Uncommon Value: The Characteristics and Investment Performance of Contrarian Funds*

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Abstract

Theories of herding behavior predict that only investors with sufficiently precise private information or those most overconfident will deviate from the crowd. Using portfolio holdings, this paper identifies contrarian funds as those pursuing distinctive investment strategies, i.e., as those most frequently trading against the "herd" (against the majority of funds). We find that contrarian funds tend to experience greater inflows and past performance, indicating that their managers either have lower career concerns or are overconfident when trading against the crowd. Our analysis of both fund holdings and trades reveals that contrarian funds possess superior stock selection information (rather than merely being overconfident), and also frequently benefit from their provision of liquidity to herding funds by trading against them. As a consequence, contrarian funds exhibit significantly higher Carhart (1997) four-factor alphas, net of expenses, even after controlling for various performance-relevant fund characteristics. We further compute a stock-level contrarian score that reflects the aggregate information possessed by contrarian funds. Top-decile contrarian stocks outperform bottom-decile stocks by a characteristic-adjusted return of 0.49% per quarter during the four quarters after portfolio formation. Further investigation shows that the stock selection information captured by the contrarian score is not subsumed by the return-predictive information contained in an extensive list of quantitative stock characteristics derived from past research. Our findings suggest that contrarian managers possess unique fundamental stock information.

"Worldly wisdom teaches that it is better for reputations to fail conventionally than succeed unconventionally"

—John Maynard Keynes

Echoing the well-known warning of Keynes, the popular media have long criticized institutional investment managers for their tendency to trade together in a "herd-like" manner, showing little ability to implement distinct investment strategies.[1] Academic studies seem to reinforce this impression by documenting commonalities in stock trades by institutional investors (e.g., Grinblatt, Titman, and Wermers, 1995, Wermers, 1999; and Sias, 2004). In a related literature, researchers have noted a significant decline in the proportion of skilled fund managers amid the rapid growth of the fund industry in recent decades (Barras, Scaillet, and Wermers, 2010; Fama and French, 2010). For example, Fama and French (2010) characterize the recent mutual fund industry growth as "the entry of hordes of mediocre funds posturing as informed managers."

Recently, several studies have attempted to identify successful investment managers by the distinctiveness of their strategies. Two representative studies, Titman and Tiu (2010) and Sun, Wang, and Zheng (2011), measure the distinctiveness of investment strategies by the correlation of hedge fund returns with either peer group returns or passive benchmark factors, and show that hedge fund managers with distinctive strategies tend to generate superior performance. Meanwhile, an on-going debate in this literature suggests that certain aspects of the link between strategy distinctiveness and investment skills deserve further examination. Bollen (2012) finds that hedge funds scoring higher on strategy uniqueness tend to have higher failure rates. He further points out that measuring strategy uniqueness based on fund returns may fail to capture the full picture of risk exposure when dynamic investment strategies are employed, or when reported returns are artificially smoothed.

[1] For instance, Louis Rukeyser of *Wall $treet Week* once lamented 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."

In this study, we identify mutual fund managers pursuing distinctive investment strategies by examining the holdings and trades of contrarian managers. Our study is motivated by the existing literature documenting the scarcity of informed fund managers. First, while some empirical research has investigated the trades and performance of institutional investors that herd or use common strategies, little is known about contrarian investors, or those with “uncommon strategies.”[2] Second, by identifying contrarians through their portfolio trades, we are able to generate a much clearer picture of contrarian investing beyond what can be learned from reported fund returns. Further, by analyzing the performance of the holdings and trades, we are better able to analyze the potential source of any performance differences between contrarian and herding managers.[3]

Specifically, we try to address several important questions about contrarian funds. First, what drives certain funds to invest in a contrarian way? Second, is there any systematic reward to the contrarian investment strategy? Third, if contrarian funds outperform, what are the economic sources of their outperformance—do they outperform simply by trading against herds, or do they follow more distinct and successful investment strategies than herds?

Whether contrarian funds outperform depends on the economic rationale for their contrarian behavior. For example, Scharfstein and Stein (1990) develop a widely cited model where "smart" managers discard their information and herd with "dumb" managers when their career concerns outweigh the expected value of their private information. In such a model, if the private information of a smart manager is precise enough, it will lead the manager to not discard this information, even with reputational risks. Therefore, under this theory, the best informed mutual fund managers are contrarian

[2] Interestingly, there is evidence of successful contrarian behavior in other areas of financial markets. For example, Clement and Tse (2005) show that bold sell-side analyst forecasts are more accurate predictors of company earnings than herding analyst forecasts.
[3] In addition to the rich data on fund level holdings, an added benefit of focusing on mutual funds is that equity mutual funds typically do not aggressively employ dynamic trading strategies and do not have much flexibility in smoothing reported returns. Therefore, our study is unlikely to suffer from the problems raised in Bollen (2012).

managers: they trade on superior private information. And, under this theory, we would expect contrarian funds to outperform herding funds.[4]

Alternatively, contrarian fund managers may arise because they are overconfident about their private signals or abilities (Daniel, Hirshleifer, and Subrahmanyan, 1998), or contrarian funds may be forced to trade against investment signals pursued by their peers because of idiosyncratic flow shocks from their investors. In either of these latter two cases, we would expect contrarian funds to underperform. Thus, an analysis of the performance and characteristics of contrarian funds through portfolio holdings and trades may reveal the true nature of contrarian behavior in the investment management industry.

The theories cited above suggest a natural approach to measuring "contrarianism". Accordingly, we identify contrarian funds, not based on any particular investment style, but based on the degree to which the fund trades against herds, whether due to private information or to overconfidence. Our method is very simple: funds with a high contrarian index are those most frequently making large trades against the herd—especially when large numbers of funds are herding—while funds with a low contrarian index are those most frequently trading with the herd. For instance, if most mutual funds are buying IBM and selling Cisco during 2001, then a fund that is selling IBM and buying Cisco during that year would exhibit a high contrarian index.

We apply our contrarian measure to analyze all actively managed U.S. domestic equity mutual funds over the 1995 to 2008 period. We find that funds with a greater contrarian index tend to be larger and have lower turnover than other funds, characteristics that may be consistent with an ability to provide liquidity to herding funds. Further, contrarian funds tend to be more successful in the past, in that they have greater past alphas and inflows and are more likely to be rated as star funds, which suggests that contrarian fund managers are either less career-concerned and, thus, less compelled to

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[4] Contrarian funds may augment this outperformance by countering the price destabilizing behavior of herding (i.e., they provide liquidity to herding funds), since recent studies show that herds generate large temporary price pressure that subsequently reverts itself (e.g., Brown, Wei and Wermers, 2011 and Puckett and Yan, 2007).

follow the crowd, or they have become overconfident from their recent successes (which may be partly due to luck). Moreover, the trades of contrarian funds exhibit low commonality among themselves. This indicates that besides trading against fund herds, contrarian funds pursue strategies quite distinctive from each other. 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 take a close look at the holdings and trades of contrarian funds to assess whether they make informed stock selection decisions. Using reported fund holdings, we compute the stock selectivity measure for each fund following Daniel et al (1997). By this measure, the most contrarian quintile of funds outperforms the least contrarian quintile (i.e., those funds that tend to herd most frequently and strongly). Moreover, this performance difference remains significantly positive for at least four quarters, suggesting that a feasible and profitable strategy is available to investors who simply obtain access to fund holdings information through their quarterly SEC filings.

