# 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" more frequently than most funds. 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 held by contrarian funds over the following four quarters by more than 5%, based upon their characteristic-adjusted returns. Finally, we investigate whether contrarian funds outperform simply because they provide liquidity to herding funds, trade on return-predictive quantitative signals, or because they possess superior information on stock fundamentals. We find that although contrarian funds do profit from liquidity provision, at least part of their superior returns derives from their superior information, relative to herding funds—contrarian funds hold stocks with much greater improvement of profitability as compared to herding funds.
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The popular media has long excoriated institutional 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 mutual 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 (e.g., Nofsinger and Sias, 1999; Wermers, 1999; and Sias, 2004), little is known about the strategies and performance of contrarian investors. Among U.S. equity mutual funds, it is interesting that few fund managers with herd-like behavior stand out with sustained investment success.[2] Indeed, star managers such as Peter Lynch or Bill Miller often 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

[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] Grinblatt, Titman, and Wermers (1995) analyze the relationship between herding and mutual fund performance. Although they find that funds exhibiting a stronger tendency to herd outperform other funds (over the 1975 to 1984 period), this outperformance disappears after controlling for momentum returns in stocks.
[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).

contrarian systematically help?[4] Do 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 investigating 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 majority of U.S. domestic equity mutual funds underperform their benchmarks, net of fees (e.g., Carhart, 1997 and Barras, et al, 2008), it would be unusual to find outperformance among funds that tend to systematically invest with the crowd. In fact, as mentioned above, Brown, Wei, and Wermers (2007) and Puckett and Yan (2007) find evidence consistent with herding funds underperforming their benchmarks.

[4] Brown, Wei, and Wermers (2007) and Puckett and Yan (2007) document 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.

[5] While there is no generally accepted theory of "contrarianism," there are several popular theories of the motivation for herding. 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).

However, since funds that invest against the crowd are, by definition, in the minority, it is possible that such funds could potentially outperform their benchmarks.

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 frequently trade with the herd. Specifically, we modify the LSV (1992) measure to arrive at a measure of buy-side or sell-side herding in a particular stock. Then, we calculate 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—valid concerns when selecting contrarian funds based on other quantitative strategies as well.

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 (LSV-measured) herd 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 over the prior year. We find that these funds tend to be larger, older, with lower flow and return volatility and turnover than other funds, characteristics that are consistent with an ability to provide liquidity to herding funds. 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 two years.

We next investigate the performance of contrarian funds. We find that the most contrarian quintile of funds 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.[7] Moreover, this performance difference remains significantly positive for up to eight quarters, suggesting that a feasible and profitable strategy is available to investors who simply obtain access to fund holdings information through the quarterly SEC filings.

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[7] 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 on their unadjusted returns or on 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. However, when we redefine fund herding using dollar trade imbalances in stocks, we do not find greater outperformance for contrarian funds, relative to their outperformance under the LSV measure (which computes herding using the simple proportion of funds trading on the same side).

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 fund size, expenses, turnover, 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, also explain four-factor alphas of funds, *CON4* maintains a positive and significant cross-sectional relation to fund alphas.

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. We next investigate whether the superior performance of contrarian funds translates into a successful stock-picking signal. To accomplish this, we create a stock-level measure of contrarianism – termed the "contrarian score"-- to determine whether stocks held predominantly by contrarian funds outperform those held mainly by herding funds. We find that stocks most heavily held by contrarian funds exhibit significantly higher characteristic-adjusted returns, using the Daniel, Grinblatt, Titman, and Wermers (1997; DGTW) benchmarks, than stocks most heavily held by herding funds. 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 exceeding 1.6% during the following quarter. Moreover, this strategy continues to outperform during quarters +2 through +4.

The stock-level approach enables us to further explore the sources of contrarian profits by taking a closer look at the characteristics of stocks with high contrarian scores. We find that the contrarian score tends to be negatively correlated with the intensity of herding, earnings momentum, and accounting profitability. On the other hand, contrarian stocks possess characteristics that are indicative of higher future returns: they have higher value characteristics, less external financing and capital investment activities, higher intangible investments (R&D and advertising), better earnings quality, and less information uncertainty. Interestingly, we find that contrarian stocks continue to outperform even after we control for the return reversals that occur in stocks with heavy herding activity and an extensive list of return-predictive quantitative characteristics.

Finally, we show that stocks with higher contrarian scores experience greater improvement (or less deterioration) in future operating performance and realize accelerated sales growth rate, thus are more likely to deliver higher future returns. Overall, the evidence suggests that contrarian funds do not merely profit from liquidity provision. They 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.[8,9] 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 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,

[8] One difference of our study is that we 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).

[9] Another possible explanation for the difference in findings is that funds whose holdings deviate a lot from their peers include both contrarian funds and extreme herding funds.

bond and preferred stock funds, and metals funds. The Thomson Financial data provide quarterly "snapshots" of portfolio holdings for most U.S.-based equity mutual funds (with semi-annual data for the remaining funds); further information on 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 omit that fund during that quarter, then 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 ratio, and other characteristics is obtained from the CRSP mutual fund database. Multiple share classes of a fund in the CRSP database are combined into a single portfolio (value-weighted, based on beginning-of-month total net asset values of each share class) 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 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):

