(54.01)	(9.46)	(1.65)	(2.14)
3	-0.0952	0.9942	0.1596	0.0931	-0.1043	0.9976	0.1575	0.0949	0.0090
	(-1.81)	(80.65)	(6.31)	(3.55)	(-1.60)	(61.25)	(6.50)	(3.61)	(0.37)
4	-0.0849	0.9780	0.1264	0.1335	-0.0697	0.9723	0.1299	0.1305	-0.0149
	(-1.63)	(77.47)	(5.38)	(4.84)	(-1.18)	(63.79)	(6.58)	(4.38)	(-0.78)
5—High	-0.0548	0.9325	0.0746	0.2067	0.0043	0.9105	0.0878	0.1952	-0.0578
	(-0.95)	(62.27)	(2.83)	(6.25)	(0.07)	(51.31)	(4.80)	(5.04)	(-2.82)
High-Low	0.0247	-0.0349	-0.1954	0.2086	0.1451	-0.0796	-0.1684	0.1851	-0.1178
	(0.28)	(-1.48)	(-5.43) [a]	(6.17) [a]	(2.34) [b]	(-3.50) [a]	(-6.34) [a]	(5.65) [a]	(-9.09) [a]

Table 6: Persistence of Contrarian Fund Performance

Each quarter we sort funds into quintile portfolios based upon their contrarian indexes. We then estimate the performance of each contrarian fund portfolio in the subsequent four quarters using Fama-French (1993) three-factor model and Carhart (1997) four-factor model and compute the returns to the zero cost portfolio that buys quintile 5 funds and sells quintile 1 funds. t-statistics calculated with Newey-West robust standard errors are in parentheses.

Model	**Carhart Four Factor Model (Before-Expense)**					**Carhart Four Factor Model (After-Expense)**				
Qtr	α(%)	RMRF	SMB	HML	UMD	α(%)	RMRF	SMB	HML	UMD
Qtr+1	0.2171	-0.1060	-0.1178	0.2269	-0.1668	0.2191	-0.1060	-0.1179	0.2270	-0.1668
	(3.39)[a]	(-5.46)[a]	(-4.07)[a]	(5.46)[a]	(-11.35)[a]	(3.43)[a]	(-5.46)[a]	(-4.08)[a]	(5.47)[a]	(-11.36)[a]
Qtr+2	0.1976	-0.1009	-0.0910	0.2481	-0.1393	0.1997	-0.1008	-0.0911	0.2481	-0.1393
	(3.30)[a]	(-4.28)[a]	(-2.69)[a]	(4.50)[a]	(-6.34)[a]	(3.34)[a]	(-4.27)[a]	(-2.69)[a]	(4.50)[a]	(-6.33)[a]
Qtr+3	0.2476	-0.0988	-0.1067	0.2344	-0.1183	0.2499	-0.0987	-0.1068	0.2343	-0.1183
	(3.49)[a]	(-4.40)[a]	(-3.35)[a]	(4.20)[a]	(-5.29)[a]	(3.52)[a]	(-4.40)[a]	(-3.36)[a]	(4.20)[a]	(-5.29)[a]
Qtr+4	0.2000	-0.0900	-0.1001	0.2521	-0.0996	0.2026	-0.0898	-0.1001	0.2521	-0.0996
	(2.78)[a]	(-3.74)[a]	(-3.08)[a]	(4.70)[a]	(-4.55)[a]	(2.82)[a]	(-3.74)[a]	(-3.09)[a]	(4.70)[a]	(-4.55)[a]

Table 7: Multivariate Analysis of the Performance of Contrarian Funds

This table reports results of panel regressions of fund performance on fund characteristics. The dependent variable is quarterly Carhart (1997) four-factor adjusted fund returns in percent. The explanatory variables include contrarian index, momentum trading index, illiquid stock trading index, logged value of fund size as proxied by total net asset value, logged value of 1 plus fund age, total expenses, turnover ratio, prior quarter fund flows. Quarter dummies are included in all regressions to control for the time fixed effect. The corresponding t-statistics reported in parentheses are based on standard errors clustered by funds.