We then analyze fund trades to explore the potential sources of superior stock selection by contrarian funds. If contrarian funds profit entirely by providing liquidity to herding funds, we would expect their trades to initially lose money due to the price pressure induced by herding funds, prior to turning a profit (when the price recovers). However, if they outperform due to their information advantage over herding funds, they should outperform herding funds much more quickly—and, they should generate superior performance even when they trade in the same direction as mutual fund herds. A breakdown of trades made by contrarian funds indicates that the superior performance of contrarian funds tends to be concentrated in quarters t+3 and t+4, when they buy stocks heavily sold by mutual fund herds during quarter t. However, when they buy stocks lightly sold by herds, where the profit from liquidity provision is likely to be minimal, contrarian funds tend to display superior performance during the immediately following quarter t+1. In addition, contrarian funds not only outperform with their contrarian trades, they also outperform with their herding trades, especially with the most heavily herded stocks, over the four quarters following the herding measurement quarter. These findings suggest that contrarian funds not only profit from liquidity provision to herding funds, they also benefit from their superior private information relative to herding funds.

Further, we investigate whether contrarian funds outperform herding funds because they have different performance-related fund characteristics. For instance, contrarian funds tend to be larger and exhibit lower turnover, which may be associated with lower trading costs. Accordingly, we examine reported after-expense returns of funds in a multivariate setting. We find evidence that the fund-level contrarian index, measured during a particular quarter, is a significant predictor of fund alphas during the subsequent four quarters, after controlling for various fund characteristics already known to be correlated with fund outperformance. In particular, we find that the ability of the contrarian index to predict fund abnormal performance remains even after controlling for the effect of strategy uniqueness (Titman and Tiu, 2010 and Amihud and Goyenko, 2011) and the effect of Active Share (Cremers and Petajisto, 2009), which might capture some aspects (but, we argue, not nearly all) of contrarianism.

Finally, we examine whether the superior performance of contrarian funds translates into a successful stock-picking signal. Since contrarian funds 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. To accomplish this, we follow the approach of Wermers, Yao, and Zhao (2011) to extract the stock selection information of contrarian funds from fund holdings. This approach results in a stock-level measure of contrarianism–termed the "contrarian score", which can be interpreted as a measure of the relative degree to which a stock is held by contrarian funds vs. herding funds. We find that stocks ranked in the top contrarian score decile at the end of quarter t exhibit significantly higher DGTW-adjusted returns than stocks ranked in the bottom decile: a zero-cost strategy earns a DGTW-adjusted alpha exceeding 0.57% during quarter t+1, and an average of 0.49% (per quarter) during quarters t+1 to t+4.

Upon further examination, we find that stocks with a high (low) contrarian score tend to be those heavily sold (bought) by the majority of herding funds. This is consistent with the contrarian nature of stock selection information. Second, stocks with higher contrarian scores exhibit stronger value-oriented characteristics, lower levels of investment and financing activities, higher operating efficiency, more intangible investments, and greater illiquidity. Third, these stocks tend to have lower earnings momentum, higher information uncertainty, and lower accounting profitability. Interestingly, we find that contrarian stocks continue to outperform even after we control for the return reversals associated with herding as well as the effects of aforementioned (and other) return-predictive quantitative characteristics. Overall, the stock level evidence confirms that contrarian funds are not merely overconfident following good (and, perhaps, partially lucky) performance. While they profit from liquidity provision to herding funds, they also appear to have better information about stock fundamentals than the majority of mutual funds.[5]

Our study is most closely related to the recent literature that identifies skilled investment managers based on the distinctiveness of the strategies they use (see, e.g., Titman and Tiu, 2010; Amihud and Goyenko, 2011 and Sun, Wang, and Zheng, 2011). A distinction of our study from these existing studies is that we identify contrarian or "uncommon" strategies based on fund trades, instead of fund returns. Our analysis of fund holdings and trades enable us to provide direct evidence on informed stock selection by contrarian managers. In addition, our stock-level approach extends the usefulness of our contrarian measure to quantitative equity investment strategies. Another important distinction between our contrarian measure and the return-based strategy uniqueness measures is that funds whose return structures deviate substantially from those of their peers (e.g., low R^2 funds in Titman and Tiu (2010) and Amihud and Goyenko (2011)) include both contrarian funds and extreme

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[5] In a recent study, Massa and Yadav (2012) show that some mutual funds engage in "sentiment contrarian" behavior, i.e., loading negatively on the market sentiment when sentiment is high. However, they find that "sentiment contrarian" funds do not outperform after controlling for the sentiment risk. Therefore, these funds appear to profit merely from sentiment-risk taking.

herding funds. Therefore, as our analysis shows, the performance-predictive power of the contrarian measure is not subsumed by strategy uniqueness measures.

Our study is also related to Kacperczyk, Sialm and Zheng (2005) and Cremers and Petajisto (2009), who study the degree of active management by mutual funds. We show that, while both herding and contrarian funds tend to deviate from benchmarks to a greater degree, our measure of contrarianism continues to predict fund returns controlling for measures of fund activeness. Finally, the evidence in our paper is consistent with Da, Gao and Jagannathan (2011) that mutual fund managers can profit from both informed trading and liquidity provision. Moreover, our study suggests a direct approach through which investors can ex-ante identify fund managers with such abilities.

I. Data and Methodology

I.A. Mutual Fund Sample

Our sample of mutual funds includes those that exist in both the Thomson-Reuters mutual fund holdings data and the CRSP mutual fund database during the period of 1995 to 2008. Funds in these two datasets are matched via the MFLINKS file (available from Wharton Research Data Services, WRDS). We focus on this period since recent research indicates that the count of mutual funds has expanded so quickly that herds have become more destabilizing to equity markets (Brown, Wei and Wermers, 2011 and Dasgupta, Prat and Verardo, 2011).[6] This provides motivation to study whether there exist funds that do not engage in herding behavior. The Thomson-Reuters data provide quarterly snapshots of portfolio holdings for most U.S.-based equity mutual funds. We infer mutual fund trades from quarterly changes of portfolio holdings for each fund, adjusting for splits and stock dividends. Prior to 2004, some funds report their holdings at the semiannual frequency. In order to obtain a timely

[6] For example, Wermers (1999) and Brown, Wei and Wermers (2011) do not find mutual fund herding to be price destabilizing prior to mid-1990s. Similarly, Dasgupta, Prat and Verardo (2011) show that persistent institutional trading leads to long-term return reversals mainly in the post-1994 period.

and precise measure of contrarian investing based upon fund trades, we do not include these fund quarters in our sample.

Information on fund net returns, flows, investment objectives and other characteristics is obtained from the CRSP mutual fund database. We combine multiple share classes of a fund in the CRSP database into a single portfolio (value-weighted, based on beginning-of-quarter total net asset values of each share class) before matching the CRSP data with the Thomson-Reuters data. Since our focus is on the trading behavior of actively managed U.S. domestic equity funds, we exclude index funds, international funds, municipal bond funds, bond and preferred stock funds, and metals funds. To be included in the final sample for a given calendar quarter, a fund is required 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 filters are imposed to reduce the potential noise in our measure of contrarianism based upon inferred fund trades.

I.B. Construction of Fund Contrarian Index

We define contrarian funds as those that tend to trade against mutual fund herds, and take the following steps to construct a measure of contrarian trading. First, we obtain 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 quarter t. $\overline{p}_t$, a proxy for the expected value of $p_{i,t}$, is the cross-sectional mean of $p_{i,t}$ over all stocks traded by all 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).[7] We exclude stocks

[7] Similar to Wermers (1999) and Brown, Wei, and Wermers (2011), we require a stock to be traded by at least ten funds during a given quarter in order to construct a meaningful measure of fund herding following Eq. (1).

that are newly issued within the prior four quarters, as funds are likely to acquire such new issues simultaneously simply because they represent new constituents of their benchmark portfolios. Furthermore, since mutual fund trades could be influenced by extreme flows as opposed to information, we exclude flow-driven trades when classifying trades.[8] Specifically, buy trades made by funds experiencing flows ranked in the top 10 percentile or sell trades made by funds experiencing flows ranked in the bottom 10 percentile during a particular quarter are excluded in the calculation of the stock-level herding measure HM in (1).