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

where $p_{i,t}$ is the proportion of mutual funds buying stock $i$ during quarter $t$, out of all funds trading that stock during that quarter. $\overline{p}_t$, a proxy for the expected value of $p_{i,t}$, is the cross-sectional mean of $p_{i,t}$ over all stocks traded by the funds during quarter t. $E(|p_{i,t} - \overline{p}_t|)$ is an adjustment factor, which equals the expected value of $| p_{i,t} - \overline{p}_t |$ 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.[10] 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 $p_{i,t} > \overline{p}_t$ (i.e., if the proportion of mutual fund buys is higher than average for that quarter). Similarly, stocks with $p_{i,t} < \overline{p}_t$ are classified as "sell-herd" stocks. The conditional buy-herding ($BHM_{it}$) and sell-herding ($SHM_{it}$) measures are calculated as follows:

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

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

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-

[10] 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.

herd" stocks into quintiles by $SHM_{it}$, and the quintile with rank $RSHM_{it}$ equals five are stocks most heavily sold by herds, according to Equation (3). This nonparametric ranking procedure reduces the influence of outlier stock-quarters, i.e., those with extreme buy- or sell-herding.[11]

Next, since the LSV herding measure captures the tendency of 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 a 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, $CM_{ijt} = -RBHM_{it}$ if the fund buys a "buy-herd" stock and $CM_{ijt} = -RSHM_{it}$ 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 $\omega_{ijt}$ is defined as

[11] Our results to follow are not materially different if we instead use each stock's parametric LSV herding measure.

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

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 net assets at the same date, and *N* being the total number of stocks traded by the fund. Therefore, the weight on a given stock trade's contrarian measure, $CM_{ijt}$, will be greater if the fund changes its holdings more dramatically, relative to other stocks.

Note that our contrarian index is constructed based upon the concurrent holdings information of mutual funds, data that is not publicly available until at least 60 days following the end of a fiscal quarter. Therefore, if contrarian mutual fund managers actually wish to trade in the opposite direction as other managers, they must rely 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.[12] Moreover, brokers may "tip" preferred fund managers with information on their other clients' actions or on upcoming analyst recommendation revisions.[13]

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,

[12] For instance, Brown, Wei, and Wermers (2007) find that mutual fund herds tend to follow analyst recommendation revisions, making this a useful public signal to gauge the sentiment of the majority of funds.
[13] 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.

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

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 liquidity driven transactions. Throughout the remainder 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 million in total net assets, the mean fund size is much larger. 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—by construction—the majority of trades made by mutual funds are considered as herding trades (and, thus, assigned a negative *CM*). In addition, the cross-sectional standard deviation of the contrarian index is 0.71, which suggests 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 systematic differences exist between herding funds and contrarian funds.

Each quarter, we sort funds into contrarian quintiles based upon their contrarian index (*CON4*), then we calculate the average contrarian index, total net assets (size), expense ratio, annualized turnover, age, quarterly flows, quarterly net return, lagged 12-month flow volatility, and lagged 36-month return volatility for each quintile (these results are presented in Panel A of Table 2). 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 ranks of quintile fund portfolios, as well as the average proportion of contrarian trades among funds in each quintile, and present these measures in Panel B. Table 2 suggests that contrarian funds are generally larger and have a lower turnover ratio and lower flow and return volatility, compared with funds that herd. These characteristics are consistent with their ability to provide liquidity to herding funds.

In terms of their holdings preferences, while contrarian funds hold stocks with a 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. Lastly, Panel B shows that about 51% of contrarian funds trades are against the herd, while 49% are with the herd. It is possible that contrarian funds choose to trade with or against herds strategically, based upon their private information.

Ex-ante, some of the characteristics of contrarian funds, including large fund size 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 examine 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 index (*CON4*). We then track the average contrarian index of these portfolios during each of the eight subsequent quarters. Table 3 presents both the four-quarter rolling contrarian measure (*CON4*) and the simple one-quarter contrarian 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. Baseline Results

When contrarians trade on the opposite side of herds, they may possess private information 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), or the value anomaly (Fama and French, 1992 and Lakonishok, Shleifer, and Vishny, 1994). Although it is tempting to conclude from such stock-level evidence 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[14]. 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.

[14] 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.

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. Furthermore, contrarian funds have significantly lower market beta than herding funds, suggesting that they perform better during market downturns.

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 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 Using 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*:

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

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.

In Figure 1, we further plot the difference in four-factor fund alphas between the top and bottom quintile fund portfolios sorted on the contrarian index, for each of the 12 quarters after fund portfolio formation. The difference in fund performance remains quite large during Qtr+5 to Qtr+10, and only starts to shrink in the last two quarters we examine: Qtr+11 and Qtr+12.

**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. To alleviate potential heteroscedasticity, we take the natural logarithms of fund size and age. 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.

Finally, given the evidence in Tables 4 and 5 that contrarian funds have significantly lower market beta compared with herding funds, we investigate whether their risk adjusted performance is better during bear market. Specifically, we define a dummy variable that takes the value of one for quarters when the market portfolio's returns (as proxied by returns of the CRSP value-weighted index return) are ranked in the bottom 33%. As show in the last column of Table 7, the interaction term between this market downturn dummy and the contrarian index is significantly positive, indicating that the risk-adjusted performance of contrarian funds is indeed more pronounced during market downturns.

## IV. Contrarian Score and the Cross-Section of Stock Returns

The empirical results so far indicate 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. The evidence on performance is thus inconsistent with the hypothesis that contrarian fund managers trade against the herd simply because of their over-confidence. However, there still exist several competing hypotheses as to why they are profitable. For example, contrarian funds may profit from the temporary price pressure/mispricing created by herding funds. Further, contrarian funds may take cues from quantitative valuation signals and invest in "cheap" stocks. Finally, it may also be possible that contrarian funds possess private information about firm fundamentals. Given that these potential explanations are not mutually exclusive, it will be interesting to examine how much each source of profits contributes to contrarian funds' performance. Specifically, we control for stock-level intensity of herding and common quantitative valuation signals to see whether contrarian funds have information that can help them outperform—beyond taking advantage of the mispricing caused by herding funds or relying on quantitative investment strategies.