Dependent Variable	**Monthly Carhart 4-Factor Adjusted Fund Returns (in %)**			
Intercept	1.2792	1.1345	0.9084	1.1280
	(7.71)[a]	(6.65)[a]	(5.09)[a]	(6.59)[a]
Contrarian Index	0.2155			0.1983
	(6.33)[a]			(6.00)[a]
Momentum Trading		-0.6523		-0.5184
		(-4.08)[a]		(-3.28)[a]
Illiquid Stock Trading			1.1382	1.0023
			(4.42)[a]	(3.90)[a]
Fund Size	-0.0521	-0.0475	-0.0444	-0.0443
	(-4.13)[a]	(-3.72)[a]	(-3.50)[a]	(-3.57)[a]
Fund Age	-0.0525	-0.0604	-0.0379	-0.0493
	(-1.84)[c]	(-2.11)[b]	(-1.30)	(-1.71)[c]
Total Expenses	-11.6964	-11.7287	-14.3023	-14.0301
	(-1.70)[c]	(-1.70)[c]	(-2.01)[a]	(-2.01)[a]
Turnover	0.0533	0.0342	0.0435	0.0545
	(0.63)	(0.41)	(0.52)	(0.64)
Past Flows	1.3332	1.5181	1.2968	1.4173
	(3.48)[a]	(3.85)[a]	(3.41)[a]	(3.65)[a]
Time Dummy	Yes	Yes	Yes	Yes
Clustering by Funds	Yes	Yes	Yes	Yes
Number of Obs	58689	58702	58711	58683

Table 8: Ownership by Contrarian Funds and the Cross Section of Stock Returns

Each quarter, we calculate a stock's contrarian score as the weighted average contrarian index of funds holding the stock. We then sort stocks into value weighted quintile portfolios based upon their contrarian scores and report their returns in the following four quarters. Panel A reports the monthly raw returns of contrarian quintile portfolios. Panel B reports their monthly DGTW (1997) characteristic-adjusted abnormal returns. We also report the performance of the zero cost portfolio that buys quintile 5 stocks and sells quintile 1 stocks. t-statistics calculated with Newey-West robust standard errors are in parentheses.

Panel A: Quarterly Raw Returns

	Equal Weighted Portfolio				Value Weighted Portfolio			
	Qtr+1	Qtr+2	Qtr+3	Qtr+4	Qtr+1	Qtr+2	Qtr+3	Qtr+4
1—Low	3.11	2.54	2.13	2.42	1.66	2.35	1.20	2.17
	(1.68)	(1.45)	(1.32)	(1.56)	(0.89)	(1.43)	(0.77)	(1.39)
2	3.55	3.48	3.28	3.50	3.23	2.94	3.08	2.95
	(2.69)	(2.77)	(2.64)	(2.83)	(2.70)	(2.46)	(2.75)	(2.51)
3	4.06	3.79	3.81	4.06	3.40	3.51	3.38	4.10
	(3.54)	(3.37)	(3.31)	(3.57)	(3.17)	(3.19)	(3.12)	(3.83)
4	3.98	4.27	4.10	4.38	3.50	3.87	4.00	4.29
	(3.52)	(3.78)	(3.63)	(3.97)	(3.28)	(3.47)	(3.71)	(4.19)
5—High	4.29	4.26	4.22	4.47	4.07	3.86	4.41	4.57
	(3.51)	(3.62)	(3.62)	(3.91)	(3.82)	(3.69)	(4.42)	(4.49)
High-Low	1.17	1.73	2.09	2.05	2.40	1.51	3.21	2.40
	(0.76)	(1.27)	(1.76) [c]	(2.02) [b]	(1.38)	(0.99)	(2.31) [b]	(1.88) [c]

Panel B: Quarterly DGTW Characteristic-Adjusted Returns

	Equal Weighted Portfolio				Value Weighted Portfolio			
	Qtr+1	Qtr+2	Qtr+3	Qtr+4	Qtr+1	Qtr+2	Qtr+3	Qtr+4
1—Low	-0.55	-0.82	-0.85	-0.65	-0.93	-0.65	-1.25	-0.54
	(-1.75)	(-2.35)	(-2.85)	(-2.71)	(-2.22)	(-1.82)	(-3.36)	(-1.51)
2	-0.08	-0.03	0.00	-0.01	-0.14	-0.34	-0.08	-0.52
	(-0.47)	(-0.14)	(0.02)	(-0.04)	(-0.60)	(-1.01)	(-0.30)	(-2.03)
3	0.34	0.11	0.28	0.31	0.04	0.09	-0.02	0.27
	(1.55)	(0.59)	(0.94)	(1.32)	(0.16)	(0.36)	(-0.09)	(0.99)
4	0.19	0.52	0.38	0.39	0.20	0.58	0.55	0.66
	(0.63)	(1.77)	(1.39)	(1.32)	(0.65)	(1.48)	(1.62)	(1.70)
5—High	0.50	0.34	0.30	0.30	0.72	0.35	0.66	0.61
	(1.99)	(1.20)	(1.00)	(1.14)	(2.25)	(0.90)	(1.62)	(1.58)
High-Low	1.05	1.16	1.15	0.95	1.66	1.00	1.91	1.15
	(2.19) [b]	(2.21) [b]	(2.17) [b]	(2.23) [b]	(2.65) [b]	(1.61)	(3.18) [a]	(2.03) [b]