Next, we classify a stock as a "buy-herd" or "sell-herd" stock depending on whether the proportion of mutual fund buys is higher or lower than the average for that quarter. The conditional buy-herding (BHM_{it}) and sell-herding (SHM_{it}) measures are calculated as follows:

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

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

The buy-herding and sell-herding measures BHM and SHM are then combined into a single variable, $HERD_{it}$. For buy-herding stocks, we rank their buy-herding measure, BHM, into quintiles, and assign $HERD_{it}$ a value ranging from 1 to 5, with 5 for stocks in the top buy-herding quintile. We rank sell-herding stocks similarly. However, we assign $HERD_{it}$ a value ranging from -5 to -1, with -5 for stocks in the top sell-herding quintile (stocks most heavily sold by herds). Thus, more positive values of HERD indicate stronger buy-herding, while more negative values indicate stronger sell-herding. This nonparametric ranking procedure reduces the influence of outliers in our classification of contrarian versus herding funds.[9]

[8] Our results remain quantitatively and qualitative similar when we do not exclude flow-driven trades.

[9] Our results to follow, however, are not materially different if we instead use each stock's parametric LSV (1992) herding measure.

Finally, we create a fund-level contrarian index, CON_{jt}, as a trade-weighted average of HERD (multiplied by -1) across all stocks traded by a fund:

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

where the trade weight ω_{ijt} is defined as

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

with $v_{ij,t}$ being stock i's dollar value held by fund j at the end of quarter t, and N being the total number of stocks traded by the fund. The lagged dollar value of holding, $v_{ij,t-1}$, is calculated using the number of shares of stock i held by fund j at time t-1, multiplied by the stock price at time t. The number of shares at t-1 is split-adjusted using the CRSP share adjustment factor so that it is defined on the same share basis as of time t. Thus, $v_{ij,t} - v_{ij,t-1}$ measures the signed dollar value of an active trade. It has a positive value for a stock bought by a fund during the period, and a negative value for a stock sold by a fund. If there is no trade but only price change between the two dates, its value is zero by construction.

Note that there is a negative sign in front of the summation operation in Equation (4). By construction, if a fund purchases a stock sold by herds, $HERD_{it}$ has a negative value and ω_{ijt} has a positive value. This trade would contribute positively to the fund's contrarian measure *CON*. On the other hand, if a fund purchases a stock bought by herds, $HERD_{it}$ has a positive value and ω_{ijt} has a positive value. This trade would contribute negatively to the fund's contrarian measure *CON*. The same logic applies to fund sales of stocks bought or sold by herds. Also note that value of *CON* is bounded between -5 to 5. For example, if all trades of a fund are contrarian trades (i.e., purchase of sell-herding stocks and sale of buy-herding stocks) in stocks with the highest herding measures (i.e., HERD taking a value of either -5 or 5), then *CON* will take a value of 5—indicating an extreme contrarian fund. Funds conducting a mixture of herding and contrarian trades will have *CON* values between -5 and 5. A *CON* value of zero means that a fund's (dollar-weighted) trades are equally split between herding and contrarian trades.

Table 1 reports summary statistics for the fund contrarian index and other fund characteristics. Note that the mean and the median of the contrarian index are both negative (-0.75 and -0.76). This is not surprising, given that—by definition of herding—the majority of trades made by mutual funds are considered as herding trades. In addition, the cross-sectional standard deviation of the contrarian index is 0.87, which suggests significant dispersion of the herding/contrarian behavior among our sample funds. Note that even the 75th percentile of *CON* is negative, at -0.23. This suggests that funds systematically pursuing contrarian investing constitute a relatively small group.

II. Explaining Contrarianism

II.A. Comparing Contrarian with Herding Funds

How are contrarian funds different? Since they trade differently from their peers by definition, it is useful to compare fund characteristics between herding funds and contrarian funds, as well as the characteristics of their holdings. First, we quantify the intensity of contrarian trades using the average frequency of contrarian trades across *CON* quintiles. This analysis allows us to understand the extent to which contrarian funds differ from herding funds in their trades. If we consider funds in the top *CON* quintile as contrarian funds and those in the bottom quintile as herding funds, Panel A of Table 2 shows that only slightly more than half (53%) of trades by contrarian funds are contrarian trades. Since the average *CON* index for these funds is significantly positive, this indicates that their contrarian trades (those trades made in a direction opposite to herds) tend to be larger in value than their other trades. This would be plausible if small trades are driven by motivations such as staying close to fund benchmarks, as opposed to private information.[10] Moreover, the fact that a significant portion of contrarian fund trading (47%) is with fund herds suggests that contrarian funds may strategically choose to trade with or against herds based upon their private information, instead of trading mechanically against them. Note that among these *CON* quintile fund portfolios, only the top quintile funds have positive *CON*. This reinforces the notion that truly contrarian funds are indeed a small group. This is not surprising, given that contrarian funds, by nature, trade against the majority of other funds. If too many funds are classified as contrarian funds, then their (contrarian) trades would more likely be classified as herding trades in the first place, given that this would imply a lot of "contrarian" trades in the same direction in the same stocks.

To further assess the uniqueness of investment strategies pursued by contrarian funds, we construct LSV (1993) herding measures using funds within each *CON* quintile.[11] A comparison across the five groups of funds will quantify the extent to which trades of funds with a certain level of contrarian index are correlated with each other. The results in columns 2 through 4 of Panel A show that there is a high correlation among trades by herding funds, as the LSV herding measure for the group is about 9%. In contrast, the herding measure for contrarian funds is only 2%, suggesting a much greater diversity of trades by these funds. That is, beyond trading against the herds on the same set of stocks (which should generate positive correlation among their trades), contrarian funds actually pursue strategies quite different from each other. Therefore, even though contrarian funds may trade against the same group of herds, their contrarian trades spread out across different herding stocks rather than concentrate on the same set of stocks. In this sense, contrarians are true mavericks.

[10] In an unreported analysis, we further decompose the contrarian index into two components, CON_buy and CON_sell, by separately accounting for the contribution of a fund's contrarian buy versus sell trades to its overall contrarian index. If contrarian funds fail to trade with the majority of funds due to the redemption pressure, we should find that variations in CON across the quintile CON index portfolios to be mostly driven by CON_sell. Our result indicates that on average, a fund's overall contrarianism is not dominated by the contrarianism in either the buy side or the sell side of the trades.

[11] The herding measures are those defined in Equations (1), (2), and (3), except that here they are only computed among trades by funds in a given *CON* quintile.

To see more precisely how the investment choices of contrarian funds differ from those of other funds, we calculate the average quintile ranks of size, book-to-market (BM), and momentum of individual fund holdings and compare them across quintile portfolios of funds with different contrarianism. Panel B of Table 2 shows that, relative to herding funds, contrarian funds tend to invest more in stocks with smaller size, higher book-to-market ratio, and lower past returns. Therefore, contrarian investing is related to value investing and negative feedback trading. This observation raises the possibility that contrarian funds tend to herd less because they are less likely to deviate from certain benchmarks. We, therefore, further examine differences in three measures of activeness and distinctiveness of fund investment: Industry Concentration, Active Share and R^2. Following Kacperczyk, Sialm and Zheng (2005), we measure a fund's industry concentration index (ICI) as a Herfindahl index of industry portfolio weights.[12] According to Cremers and Petajisto (2009), Active Share measures the share of portfolio holdings that differs from the benchmark index holdings.[13] R^2 is the *R*-square from regressing monthly fund returns on the Carhart (1997) four factors, using past 12 months of data. Prior studies argue that lower R^2 indicates more active investment strategies and funds with lower R^2 significantly outperform those with higher R^2 (see, e.g., Amihud and Goyenko, 2011 and Titman and Tiu, 2010).