Naturally, such analysis can be better carried out at the individual stock level. For this reason, we shift our focus from contrarian fund performance to returns of individual stocks that are held/traded by contrarian funds. 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/trades by adopting an approach developed by Wermers, Yao, and Zhao (2007). A salient feature of this approach is that it makes use of information of all funds, rather than focusing on merely a small subset of funds (e.g., the top or bottom quintile of funds).

### A. The Contrarian Score of Individual Stocks

Wermers, Yao, and Zhao (2007) start from the assumption that fund alpha is the weighted average of alphas of individual stocks held by the fund, where the weights are portfolio weights on stocks:

$$E(\alpha_{jt}^{F}) = \sum_{i=1}^{N} \omega_{ijt-1} E(\alpha_{it}^{S})$$

where $\alpha_{jt}^{F}$ is the fund alpha (j=1, …, M), and $\alpha_{it}^{S}$ is the stock alpha (i=1, …, N), and $\omega_{ijt}$ is the portfolio weight of fund j on stock i at the beginning of a holding period. From this, they show that an approximate but intuitive expression for $E(\alpha_{it}^{S})$ exists – the expected alpha of an individual stock is weighted average of expected fund alphas, where weights are proportional to the portfolio weights (referred to as the "weighted-average alpha"):

$$E(\alpha_{it}^{S}) = \frac{\sum_{j=1}^{M} \omega_{ijt-1} E(\alpha_{jt}^{F})}{\sum_{j=1}^{M} \omega_{ijt-1}}$$

Our empirical evidence so far suggests that the fund contrarian index, *CON4*, is informative of fund alpha. If we further assume a linear relationship between expected fund alpha and *CON4*, we can re-define $E(\alpha_{it}^{S})$ as,

$$E(\alpha_{it}^{S}) = \frac{\sum_{j=1}^{M} \omega_{ijt-1} CON4_{jt-1}}{\sum_{j=1}^{M} \omega_{ijt-1}} \tag{10}$$

We employ this measure as the contrarian score for individual stocks. Intuitively, the contrarian score of a stock is the weighted average contrarian indexes of funds holding the stock. If a stock is more heavily owned by contrarian funds relative to herding funds, its contrarian score is higher. In addition, the more contrarian funds holding a stock, the higher is the stock's contrarian score. Therefore, both the size and the commonality of the "bet" on a stock, by contrarian funds, matter.

**B. Contrarian Score and Stock Returns**

To evaluate the return-predictive power of the contrarian score at the individual stock level, we use the sorted portfolio approach. At the beginning of each calendar quarter, we classify sample stocks into quintiles based on the contrarian score. 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, Wermers, Yao, and Zhao (2007) show that the weighted average alpha approach performs better with more funds holding the stock, we require stocks to be 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 raw 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 to better control for changes in stock characteristics within the quarter.

Table 8 reports the results. For the equal-weighted portfolios, the average returns to the portfolio with 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 differences. The *t*-statistics are significantly positive for the unadjusted return spreads of Q3 and Q4 and for the characteristic-adjusted spreads during all four quarters. In addition, the value-weighted portfolios exhibit similar return patterns. These results suggest that stocks with high contrarian scores outperform stocks with low contrarian scores, especially after we control for momentum and other stock characteristics.

In unreported analyses, we have constructed the contrarian score based on fund trades instead of fund holdings. That is, we replace the portfolio weights in Equation (10) with portfolio weight changes during the past 4 quarters. We find that the trade-based contrarian score predicts future stock returns in a way similar to the holdings-based contrarian score (as reported in Table 8). However, the performance of portfolios formed on the trade-based contrarian score is noisier given noise in measuring fund trades. Therefore, we focus on the holdings-based contrarian score in subsequent analyses.

### C. Contrarian Score and Stock Characteristics

Next, we seek to understand the characteristics of stocks picked by contrarian funds. In Table 2, we already find evidence that contrarian funds strongly prefer high BM stocks and past losers. To obtain a broad view of the holding preferences of contrarian funds, here we examine an extensive list of stock characteristics, or quantitative signals.

First, we construct a stock-level herding index, HERD. This measure 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 most heavily sold by herds). Note that the contrarian score measures the degree to which a stock is held by contrarian funds, while HERD measures the degree to which a stock is bought or sold by herding funds.

We then construct eight stock characteristic measures. These measures represent stock characteristics in eight different dimensions – value, earnings momentum, investing and financing activities, intangible investments, earnings quality, uncertainty, profitability, and liquidity. Each measure is based on multiple variables constructed using data on stock price, trading volume, financial statements, and analyst forecasts, from CRSP, COMPUSTAT, and

IBES. Details of these measures are provided in the Appendix. Inputs for constructing these measures have been documented by existing literature to be related to subsequent stock returns. Understanding the relationship between the contrarian score and these characteristics can help us understand whether contrarian funds rely on certain quantitative criteria to select stocks.

In each quarter t, we sort stocks into quintiles based on their contrarian scores. Table 9 reports the average value of the eight sock characteristics as well as the average herding measure (HERD) during the most recent four quarters (quarters Qtr-3 to Qtr 0) for each contrarian score quintile portfolio. Not surprisingly, the contrarian score is significantly negatively correlated with the herding intensity, HERD, during the current (Qtr 0) and past three quarters (Qtr-3 to Qtr-1). In addition, stocks with higher contrarian scores have higher value characteristic, with lower earnings momentum, less investment and financing activities, higher intangible investments, better earnings quality, and lower information uncertainty.[15] They are also less profitable, and more illiquid.