Table 9: Returns of Contrarian Portfolios after Controlling for Returns of Herding Portfolios

Each quarter we calculate a stock's contrarian score as the weighted average contrarian index of funds holding the stock. We then run quarterly Fama-MacBeth regressions of the DGTW (1997) characteristic-adjusted returns of each stock in the following quarter on their current contrarian scores and adjusted herding measures in the most recent four quarters. The time series average coefficients and their corresponding t-statistics (in parentheses) are reported.

MODEL	Qtr	Contrarian Score	Adjherd $_{t-1}$	Adjherd $_{t-2}$	Adjherd $_{t-3}$	Adjherd $_{t-4}$
MODEL1	Qtr+1	0.3025				
		(2.61) [b]				
	Qtr+2	0.3114				
		(2.55) [b]				
	Qtr+3	0.2496				
		(2.11) [b]				
	Qtr+4	0.2141				
		(2.16) [b]				
MODEL2	Qtr+1	0.2156	-0.0503	-0.0455	-0.0632	-0.0971
		(2.06) [b]	(-0.97)	(-1.54)	(-2.22) [b]	(-3.31) [a]
	Qtr+2	0.2067	-0.0652	-0.0669	-0.0723	-0.1015
		(1.98) [c]	(-2.00) [b]	(-2.14) [b]	(-2.76) [a]	(-2.36) [b]
	Qtr+3	0.1633	-0.0813	-0.0741	-0.0767	0.0027
		(1.65)	(-2.39) [b]	(-2.64) [b]	(-2.21) [b]	(0.08)
	Qtr+4	0.1507	-0.0691	-0.0895	-0.0030	0.0121
		(1.71) [c]	(-2.13) [b]	(-2.36) [b]	(-0.10)	(0.32)

Table 10: Ownership by Contrarian Funds and Change of Industry Adjusted ROA

Each quarter, we sort stocks into equal-weighed and value-weighted quintile portfolios based upon their contrarian scores and report their industry adjusted ROAs in the following four quarters. We also report ROA of the zero cost portfolio that buys quintile 5 stocks and sells quintile 1 stocks. t-statistics calculated with Newey-West robust standard errors are in parentheses.

	Equal Weighted Portfolio				Value Weighted Portfolio			
	Qtr+1	Qtr+2	Qtr+3	Qtr+4	Qtr+1	Qtr+2	Qtr+3	Qtr+4
1—Low	-0.0934	-0.1774	-0.2122	-0.1807	-0.0684	-0.1411	-0.2262	-0.1393
	(-2.52)	(-5.18)	(-6.29)	(-6.76)	(-1.63)	(-3.25)	(-4.22)	(-3.34)
2	-0.0557	-0.0926	-0.0843	-0.1002	-0.0598	-0.1020	-0.0309	-0.1271
	(-2.14)	(-4.66)	(-3.10)	(-4.50)	(-1.56)	(-2.98)	(-1.13)	(-3.50)
3	-0.0811	-0.0727	-0.0506	-0.0689	-0.0415	-0.0788	-0.0669	-0.0654
	(-3.30)	(-3.02)	(-2.81)	(-3.07)	(-1.25)	(-2.68)	(-1.90)	(-1.66)
4	-0.0375	-0.0540	-0.0531	-0.0038	-0.0386	-0.0111	-0.0344	0.0006
	(-1.86)	(-2.62)	(-3.09)	(-0.19)	(-1.43)	(-0.39)	(-1.09)	(0.02)
5—High	-0.0510	-0.0129	0.0059	0.0022	-0.0491	0.0014	0.0124	-0.0019
	(-2.32)	(-0.61)	(0.29)	(0.09)	(-1.89)	(0.05)	(0.44)	(-0.06)
High-Low	0.0424	0.1645	0.2181	0.1829	0.0193	0.1424	0.2386	0.1374
	(1.09)	(5.18) [a]	(6.19) [a]	(6.39) [a]	(0.40)	(2.87) [a]	(4.13) [a]	(3.06) [a]