The result in Panel B suggests that there is no monotonic relation between the contrarian index and the ICI: both herding funds and contrarian funds tend to have greater industry concentration relative to the average fund. In addition, there is a positive relation between fund contrarian index and

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[12] The industry concentration index for a fund is $ICI_t = \sum_{j=1}^{10} (w_{j,t} - \tilde{w}_{j,t})^2$, where j=1 to 10 representing 10 different industries. $w_{j,t}$ is the portfolio weight of a mutual fund in industry j, and $\tilde{w}_{j,t}$ is the weight of industry j in the CRSP market portfolio. The 10-industry classification is provided in Appendix B of Kacperczyk et al. (2005).

[13] Data on Active Share are downloaded from Antti Petajisto's website: http://www.petajisto.net/data.html. Since the data are only available before 2007, all analyses involving Active Share only use data during the 1995 to 2006 period.

Active Share, indicating that contrarian funds tend to be more active. Note, however, that the difference in Active Share between contrarian funds and herding funds is relatively small. Thus, both herding funds and contrarian funds tend to deviate from their benchmarks more often than funds that exhibit neither behavior. Further, the relation between *CON* and R^2 is inverse U-shaped – funds in the bottom and top *CON* quintiles tend to have a lower R^2, relative to funds in the middle *CON* quintiles. Given prior findings that low R^2 funds deliver higher abnormal performance, we will take a closer look at which type of funds, contrarian versus herding, delivers better performance in more details in Section III.

II.B. Multivariate Analysis of CON

To understand why contrarian funds choose to deviate from the crowd, we examine whether managers in these funds face different incentives. Herding by mutual fund managers may be motivated by non-fundamental information related incentives, such as short-term career concerns, as modeled by Scharfstein and Stein (1990) and tested by Chevalier and Ellison (1999). We therefore compare the recent performance and flows of herding versus contrarian funds to determine whether managers of contrarian funds might be less career-concerned. Alternatively, among funds with good performance, contrarianism may also be motivated by overconfidence.

Specifically, we run a panel regression of *CON* on measures of past fund performance, prior quarter flows, and fund characteristics including fund size, expense ratio, turnover, and fund age. We employ two measures of past fund performance. First, we estimate each fund's Carhart (1997) four-factor fund alpha during the past 36 months using rolling regressions of monthly fund returns. Second, we obtain a commonly used aggregate indicator of past performance by investors: a fund's Morningstar star performance rankings. We use a dummy variable to indicate funds that have been ranked as five-star funds based on their performance during the prior three years. If the career-concerns and/or overconfidence stories hold, we would expect that managers of funds with higher risk-adjusted performance or with star rankings are less likely to engage in herding behavior. Furthermore, since managers are compensated based upon total assets under management, we also expect weaker herding by funds attracting large inflows. In all of our regression specifications, we include time dummies to capture any fixed effect in fund contrarianism over time. In addition, we compute t-statistics using heteroskedasticity robust standard errors clustered by funds to alleviate potential concerns over serial correlation in certain funds attributes.

Model 1 of Table 3 shows that funds with a higher *CON* index indeed have significantly greater recent Carhart (1997) four-factor alphas. Moreover, they are also more likely to be rated as five-star funds by Morningstar. Consistent with the well documented phenomenon of flow chasing past performance, contrarian funds attract large inflows in the prior quarter as indicated by the significantly positive coefficient on Past Flows. Therefore, the results suggest that managers of contrarian funds tend to have stellar recent performance and thus have lower immediate reputational concerns or higher levels of overconfidence. As result, they may be more inclined to deviate from their peers and rely more on their private information (that may not be available to other funds) when making investment decisions.

The results in the table also indicate that contrarian funds appear to be larger and exhibit relatively lower turnover. These features along with the fact that contrarian funds have larger inflows and better past performance suggest that these managers are likely to be a group of patient investors who have the ability to provide liquidity to mutual fund herds and can sustain short-term losses from the trading pressure induced by fund herding.

In our second regression model, we further consider the effects of return volatility and flow volatility on the degree of contrarian investment. We use the standard deviation of Carhart (1997) four-factor adjusted returns during the past 36 months to measure return volatility, and the standard deviation of monthly flows during the past 12 months to measure flow volatility.[14] The result in Model 2 of the table suggests that while contrarian funds have better overall risk-adjusted performance, they appear to have greater volatility of fund flows. This finding suggests that contrarian funds bear significant risk, at least in the short-run, when trading against the crowd. Therefore, it is possible that they face certain constraints or limits to arbitrage which may explain why contrarian funds only constitute a small minority of the actively managed fund industry. Few fund managers might be able afford to persistently trade against herds, as they need to withstand initial losses from the price pressure associated with herding. We would expect fund managers with high recent performance to be most immune from investor outflows from short-term underperformance.

II.C. Persistence of Contrarian Investing

If herding is due to behavioral biases, some contrarian investors may intentionally trade against a herd to provide liquidity. Contrarian funds may also unintentionally trade against a herd when they act on their own private information that may not be available to their peers. In either of these cases, we would expect contrarian fund trading behavior to be persistent over time. On the other hand, if a fund chooses to sell certain stocks while other funds are buying them because the fund has been hit by an idiosyncratic redemption shock, its contrarian trading behavior this period may be followed by herding behavior during the next period. Therefore, we examine whether the identity of contrarian funds is persistent to see whether contrarian investing represents a systematic investment strategy.

When we group funds into quintiles based on their contrarian index (*CON*), we find that funds ranked in the top contrarian index quintile continue to exhibit a significantly higher contrarian index than those ranked in the bottom quintile, during at least the subsequent eight quarters. In addition, the persistence of the contrarian index over time remains significant in a multivariate regression analysis

[14] Our results are not materially different if we measure the volatility of fund flows over the past 36 months.

that controls for fund investment styles. Thus, we conclude that a fund's tendency to trade against herds is a very stable characteristic. For brevity these results are not tabulated in the paper.

III. Performance of Contrarian Funds

Since trades by contrarian funds may be driven by private information not available to others, they may outperform their peers. Da, Gao and Jaganathan (2011) 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 particularly profitable private information, they may still outperform herds in the long-run from their capacity as liquidity providers because they may benefit from return reversals generated by herds (e.g., Brown, Wei and Wermers, 2011 and Puckett and Yan, 2007). On the other hand, some contrarian managers may be overconfident in their abilities. In addition, the contrarian strategy involves long investment horizons and betting against potentially profitable price momentum. Therefore, it would be interesting to examine the relation between the degree to which a fund employs contrarian strategies and its future performance.

III.A. Performance Analysis Based on Fund Holdings

We start by analyzing fund performance based on the performance of fund holdings. We are interested in a holdings-based performance measure because it allows us to assess fund performance as a result of managers' stock-selection skills.

At the end of each quarter t, we compute the buy-and-hold hypothetical return of a fund's equity portfolio for each of the subsequent four quarters (t+1 to t+4) along with the four-quarter cumulative returns. Since Table 2 indicates that holdings of herding funds and contrarian funds differ systematically in some of the return predictive stock characteristics, we also compute the DGTW (1997) characteristic-adjusted returns. The characteristic-adjusted return for a given stock is the stock return during a quarter in excess of the return to its characteristic benchmark portfolio. The characteristic benchmark portfolios are constructed following Daniel, Grinblatt, Titman, and Wermers (DGTW, 1997), but in this paper we measure size, book-to-market ratio, and momentum characteristics at the end of each quarter, rather than only on June 30th of each year.[15] The more frequent update of the benchmark portfolio can help us better control for changes in stock characteristics. Given that contrarian funds persistently trade again herds, they may lose money in the short term due to the temporary price pressure associated mutual fund herding and turn a profit in the longer term when the price pressure subsides and reverses. We thus examine longer horizon buy-and-hold returns as well as quarter-by-quarter performance of these funds to better capture their overall profitability.