### D. Sources of Superior Performance: Liquidity Provision, Quantitative Signals, or Fundamental Information?

To investigate potential sources of contrarian profit, we perform the following Fama-MacBeth regressions. The dependent variable is the DGTW characteristic-adjusted stock return during each of the four quarters after portfolio formation (Qtr+1 to Qtr+4). The main explanatory variable is the quintile rank of contrarian score of individual stocks. The control

[15] Note that we add negative signs to CAPEX, AG, and NS before combining them into the INVFIN variable. Stocks with high INVFIN are those with less investment and financing activities. The similar is for the UNCTN variable: the higher UNCTN, the less uncertainty.

variables include stock-level herding indexes (HERD) during the past four quarters (Qtr -3 to Qtr 0), as well as the eight return-predictive stock characteristics. Brown, Wei, and Wermers (2007) show that HERD is positively correlated with stock returns during the immediate following quarter, while being negatively correlated with stock returns in the subsequent three quarters.

The time series averages of the quarterly Fama-MacBeth regression coefficients and the corresponding *t*-statistics are reported in Table 10. When we do not include any control variables, the coefficient for the contrarian score is significantly positive during all four quarters (Qtr+1 to Qtr+4). When the herding indexes (HERD) for the past four quarters (Qtr -3 to Qtr 0) are included as control variables, the coefficients for the contrarian score become smaller, but are still significantly positive.[16] For example, during Qtr+1, the coefficient changes from 0.30 (without controls) to 0.22 (with controls for herding), but the t-statistics are always significant at the 5% level. 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. When we additionally include the eight return-predictive stock characteristics as control variables, the effect of contrarian score remains significant in quarters Qtr+1 and Qtr+2, but becomes weaker during Qtr+3 and Qtr+4. Therefore, trading on quantitative stock valuation signals partially explains the return-predictive information contrarian funds possess. However, neither liquidity provision nor reliance on quantitative

[16] 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 inclusion of herding measures in all four quarters prior to portfolio formation. Essentially, the persistence of fund herding delays the return reversal process.

signals can fully explain the stock picking ability of contrarian funds – thus the evidence is consistent with the hypothesis that contrarian funds also have value-relevant private information.

The private information of contrarian funds is unobservable by definition and difficult to quantify. However, we conjecture that if such information helps predict abnormal returns of a stock, it is likely related to the future operating performance of the firm. We therefore examine the operating performance of stocks with different contrarian scores, during the four quarters (Qtr+1 to Qtr+4) after portfolio formation. The operating performance measures include: Change in quarterly return on assets from 4 quarters ago (ΔROA), change in quarterly return on equity from 4 quarters ago (ΔROE), and change in sales growth over four quarters ago (ΔSG). We further compute the characteristic-adjusted and industry-adjusted operating performance measures. The characteristic-adjusted measures are the raw measures in excess of the median measure for the DGTW (1997) benchmark portfolios based on size, book-to-market, and momentum. The industry-adjusted measures are the raw measures in excess of industry median, where we use the first two digits of the SIC code for industry classification.

In each quarter we calculate the equal-weighted and value-weighted average operating performance measures for each stock quintile formed on the contrarian score, and then compute the time-series averages. The results are reported in Table 11. To save space we only report the operating performance measures averaged over the four quarters after portfolio formation (i.e., averaged over Qtr+1 to Qtr+4). The result on stocks' future operating performance reveals a quite consistent pattern: contrarian stocks have significantly higher

$\Delta$ROA, $\Delta$ROE, and $\Delta$SG in the following quarters, with or without characteristics/industry adjustments. Overall, the evidence on operating performance suggests that contrarian funds favor stocks that have improved profitability and accelerated sales growth – thus more likely to deliver positive future returns.

## 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."

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 two years. 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 is persistent for up to eight quarters and 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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## Appendix: Stock Characteristics Measures

We construct the following stock characteristic variables based on data from CRSP, COMPUSTAT, and IBES. The variables are measured at the end of each quarter t. m is the index for the last month of quarter t. When COMPUSTAT data is involved, a variable of quarter t means a variable for the fiscal quarter reported in calendar quarter t. The reporting date is from the COMPSTAT quarterly file. If the COMPUSTAT reporting date is missing, we assume a two month time lag between fiscal quarter end and reporting date.

**1. Value (VALUE)**

1) Earnings to price ratio (E/P): net income of quarter t, divided by market capitalization of common shares at the end of quarter t.

2) Long term growth forecast (LTG): analyst consensus forecast for long term growth rate during month m.

3) Sales growth (SG): Sales revenue of quarter t divided by sales revenue of quarter t-3.

**2. Earnings Momentum (EMOM)**

4) Analyst forecast revision (FREV): analyst consensus EPS forecast for the currently unreported fiscal quarter during month m, in excess of the consensus EPS forecast for the same fiscal quarter made during month m-3, divided by stock price at the time the consensus forecast of month m is measured.

5) Standardized unexpected earnings (SUE): EPS change from 4-quarter ago (i.e., EPS for quarter t minus EPS for quarter t-3), divided by the standard deviation of EPS changes from 4-quarter ago. The standard deviation is measured using EPS change of past 8 quarters, with a minimum of 4 quarters of observations required.