In Table 4, we average these quarterly and four-quarter cumulative raw returns and DGTW-adjusted abnormal returns across funds in the same *CON* quintile, and report the time- series averages. The table shows that stock portfolios held by contrarian funds (i.e., top *CON* quintile) significantly outperform herding funds (i.e., bottom *CON* quintile) in each of the following four quarters. The characteristic-adjusted returns of contrarian funds during quarters t+1 to t+4 are 0.23%, 0.37%, 0.40%, and 0.45% respectively, significantly higher than those for the herding funds, at -0.01%, -0.15%, -0.24%, and -0.24% respectively. We find a similar pattern with raw returns. In the last column of the table, we further present the cumulative returns over the four quarters. The result indicates that contrarian funds on average outperform herding funds by 1.47% over the following four quarters, based upon DGTW (1997) characteristic-adjusted returns. This difference is statistically significant at the 1% level, according to t-statistics computed with Newey-West robust standard errors. Therefore, contrarian funds appear to exhibit greater stock selection ability.

III.B. Performance Analysis Based on Fund Trades

[15] For the raw portfolio returns as well as for the DGTW benchmark portfolios, we follow Shumway (1997) to deal with stock delisting: when the CRSP delisting return is missing, we replace it with -30% if the delisting is performance related, and zero, otherwise.

The results reported in Table 4 indicate that stocks held by contrarian funds tend to outperform those held by herding funds. Since fund holdings at the end of a given quarter are the outcome of fund trades during the past several quarters, we further examine exactly what types of trades contribute to their good performance. First, contrarian trades for liquidity provision to herding funds tend to lose money initially but may turn a profit in the long run, while their trades driven by private information are more likely to generate profits in the short run. We thus analyze the performance of their trades in the following four quarters to better capture the long-term performance of contrarian funds. In addition, given that contrarian funds make both contrarian and herding trades, we examine these two types of trades separately to better understand the contribution of contrarian trades to fund performance.

Specifically, in each quarter t, we consider fund trades along three dimensions: the strength of the fund's contrarian index (as indicated by its quintile rank), the direction of a trade (i.e., buy or sell), and the contrarian/herding nature of the trade. To gauge the information content of individual trades, we further classify contrarian/herding trades into the following four types:

Type 1: a contrarian trade of a stock with a high herding measure,

Type 2: a contrarian trade of a stock with a low herding measure,

Type 3: a herding trade of a stock with a high herding measure,

Type 4: a herding trade of a stock with a low herding measure.

We consider high herding measure stocks as those with buy-herding (BHM) or sell herding (SHM) measures ranked in the top two quintiles among all stocks during the same quarter, and the rest as low herding measure stocks. For example, a type 1 buy trade is a purchase of a stock heavily sold (i.e., with a sell-herding rank of four or five) by funds. Essentially, any performance difference of type 1 or type 3 trades between contrarian and herding funds is more likely to be influenced by the price pressure associated with fund herding, while that of type 2 or type 4 trades is more likely to be driven by differences in private information between these two groups of funds. Trading profits are measured as DGTW (1997) characteristic-adjusted abnormal returns of individual trades.

We first focus on the performance of buy trades. The results in Panel A of Table 5 indicate that contrarian funds significantly outperform herding funds in their contrarian trades (type 1 and type 2 trades). While it is expected that their liquidity provision to strong herding trades made by herding funds should generate positive abnormal returns due to herding-induced return reversals, it is especially noteworthy that contrarian funds also outperform herding funds on their contrarian trades of weak herding stocks, where the profit from liquidity provision is likely to be minimal. Since the trading profit from contrarian trades of weak herding stocks are more likely to be driven by differences in information possessed by funds, the outperformance of contrarian funds on type 2 trades suggests that their overall superior performance over herding funds can be attributed to both the superiority of their private information and their ability to provide liquidity to herding funds.

The result for type 3 and type 4 trades further indicate that contrarian funds' superior performance is unlikely to be entirely driven by liquidity provision, because they outperform herding funds even in their herding trades. While herding funds experience significantly negative returns for their herding trades on high herding measure stocks, contrarian funds seem to just break even on those trades, despite the return reversals associated with herding. Moreover, they earn significantly positive profits from their herding trades of low herding measure stocks, whose returns are, again, more likely to be related to private information possessed by fund managers as compared to price pressure effects.

These findings on fund trades corroborate our earlier evidence that contrarian funds do not just mechanically trade again herding funds, as a significant portion of their trades are in the same direction as fund herds. Rather, they seem to selectively trade with or against herds depending on their private information. The result in this table strongly suggests that they profit from their private information (that is different from that of herds) as well as liquidity provision to herding funds.

Note that the performance of sell trades by contrarian funds is, in general, not significantly different from that of herding funds, as shown in Panel B of Table 5. In fact, sometimes stocks sold by contrarian funds even *outperform* those sold by herding funds subsequently. This finding is consistent with Chen, Jegadeesh and Wermers (2000). Essentially, since mutual funds do not short-sell stocks, the stocks contrarian funds sell must be from their existing holdings. While such stocks may be expected to underperform those stocks they buy, they may not necessarily underperform stocks held or sold by herding funds, which tend to be less skillful in their stock selection as suggested by their poor overall performance.

III.C Multivariate Regression Analysis of Fund Performance

In the prior two subsections, we have shown that stock holdings and trades by contrarian funds significantly outperform those of herding funds. To further pin down the sources of their outperformance, it is important to consider differences in fund characteristics. As indicated in Table 3, contrarian and herding funds have different size, age, turnover and flow characteristics, some of which may be relevant for fund performance as well. For example, it is possible that the superior performance 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. In addition, since contrarian funds charge slightly higher expenses, it is important to also compare their net-of-expense fund returns earned by average investors. We thus use multivariate regressions to examine the relation between reported net fund returns and contrarian index, controlling for various fund characteristics.

During each quarter, we compute the abnormal return of a fund as the difference between its realized return, net of expenses, and the expected return under the Carhart (1997) four-factor model. We estimate factor loadings using monthly returns of the fund during the past 36 months to estimate the expected returns for a particular quarter. Such rolling-window estimation allows for time variation in the factor loadings of individual funds. Finally, we implement a panel regression of cumulative four-factor alphas in the following four quarters on the contrarian index (*CON*), controlling for fund characteristics. Since the dependent variable is fund performance over four quarters, t-statistics are computed using standard errors clustered by funds to account for serial correlation of fund performance. We also include quarter dummies to control for time fixed-effects.

The results in Table 6 show that a larger contrarian index leads to significantly greater abnormal fund performance during the following four quarters, after we control for differences in fund characteristics such as fund size, age, expense ratio, turnover, and past fund flows. In Model (2) of the table, we further control for differences in characteristics of fund holdings to account for the possibility that the performance of contrarian funds comes from their adoption of a certain investment style that may not be entirely captured by the linear Carhart (1997) four-factor model that we use to measure fund alpha. Therefore, we further include the average size, book-to-market and momentum quintile ranks of the fund portfolios as control variables. Despite the control of investment styles, the effect of the contrarian index on fund performance remains significantly positive.

As shown in Table 2, contrarian funds have slightly higher Active Share (Cremers and Petajisto, 2009) and lower R^2 than herding funds (although the difference is rather small), both of which may matter for performance given that previous studies show that funds employing more active and unique strategies deliver significantly better risk-adjusted performance (Titman and Tiu, 2010 and Amihud and Goyenko, 2011). As shown in Models 3 and 4, the effect of the contrarian index is again not affected by these additional controls.

Finally, we also include as an explanatory variable the interaction between the fund contrarian index, *CON*, and the past fund flow, Flow. Since Table 2 indicates that contrarian funds on average experience greater inflows, we are interested in learning whether their performance tends to be greater when they experience greater inflows and, therefore, are less constrained by redemption pressure. The coefficient on the interaction term *CON**Flow* is significantly positive, suggesting that performance is indeed enhanced for “deep-pocket” contrarian funds. That is, contrarian funds receiving large inflows–even temporarily–are better positioned to provide liquidity to other funds and take positions against herds.

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

The empirical results so far indicate that contrarian funds hold and buy stocks that outperform those held and bought by herding funds, respectively, both measured in raw returns and in DGTW-adjusted returns. They also outperform herding funds in terms of their after-fee returns. 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 beyond taking advantage of the temporary price pressure/mispricing created by herding funds. For example, contrarian funds may take cues from publicly available fundamental valuation signals and invest in “cheap” stocks. Further, it is also plausible that contrarian funds possess private information about firm fundamentals not accessible to their peers. Given that these potential explanations are not mutually exclusive, it is important to examine how much each source of returns contributes to the total performance of contrarian funds.

Chen, Jegadeesh, and Wermers (2000) suggest that measuring the performance of stocks held in common by certain types of funds may be a more powerful approach to detecting skills than measuring the performance of funds that have similar characteristics (such as contrarianism). For this reason, we shift our focus from contrarian fund performance to returns of individual stocks that are held 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 a new approach developed by Wermers, Yao, and Zhao (2011). A salient feature of this approach is that it aggregates information of all funds with varying degrees of contrarianism, rather than focusing on merely a small subset of funds with extreme contrarianism (e.g., as per Chen, Jegadeesh, and Wermers, 2000).

IV.A. The Contrarian Score of Individual Stocks

Our stock level contrarian score follows the generalized inverse approach of Wermers, Yao, and Zhao (2011) that extracts stock selection information from portfolio holdings of funds with varying stock selection abilities. The contrarian score is defined as

$$\alpha_{CON} = (\mathbf{V'DV})\mathbf{W'CON} \tag{6}$$

where $\mathbf{W}$ is the M by N matrix of fund portfolio weights, *CON* is the M by 1 vector of fund contrarian index. $\mathbf{V}$ is the first K eigenvector of $\mathbf{W'W}$ corresponding to the K largest eigenvalues and $\mathbf{D}$ is an M by M diagonal matrix with the first K diagonal elements being the inverse of the largest K eigenvalues of $\mathbf{W'W}$, and the remaining M-K diagonal elements being zeros. Following Wermers, Yao, and Zhao (2011), K is set to M/2. Details of the contrarian score are provided in Appendix A. α_{CON} can be interpreted as the aggregate stock selection information on individual stocks extracted from portfolios holdings of funds with varying degree of contrarianism. There is a simple interpretation of the contrarian score when we abstract away from the complication of fund holding correlations induced by the expression $(\mathbf{V'DV})^{-1}$ – the higher the contrarian index *CON* of a fund, and the greater weight a high-CON fund puts on the stock, the higher is the contrarian score α_{CON} for the stock. The expression $(\mathbf{V'DV})^{-1}$ further takes into account the correlation of holdings across funds when aggregating fund managers' information on a given stock.

The fund-level contrarian index *CON* used in (6) is the rolling four-quarter average of the quarterly *CON* (averaged over qtr -3 to Qtr 0, where Qtr 0 is the quarter α_{CON} is measured), with the requirement that a fund has a valid *CON* observation during at least one of the two most recent quarters (Qtr -1 to Qtr 0). The rationale for this rolling average approach is the following. First, as Wermers, Yao, and Zhao (2011) point out, the power of their approach depends on the size of the cross-section of funds—the larger the cross-section, the more precise is the aggregated signal provided by the statistic. During the mid-1990s until 2004, many funds report holdings semiannually and, thus, are not included in our earlier analysis at the fund level during quarters when these funds do not report holdings. Taking the rolling average of *CON* is a natural way to include these funds and increase the cross-sectional sample size. Second, as shown in our analysis earlier, trades by contrarian funds often deliver profits after a few initial quarters. Taking a rolling average has the effect of including fund actions from earlier quarters rather than focusing narrowly on the most recent quarter. Therefore, if contrarian funds do have stock selection ability, we expect the rolling average approach to enable α_{CON} to predict stock returns in initial quarters after portfolio formation, as well as in later quarters.

IV.B. Contrarian Score and Stock Returns

To evaluate the return-predictive power of the contrarian score at the individual stock level, we first employ a sorted portfolio approach. At the beginning of each calendar quarter, we classify stocks into deciles based on the contrarian score, α_{CON}. To avoid market microstructure issues in measuring returns, and to allow for plausible short positions, we require that the stock price at the end of the formation quarter be no less than \$5.

We form equal-weighted portfolios within each α_{CON} decile and hold the portfolios over the next four quarters with quarterly rebalancing. To evaluate portfolio performance, we examine both raw returns and the characteristic-adjusted returns of DGTW (1997). We reconstitute DGTW size, book-to-market ratio, and momentum characteristic benchmarks at the end of each quarter (rather than each year) to better control for changes in stock characteristics during a particular year. We also report the Carhart (1997) four-factor alphas for these portfolios for comparison. The four-factor alphas are estimated by regressing the time series of portfolio returns during the entire sample period (from 1995Q2 to 2008Q4) on the time series of the four factors.

In order to provide a summary performance measure over the entire four-quarter holding period, we further adopt an overlapping portfolio approach. In any given quarter, we consider four portfolios with the same decile ranking, but formed during each of the prior four quarters. We further combine these four portfolios in equal weights into a single portfolio and hold it during the next quarter. This portfolio formation procedure is similar to the overlapping momentum portfolio procedure of Jegadeesh and Titman (1993), which is adopted by Wermers, Zhan, and Yao (2011). We refer to this as the "JT4" approach.

Table 7 reports the results of this sorted portfolio analysis. The average returns to the top $\boldsymbol{\alpha}_{\mathbf{CON}}$ decile portfolio are 2.45, 2.75, 2.73, and 2.65 percent during the next four quarters, respectively, and 2.31 percent for the JT4 four-quarter overlapping portfolio approach. The corresponding returns for the bottom α_{CON} decile are 1.78, 2.02, 2.04, and 2.14 percent and 1.75 percent for the JT4 approach. The t-statistics show that return spreads between the top and bottom α_{CON} deciles are all significantly positive. Thus, stocks with higher α_{CON} earn significantly higher returns in each of the four quarters after portfolio formation.

The patterns for the characteristic-adjusted returns and for the Carhart (1997) four-factor alphas are similar. The top-bottom decile spreads in characteristic-adjusted returns are 0.57, 0.53, 0.60, and 0.45 percent during the four quarters and 0.49 percent for the JT4 approach, all significantly positive. Further, the four-factor alphas for the return differences are all significantly positive.

These results suggest that stocks with high contrarian scores significantly outperform stocks with low contrarian scores, before and after controlling for size, book-to-market, and momentum.

IV.C. Contrarian Score and Stock Characteristics

The results in Table 7 confirm that α_{CON} represents valid stock-selection information extracted from portfolio holdings of funds with varying degree of contrarianism. In this section, we seek to understand the characteristics of stocks picked by contrarian funds to further understand the nature of such stock selection information. In Table 2, we already find that contrarian funds strongly prefer high BM stocks and past losers. To obtain a broader view of the holding preferences of contrarian funds, we next examine an extensive list of stock characteristics.

We begin with the stock level measure of herding among mutual funds, HERD, which is introduced earlier in Section I.B. HERD takes a value -5 for extreme sell-herding stocks and a value of 5 for extreme buy-herding stocks. More positive values of HERD indicate stronger buy-herding while more negative values indicate stronger sell-herding.