6) Earnings surprise (SUR): reported EPS for quarter t minus the last consensus EPS forecast prior to earnings announcement.

**3. Investment and Financing Activities (INVFIN):**

7) Capital expenditure (CAPEX): capital expenditure during quarter t-3 to quarter t, divided by the total assets of quarter t.

8) Asset growth (AG): total assets of quarter t divided by total assets of quarter t-3.

9) Net share issues (NS): total shares outstanding at the end of month m divided by total shares outstanding at the end of month m-11.

**4. Earnings Quality (EARNQUAL):**

10) Accruals (ACC): balance-sheet measure of accruals from quarter t-3 to quarter t, divided by the average total assets of quarter t-3 and quarter t. The balance-sheet measure of accruals is change in current assets, minus change in cash and short-term investments, minus change in current liabilities, plus change in debt in current liabilities, plus change in deferred taxes, minus depreciation.

11) Net operating assets (NOA): operating assets of quarter t minus operating liabilities of quarter t, divided by total assets of quarter t. Operating assets is total assets minus cash and short-term investments. Operating liabilities is total assets minus debt in current liabilities, minus long term debt, minus minority interests, minus preferred shares, minus common equity.

**5. Intangible Investments (INTANG)**

12) R&D Expenditure (RND): research and development expenditure of most recently reported fiscal year, divided by market cap at the end of the reported fiscal year. Note that we use annual data instead of quarterly data, because R&D data reported in COMPUSTAT quarterly file tends to be sporadic.

13) Advertising Expenditure (ADV): Advertising expenditure of most recently reported fiscal year, divided by market cap at the end of the reported fiscal year. Again we use the annual data for this measure because advertising expenditure is not reported in the COMPUSTAT quarterly file.

**6. Uncertainty (UNCTN)**

14) Idiosyncratic volatility (IVOL): standard deviation of residuals from regressing daily stock returns during quarter t onto daily market returns and 3 leads and 3 lags of market returns. CRSP value-weighted index is used as proxy for the market.

15) Analyst forecast dispersion (DISP): the cross-sectional standard deviation of EPS forecast for the unreported fiscal year, made during month m, divided by the stock price measured at the time of forecast.

**7. Profitability (PROF)**

16) Return on assets (ROA): net income of quarter t divided by the total assets at beginning of quarter t.

**8. Illiquidity (ILLIQ)**

17) Trading turnover (TURN): trading volume during quarter t divided by total shares outstanding at end of quarter t. A minimum of 44 daily observations are required.

18) Amihud illiquidity ratio (AMIHUD): the absolute daily return divided by the dollar amount of trading (number of shares traded multiplied by end-of-day stock price), averaged over quarter t. A minimum of 44 daily observations are required.

After constructing the 18 characteristic variables, we perform the following steps:

First, we adjust the sign of each variable so that variables of similar nature are in the same direction. For example, a high value of TURN is an indication of liquidity, while a high value of AMIHUD is an indication of illiquidity. So is the relationship between EP and SG. To make these variables consistent with each other, we add a negative sign in front of the following variables: LTG, SG, CAPEX, AG, NS, ACC, NOA, IVOL, DISP, TURN. After adjusting the signs, all the variables are expected to be positively correlated with future stock returns, based on evidence from existing literature.

Second, in each quarter we cross-sectionally rank all 18 signed variables into percentiles to make them comparable. For the two variables involving trading volume, TURN and AMIHUD, since NYSE/AMEX and NASDAQ report trading volume differently, we rank stocks mainly traded on NYSE/AMEX separately from those traded on NASDAQ.

Third, we combine 18 variables into 8 characteristic measures by taking the average of the percentile ranks. Specifically, Value is the average of percentile ranks of EP, -LTG, -SG. Earnings momentum is the average of percentile ranks of FREV, SUE, and SUR. Investment and Financing (INVFIN) is the average percentile ranks of CAPEX, AG, and NS. Intangible investment (INTANG) is the average percentile ranks of RND and ADV. Earnings quality (EARNQUAL) is the average percentile ranks of ACC and NOA. Uncertainty (UNCTN) is the average percentile ranks of IVOL and DISP. Profitability (PROF) is the percentile rank of a single variable, ROA. Finally, illiquidity (ILLIQ) is the average percentile ranks of TURN and AMIHUD.

If any of the 18 variables is missing, it is not used to compute the corresponding characteristic measure. We require a minimum of 9 non-missing characteristic variables for a stock to be included in our sample. If any of the resulting 8 characteristic measure is still missing, we replace it with the cross-sectional mean (across all valid stocks during the quarter t). However, if more than four resulting characteristic measures are missing the stock is excluded from the sample.

## 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 characteristics. Panel A reports total net asset value (TNA), total expenses, turnover ratio, age, quarterly fund flows, raw quarterly returns, volatility of flows in the past 12 months, volatility of returns in the past 36 months. Panel B reports the average size, B/M and momentum ranks of their stock holdings, and average proportion of contrarian trades. 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.