Next, we consider an extensive set of stock characteristics related to valuation fundamentals that are known to be predictive of stock returns (18 in total). Based on their nature, we group them into 9 categories: 1) value (VALUE), 2) investment and financing activities (INVFN), 3) earnings quality (EQAL), 4) efficiency (EFF), 5) intangible investments (INTANG), 6) earnings momentum (EMOM), 7) information uncertainty (UNCT), 8) profitability (PROF), and 9) illiquidity (ILLIQ). The original 18 variables forming these 9 categorical variables are signed so that they are positively related to future stock returns, according to existing literature. We combine variables in each group by a simple average of their cross-sectional percentile ranks to obtain the 9 categorical variables. Stocks are then cross-sectionally ranked into percentiles in each quarter based upon each of these 9 categorical variables. Details for constructing the 18 individual firm characteristics and the 9 categorical variables are provided in Appendix B.

During each quarter, t, we sort stocks into deciles, based on the contrarian score, and report, for each quintile, HERD during each of the preceding four quarters (Qtr t-3 to t), and the percentile ranks of the 9 stock characteristic measures during quarter t. The results are shown in Table 8.

The contrarian score is significantly negatively correlated with the herding intensity measure, HERD, during the current (Qtr 0) and past three quarters (Qtr-3 to Qtr-1). In addition, stocks with higher contrarian scores have stronger value-oriented characteristic, fewer investment and financing activities, higher operating efficiency, more intangible investments, and greater illiquidity. Further, they have lower earnings momentum, higher uncertainty, and lower profitability.[16] By and large, these results are consistent with the view that contrarian funds prefer value stocks and shy away from glamorous, profitable, or liquid stocks. It is noteworthy that while the correlations of the contrarian score with some of these characteristics (i.e., VALUE, INVFN, EFF, INTAG, and ILLIQ) suggest high future returns for stocks with high contrarian scores, its correlations with other characteristics (i.e., EMOM, UNCT, and PROF) suggest otherwise. Therefore, it is unlikely that the return-predictive power of the contrarian score can be completely explained by its relations with prior documented return predictive stock characteristics.

IV.D. Sources of Superior Performance: Liquidity Provision, Public Valuation Signals, or Private Fundamental Information?

To further investigate potential sources of the contrarian profit, we perform the following Fama-MacBeth regressions of stock returns on the contrarian score, controlling for the price pressure effect associated with herding and the aforementioned common valuation signals. The dependent variable is the DGTW (1997) characteristic-adjusted stock return during each of the four quarters after portfolio formation (Qtr+1 to Qtr+4). The main explanatory variable is the cross-sectional percentile rank of the contrarian score of individual stocks, α_{CON}. We consider two sets of control variables. The first set of controls includes stock-level herding indexes (HERD) during each of the past four quarters (Qtr-3 to Qtr 0). The second set of controls includes the 9 fundamental valuation variables we consider in Table 8. These variables are shown in the existing literature to be predictive of stock returns and form the basis of popular quantitative stock selection models. To obtain a summary measure of return-predictability of α_{CON} over the entire four quarters following portfolio formation, we again adopt the

[16] Note that these variables are signed and the interpretation of the results must take into account their signs. For example, since both idiosyncratic volatility and analyst forecast dispersion are negatively correlated with stock returns, they enter with negative signs into the composite variable UNCT. Thus, a positive relation between the contrarian score and UNCT means that stocks with higher contrarian scores have higher idiosyncratic volatility and dispersion, i.e., higher uncertainty.

Jegadeesh and Titman (1993) approach to compute the four-quarter average coefficients (JT4). Specifically, during each quarter t, we perform four sets of cross-sectional regressions. The dependent variable is the DGTW (1997) characteristic-adjusted stock returns during that quarter. The explanatory variables are measured during each of the previous four quarters (t-4 to t-1). We average the four sets of coefficients on the same explanatory variable across these four regressions, and then compute their time-series averages and the corresponding time-series t-statistics.[17]

Table 9 reports the results of the JT4-style average coefficients from the quarterly Fama-MacBeth regressions. In the univariate regression with the contrarian score as the only explanatory variable, the coefficient for the contrarian score is 0.0088, which is highly statistically significant. When herding indexes (HERD) for the past four quarters (Qtr-3 to Qtr 0) are included as control variables, the coefficient for the contrarian score is reduced to 0.0067, but is still highly significant. The change in the coefficient for the contrarian score suggests that about 24% of the return-predictive information contained in the contrarian score is related to the price pressure effect of mutual fund herding. When we include the 9 fundamental stock characteristics as control variables, the coefficient for the contrarian score remains significant, at 0.0063, which suggests that over a 4-quarter horizon, about 28% of the return-predictive information contained in the contrarian score is related to the quantitative valuation signals. Finally, when we jointly include the herding indexes and quantitative signals as control variables, the coefficient for the contrarian score remains significant, at 0.0049. Overall, a little over half of the return predictive power of the contrarian score is attributable to neither herding induced price pressure nor quantitative valuation signals.

[17] As noted in the Appendix B, a fairly large number of stocks have missing stock characteristics in a given quarter. To avoid large reduction of sample size in multivariate regressions, we implement a multiple imputation procedure to "fill in" missing stock characteristics. Specifically, in each quarter, we use simulated variables to replace missing variables using the Monte Carlo Markov Chain (MCMC) before performing multivariate regressions. The regression t-statistics are adjusted to take into account such simulated values. The details of the simulation procedure and associated statistical inference are described in Wermers, Yao, and Zhao (2011).

Therefore, neither liquidity provision nor reliance on public quantitative signals can fully explain the stock picking ability of contrarian funds. Thus, the evidence from our stock level return decomposition supports the hypothesis that value-relevant private information is at least part of the sources of contrarian profits.

V. Conclusion

In this study, we identify a group of "contrarian funds" whose investment strategies are not only vastly different from those of the majority of other funds, they are also distinct from those of funds within their own ranks. Yet these contrarian funds on average manage to generate better performance than their peers.

We show that contrarian funds typically have greater recent success in terms of performance and flows. Based on analyses of fund holdings, trades and reported returns, we find that contrarian funds outperform their herding counterparts in terms of raw and risk-adjusted returns, before and after fees, and when we control for differences in fund characteristics. In addition, contrarian funds outperform not only because they provide liquidity to mutual fund herds, but also because they possess superior private information. Moreover, although contrarian funds are associated with lower *R*-square with respect to systematic factors, higher industry concentration, and higher Active Share, the return predictability of the contrarian index cannot be subsumed by these existing measures of strategy uniqueness.

We extract the stock selection information contrarian funds possess based on their portfolio holdings and convert such information into a stock level contrarian score. Stocks in the highest contrarian score decile outperform stocks in the lowest contrarian score decile by 0.49% per quarter in terms of DGTW (1997) characteristic-adjusted abnormal returns during the four quarters following portfolio formation. The contrarian score is anti-herding in nature, and exhibit deep value characteristics. However, its return predictive power is not subsumed by the return reversal effect of fund herding and an extensive list of quantitative investment signals. This further confirms that the stock selection information contrarian funds possess has “uncommon value.”