### Panel A: Fund Level Characteristics

| Contrarian Quintiles | CON4 | Fund Size | Total Exp. (%) | Turnover (%) | Fund Age | Flow (%) | Raw Ret (%) | Flow Volatility (%) | Return Volatility (%) |
|---|---|---|---|---|---|---|---|---|---|
| 1 | -1.6726 | 887 | 1.3401 | 90.4370 | 14.0981 | 2.0131 | 2.8975 | 3.6623 | 5.2562 |
| 2 | -1.0866 | 1031 | 1.3056 | 99.3530 | 15.2007 | 1.4413 | 2.8747 | 3.3708 | 4.9346 |
| 3 | -0.7716 | 1122 | 1.2789 | 94.9080 | 14.9914 | 1.3036 | 2.8805 | 3.2871 | 4.7311 |
| 4 | -0.4391 | 1163 | 1.2672 | 86.3670 | 15.2082 | 1.3943 | 2.8498 | 3.2951 | 4.5836 |
| 5 | 0.2651 | 1293 | 1.2995 | 67.6900 | 15.2269 | 1.9726 | 2.9521 | 3.3574 | 4.4386 |
| 5-1 | 1.9377 | 406 | -0.0406 | -22.7470 | 1.1288 | -0.0004 | 0.0546 | -0.3049 | -0.8176 |
| | (74.32)[a] | (3.42)[a] | (-2.66)[b] | (-7.10)[a] | (2.89)[a] | (-0.05) | (0.10) | (1.51) | (8.92)[a] |

**Panel B: Holdings/Trade Characteristics**

| Contrarian Quintiles | Size Rank | B/M Rank | Mom Rank | % of Contrarian Trades |
|---|---|---|---|---|
| 1 | 4.3121 | 2.3203 | 3.1853 | 0.3337 |
| 2 | 4.3901 | 2.4536 | 3.1122 | 0.3820 |
| 3 | 4.4422 | 2.5844 | 3.0075 | 0.4121 |
| 4 | 4.4738 | 2.7099 | 2.9002 | 0.4454 |
| 5 | 4.4827 | 2.8591 | 2.7636 | 0.5066 |
| 5-1 | 0.1706 | 0.5388 | -0.4217 | .0.1729 |
| | (2.64) [b] | (14.84) [a] | (-17.07) [a] | (44.97)[a] |

## 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 (*CON* ) 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.

| Contrarian Index | Low (Q1) | 2 | 3 | 4 | High (Q5) | High-Low (Q5-Q1) |
|---|---|---|---|---|---|---|
| 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, and the interaction term between the contrarian index and a dummy variable indicating market downturns (defined as quarters with market returns in the bottom 33%). 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** | **Quarterly Carhart 4-Factor Adjusted Fund Returns (in %)** | | | | |
|---|---|---|---|---|---|
| **Intercept** | 1.2792 | 1.1345 | 0.9084 | 1.1280 | 1.2603 |
| | (7.71)[a] | (6.65)[a] | (5.09)[a] | (6.59)[a] | (7.37)[a] |
| **Contrarian Index** | 0.2155 | | | 0.1983 | 0.1157 |
| | (6.33)[a] | | | (6.00)[a] | (3.42)[a] |
| **Momentum Trading** | | -0.6523 | | -0.5184 | -0.5012 |
| | | (-4.08)[a] | | (-3.28)[a] | (-3.17)[a] |
| **Illiquid Stock Trading** | | | 1.1382 | 1.0023 | 0.9875 |
| | | | (4.42)[a] | (3.90)[a] | (3.85)[a] |
| **Fund Size** | -0.0521 | -0.0475 | -0.0444 | -0.0443 | -0.0437 |
| | (-4.13)[a] | (-3.72)[a] | (-3.50)[a] | (-3.57)[a] | (-3.52)[a] |
| **Fund Age** | -0.0525 | -0.0604 | -0.0379 | -0.0493 | -0.0493 |
| | (-1.84)[c] | (-2.11)[b] | (-1.30) | (-1.71)[c] | (-1.71)[c] |
| **Total Expenses** | -11.6964 | -11.7287 | -14.3023 | -14.0301 | -14.0008 |
| | (-1.70)[c] | (-1.70)[c] | (-2.01)[b] | (-2.01)[b] | (-2.01)b |
| **Turnover** | 0.0533 | 0.0342 | 0.0435 | 0.0545 | 0.0544 |
| | (0.63) | (0.41) | (0.52) | (0.64) | (0.64) |
| **Past Flows** | 1.3332 | 1.5181 | 1.2968 | 1.4173 | 1.4150 |
| | (3.48)[a] | (3.85)[a] | (3.41)[a] | (3.65)[a] | (3.64)[a] |
| **Contrarian Index*down** | | | | | 0.2438 |
| | | | | | (3.78)[a] |
| **Time Dummy** | Yes | Yes | Yes | Yes | Yes |
| **Clustering by Funds** | Yes | Yes | Yes | Yes | Yes |
| **Number of Obs** | 58689 | 58702 | 58711 | 58683 | 58683 |

### Table 8: Contrarian Scores 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: Contrarian Score, Herding Intensity, and Quantitative Stock Characteristics**

In each quarter t we sort stocks into quintiles based on the contrarian score. For each quintile we calculate the average herding index (HERD) for the four quarters from quarters Qtr-3 to Qtr 0, as well as eight stock characteristic measures. HERD is herding intensity based on the quintile ranks of buy-herd and sell-herd measures. VALUE is the value measure. EMOM is earnings momentum. INVFIN is a measure of investment and financing activities. INTANG measures intangible investments. EARNQUAL is an earnings quality measure. UNCTN is a measure of uncertainty. PROF is a profitability measure. ILLIQ is a measure if illiquidity. These measures are constructed by averaging over the percentile ranks of underlying variables, the details of which are provided in Appendix. The underlying variables are signed so that a higher value of the variable is associated with higher subsequent stock return based on evidence from existing literature. We also report the difference in herding intensity and stock characteristics between the top and bottom stock quintiles. Inside parentheses are the Newey-West t-statistics.

| Contrarian Score | HERD (Qtr 0) | HERD (Qtr-1) | HRED (Qtr-2) | HERD (Qtr-3) | VALUE | EMOM | INVFIN | INTANG | EARN-QUAL | UNCTN | PROF | ILLIQ |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 (Low) | 1.12 | 1.47 | 1.45 | 1.34 | 39.04 | 56.15 | 34.95 | 29.74 | 46.10 | 58.67 | 67.11 | 23.50 |
| 2 | 0.62 | 0.81 | 0.81 | 0.80 | 48.15 | 53.81 | 41.86 | 34.56 | 47.08 | 62.15 | 64.20 | 25.91 |
| 3 | 0.33 | 0.44 | 0.47 | 0.49 | 54.32 | 51.87 | 46.66 | 38.41 | 47.71 | 63.69 | 62.90 | 27.63 |
| 4 | 0.10 | 0.12 | 0.17 | 0.18 | 57.94 | 48.94 | 50.21 | 41.21 | 48.51 | 63.65 | 60.94 | 28.76 |
| 5 (High) | -0.26 | -0.35 | -0.30 | -0.19 | 59.52 | 45.81 | 53.73 | 46.94 | 48.54 | 60.37 | 57.23 | 31.26 |
| High - Low | -1.39 | -1.82 | -1.75 | -1.53 | 20.48 | -10.34 | 18.78 | 17.20 | 2.44 | 1.70 | -9.88 | 7.76 |
| | (-15.66) | (-23.10) | (-19.66) | (-19.89) | (22.40) | (-27.41) | (30.36) | (18.77) | (3.09) | (2.14) | (-14.26) | (9.52) |

## Table 10: Fama-MacBeth Regressions: Contrarian Score, Herding, Quantitative Signals, and Stock Returns

This table reports results from quarterly Fama-MacBeth regressions. The dependent variable is the DGTW (1997) characteristic-adjusted stock return of each stock in one of the four quarters after portfolio formation, Qtr+1 to Qtr+4. The main explanatory variable is the contrarian score for individual stocks. The control variables include the herding intensity measure HERD in the most recent four quarters (Qtr -3 to Qtr 0), and the eight quantitative stock characteristics measured for the portfolio formation quarter (Qtr 0). The time series averages of coefficients and their corresponding t-statistics, using the Newey-West covariance procedure, are reported in parentheses.

| Dependent Variable | Characteristics-adjusted Returns | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Qtr +1 | Qtr +2 | Qtr +3 | Qtr +4 | Qtr +1 | Qtr +2 | Qtr +3 | Qtr +4 | Qtr +1 | Qtr +2 | Qtr +3 | Qtr +4 |
| Contrarian Score | 0.30 | 0.31 | 0.25 | 0.21 | 0.22 | 0.21 | 0.16 | 0.15 | 0.23 | 0.16 | 0.01 | 0.05 |
| | (2.61) | (2.55) | (2.11) | (2.16) | (2.06) | (2.98) | (1.65) | (1.71) | (2.33) | (1.92) | (0.06) | (0.69) |
| HERD (Qtr 0) | | | | | -0.05 | -0.07 | -0.08 | -0.07 | 0.01 | -0.03 | -0.09 | -0.06 |
| | | | | | (-0.97) | (-2.00) | (-2.39) | (-2.13) | (0.31) | (-1.10) | (-2.79) | (-1.82) |
| HERD (Qtr -1) | | | | | -0.05 | -0.07 | -0.07 | -0.09 | -0.01 | -0.08 | -0.04 | -0.07 |
| | | | | | (-1.54) | (-2.14) | (-2.64) | (2.36) | (-0.44) | (-2.47) | (-1.48) | (-1.71) |
| HERD (Qtr -2) | | | | | -0.06 | -0.07 | -0.08 | -0.03 | -0.05 | -0.05 | -0.04 | 0.00 |
| | | | | | (-2.22) | (-2.76) | (-2.21) | (-0.70) | (-1.70) | (-1.85) | (-1.26) | (0.16) |
| HERD (Qtr -3) | | | | | -0.10 | -0.10 | 0.01 | 0.01 | -0.06 | (-0.09) | 0.03 | 0.07 |
| | | | | | (-3.31) | (-2.36) | (0.08) | (0.32) | (-1.66) | (-2.27) | (1.11) | (1.66) |
| VALUE | | | | | | | | | -4.09 | -2.39 | -0.65 | -0.56 |
| | | | | | | | | | (-2.78) | (-1.76) | (-0.53) | (-0.41) |
| EMOM | | | | | | | | | -1.34 | -0.32 | -0.79 | -0.21 |
| | | | | | | | | | (-1.70) | (-0.34) | (-0.92) | (-0.28) |
| INVFIN | | | | | | | | | 1.66 | 0.50 | -0.31 | 0.03 |
| | | | | | | | | | (1.81) | (0.57) | -(0.46) | (0.05) |
| INTANG | | | | | | | | | 2.66 | 2.00 | 1.80 | 1.25 |
| | | | | | | | | | (2.93) | (2.53) | (2.25) | (1.32) |
| EARNQUAL | | | | | | | | | 4.73 | 3.59 | 3.35 | 3.66 |
| | | | | | | | | | (5.18) | (4.19) | (4.12) | (4.12) |
| UNCTN | | | | | | | | | -2.20 | -1.93 | -2.28 | (-1.69) |
| | | | | | | | | | (-1.56) | (-1.37) | (-1.72) | -(1.23) |
| PROF | | | | | | | | | 0.02 | 0.01 | 0.01 | 0.02 |
| | | | | | | | | | (2.34) | (1.01) | (1.07) | (2.51) |
| ILLIQ | | | | | | | | | -0.84 | -0.53 | 0.15 | 0.26 |
| | | | | | | | | | (-0.65) | (-0.39) | (0.11) | (0.19) |

## Table 11: Contrarian Score and Operating Performance

In each quarter, we sort stocks into equal-weighed (Panel A) and value-weighted (Panel B) quintile portfolios based upon their contrarian scores and report their average operating performance measures: changes quarterly return on assets (ΔROA), changes of quarterly return on equity (ΔROE), and changes of quarterly sales over 4 quarter ago (ΔSG). We further report the characteristics-adjusted and industry-adjusted operating performance measures, which are calculated as the raw measures in excess of the DGTW characteristics benchmarks and industry benchmarks. The operating performance measures reported in the table are the averages over the four quarters after portfolio formation (i.e., averaged from Qtr+1 to Qtr+4). t-statistics calculated with Newey-West robust standard errors are reported in parentheses.

### Panel A: Equal-weighted Portfolios

| | Unadjusted Measures | | | Characteristics-adjusted Measures | | | Industry-adjusted Measures | | |
|---|---|---|---|---|---|---|---|---|---|
| Contrarian Score | ΔROA | ΔROE | ΔSG | ΔROA | ΔROE | ΔSG | ΔROA | ΔROE | ΔSG |
| 1 (Low) | -0.30 | -1.25 | -3.54 | -0.27 | -0.96 | -2.66 | -0.24 | -0.93 | -2.83 |
| | (-3.08) | (-8.37) | (-5.11) | (-4.35) | (-11.0) | (-7.29) | (-3.59) | (-9.46) | (-7.41) |
| 2 | -0.12 | -0.93 | -1.69 | -0.07 | -0.72 | -1.14 | -0.08 | -0.68 | -1.19 |
| | (-1.74) | (-6.13) | (-3.30) | (-1.92) | (-7.34) | (-4.54) | (-1.99) | (-6.79) | (-5.15) |
| 3 | -0.14 | -0.70 | -0.74 | -0.09 | -0.52 | -0.36 | -0.11 | -0.47 | -0.39 |
| | (-1.93) | (-4.41) | (-1.68) | (-2.06) | (-4.82) | (-1.77) | (-2.55) | (-4.59) | (-2.20) |
| 4 | -0.11 | -0.65 | 0.03 | -0.06 | -0.49 | 0.33 | -0.07 | -0.42 | 0.21 |
| | (-1.84) | (-3.66) | (0.10) | (-1.53) | (-3.90) | (2.45) | (-2.24) | (-3.86) | (1.26) |
| 5 (High) | -0.08 | -0.64 | 0.43 | 0.00 | -0.43 | 0.75 | -0.02 | -0.38 | 0.54 |
| | (-1.04) | (-3.15) | (1.38) | (-0.07) | (-2.76) | (5.51) | (-0.51) | (-2.77) | (4.79) |
| High-Low | 0.23 | 0.61 | 3.96 | 0.27 | 0.54 | 3.41 | 0.22 | 0.55 | 3.37 |
| | (3.19) | (4.51) | (8.45) | (4.24) | (3.91) | (9.72) | (3.38) | (4.32) | (8.65) |

**Panel B: Value-weighted Portfolios**

| Contrarian Score | Unadjusted Measures | | | Characteristics-adjusted Measures | | | Industry-adjusted Measures | | |
|---|---|---|---|---|---|---|---|---|---|
| | ΔROA | ΔROE | ΔSG | ΔROA | ΔROE | ΔSG | ΔROA | ΔROE | ΔSG |
| 1 (Low) | -0.36 | -1.48 | -3.74 | -0.33 | -1.16 | -2.89 | -0.30 | -1.15 | -2.89 |
| | (-2.50) | (-6.22) | (-5.15) | (-3.25) | (-6.82) | (-7.44) | (-2.63) | (-6.17) | (-6.46) |
| 2 | -0.01 | -0.54 | -1.68 | 0.00 | -0.38 | -1.25 | 0.04 | -0.23 | -1.10 |
| | (-0.13) | (-2.47) | (-4.22) | (-0.05) | (-2.35) | (-5.94) | (0.67) | (-1.40) | (-5.58) |
| 3 | -0.05 | -0.21 | -0.61 | -0.06 | -0.11 | -0.39 | -0.02 | 0.04 | -0.38 |
| | (-0.78) | (-1.45) | (-1.66) | (-1.32) | (-1.05) | (-2.30) | (-0.55) | (0.31) | (-2.29) |
| 4 | 0.02 | -0.02 | 0.06 | 0.04 | 0.08 | 0.22 | 0.06 | 0.19 | 0.30 |
| | (0.28) | (-0.13) | (0.18) | (0.80) | (0.76) | (1.24) | (1.30) | (1.53) | (1.48) |
| 5 (High) | -0.06 | -0.31 | 0.13 | -0.02 | -0.18 | 0.32 | 0.00 | -0.07 | 0.20 |
| | (-0.70) | (-1.19) | (0.38) | (-0.38) | (-0.90) | (1.47) | (0.01) | (-0.34) | (0.82) |
| High-Low | 0.31 | 1.17 | 3.87 | 0.31 | 0.98 | 3.21 | 0.30 | 1.08 | 3.10 |
| | (2.63) | (4.02) | (7.52) | (3.19) | (3.79) | (8.65) | (2.84) | (4.11) | (7.46) |

**Figure 1: Difference in Carhart (1997) Four-factor Alpha between Top and Bottom Fund Quintiles Sorted on Contrarian Index**