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Appendix A: The Stock-level Contrarian Score

Wermers, Yao, and Zhao (2011) start from the definition of Daniel, Grinblatt, Titman, and Wermers (1997) that a fund's stock selection ability is the weighted average of alphas of individual stocks held by the fund, where the weights are portfolio weights on stocks:

$$S_{jt+1} = \sum_{i=1}^{N} \omega_{ijt} \alpha_{it+1}^{S}$$

where S_{jt+1} is the fund j's stock selection ability in period t+1 (j=1, …, M). α_{it+1}^{S} is the stock alpha in period t+1 (i=1, …, N). ω_{ijt} is the portfolio weight of fund j on stock i at the end of period t (beginning of period t+1). They further assume is that S_{jt+1} can be measured, with noise, by information available at the end of period t (in our case, the fund contrarian index *CON*). Let $\hat{S}_{jt}$ denote the expected stock selection ability for the period t+1 based on information available at time t. The specific assumption is $\hat{S}_{jt} = S_{jt+1} + e_{jt+1}$, where e_{jt+1} is the information noise, or an error term. Combining the two expressions above, we have,

$$\hat{S}_{jt+1} = \sum_{i=1}^{N} \omega_{ijt} \alpha_{it+1}^{S} + e_{jt+1}$$

In matrix form, this is (dropping time subscript):

$$\mathbf{S} = \mathbf{W}\boldsymbol{\alpha} + \mathbf{e}$$

where **S** is the M by 1 vector of $\hat{S}_{jt}$, **W** is the M by N matrix of fund portfolio weights ω_{ijt}, **α** is the N by 1 vector of stock alpha α_{it+1}^{S}, and **e** is the M by 1 vector of the noise term e_{jt+1}. **α** here can be treated as parameters and estimated from observed **S** and **W**.

Wermers, Yao, and Zhao (2011) point out that due to the dimensionality problem (i.e., the fund number M is typically smaller than the stock number N), the N by N matrix W'W is singular and not invertible, and thus the usual OLS estimator $\boldsymbol{\alpha}_{\mathbf{OLS}} = \mathbf{(W'W)^{-1}W'S}$ cannot be implemented. They suggest an alternative estimator based on the generalized inversion, which is a well-developed statistical method to address the singularity or near-singularity problem in regressions. The generalized inverse alpha is:

$$\boldsymbol{\alpha}_{\mathbf{GI}} = \mathbf{(V'DV)W'S}$$

where **V** is the first K eigenvector of **W'W** corresponding to the K largest eigenvalues and **D** is a M by M diagonal matrix with the first K diagonal elements being the inverse of the largest K eigenvalues of **W'W**, and the remaining M-K diagonal elements being zeros.

Implementing the generalized inverse approach in our setting is straightforward. We simply set **S** to the M by 1 vector of fund contrarian index **CON** available at the end of period t. The stock-level contrarian score is thus,

$$\boldsymbol{\alpha}_{\mathbf{CON}} = \mathbf{(V'DV)W'CON}$$

Appendix B: Stock Characteristics Measures

A. Constructing Individual Stock Characteristics:

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. When Compustat variables are involved they are indicated in bracket [.].

1. Value (VALUE)

1) Earnings to price ratio (E/P): average EPS [EPSPXQ] from quarter t-3 to quarter t, divided by stock price [PRCCQ] at the end of fiscal quarter in t.

2) Sales growth (SG): Average sales revenue [SALEQ] of quarter t-3 to t divided by average sales revenue of quarter t-7 to t-4.

2. Investment and Financing Activities (INVFN):

3) Capital expenditure (CAPEX): capital expenditure [based on CAPXY] during quarter t-3 to quarter t, divided by the average total assets [ATQ] of quarter t-4 and quarter t.

4) Asset growth (AG): total assets [ATQ] of quarter t divided by total assets of quarter t-4.

5) Net share issues (NS): total shares outstanding (from CRSP) at the end of month m divided by the split-adjusted total shares outstanding at the end of month m-12.

3. Earnings Quality (EQAL):

6) Accruals (ACC): balance-sheet measure of accruals from quarter t-3 to quarter t, divided by the average total assets [ATQ] of quarter t-4 and quarter t. The balance-sheet measure of accruals is change in current assets [ACTQ], minus change in cash and short-term investments [CHEQ], minus change in current liabilities [CLTQ], plus change in debt in current liabilities [DLCQ], plus change in deferred taxes [TXDIQ], minus depreciation [DPQ].

4. Efficiency (EFF):

7) 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 [ATQ] minus cash and short-term investments [CHEQ]. Operating liabilities is total assets [ATQ] minus debt in current liabilities [DLCQ], minus long term debt [LTDQ], minus minority interests [MIIQ], minus preferred shares [PSTKQ], minus common equity [CEQQ].

8) Sales turnover [STURN]: total sales revenue [SALES] from quarter t-3 to t, divided by the average total assets [ATQ] at quarter t-4 and t.

5. Intangible Investments (INTAG):

9) R&D expenditure (RDE): annual R&D expenditure [XRD] for the fiscal year reported prior to quarter t, divided by market capitalization (from CRSP) at the end of quarter t. We use the annual R&D data because quarterly R&D expenditure data are spotty.

10) Advertisement expenditure (ADV): annual advertisement expenditure [XAD] for the fiscal year reported prior to quarter t, divided by market capitalization (from CRSP) at the end of quarter t. We use annual advertisement data because there is no quarterly advertisement data in Compustat.

6. Earnings Momentum (EMOM):

11) Standardized unexpected earnings (SUE): change in split-adjusted EPS ([EPSFXQ/ADJEXS] from quarter t-3 to t, divided by the standard deviation of 4-quarter EPS changes. The standard deviation is measured using 4-quarter EPS changes during past 8 quarters, with a minimum of 4 quarters of observations required.

12) Analyst forecast revision (FRV): analyst average EPS forecast (from IBES) for the currently unreported fiscal year FY1 during month m, in excess of the average EPS forecast for the same fiscal year made during month m-3, divided by stock price at the time the average forecast of month m is measured.

7. Profitability (PROF):

13) Return on assets (ROA): net income [NIQ] of quarter t divided by the total assets [ATQ] of quarter t-1.

14) Gross margin (GM): gross margin averaged over quarter t-3 to t. Quarterly gross margin is sales revenue [SALEQ] minus costs of goods sold [COGSQ], divided by sales revenue.

8. Uncertainty (UNCT):

15) Idiosyncratic volatility (IVOL): standard deviation of residual returns from regressing daily stock returns onto contemporaneous and three lags of daily returns to CRSP value-weighted index. The regression is performed using daily returns in quarter t. A minimum of 44 daily observations is required. The data is from CRSP.

16) Analyst forecast dispersion (DISP): the standard deviation of analyst EPS forecasts for the unreported fiscal year FY1, divided by the absolute value of the average analyst EPS forecast for the same fiscal year, measured in month m. The data are from IBES.

9. Illiquidity (ILLIQ):

17) Trading turnover (TURN): quarterly trading turnover, defined as monthly trading volume divided by end-of-month shares outstanding, averaged over quarter t, using CRSP data.

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. The data are from CRSP. A minimum of 44 daily observations are required.

B. Signing and Combining Variables:

After constructing the 18 individual 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 in measuring value. To make these variables consistent with each other, we add a negative sign in front of the following variables: SG, CAPEX, AG, NS, ACC, NOA, IVOL, DISP, and 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 14 signed variables into percentiles to make them comparable. Since NYSE/AMEX and NASDAQ report trading volume differently, for the two variables involving trading volume, TURN and AMIHUD, we rank NYSE/AMEX stocks and NASDAQ stocks. Separately to obtain their cross-sectional percentile ranks.

Third, we combine 18 variables into 9 characteristic measures by taking the average of the percentile ranks. Specifically, VAL is the average of percentile ranks of EP and -SG. INVFIN is the average percentile ranks of -CAPEX, -AG, and -NS. EQAL is the percentile rank of -ACC. EFF is the average percentile ranks of -NOA and STURN. INTAG is the average percentile ranks of RDE and ADV. EMOM is the average of percentile ranks of SUE and FRV. PROF is the average percentile ranks of ROA and GM. UNCT is the average percentile ranks of -IVOL and -DISP. Illiquidity (ILLIQ) is the average percentile ranks of -TURN and AMIHUD.

When combining multiple characteristics into a categorical variable, if any individual characteristic is missing, we use the remaining valid characteristics in the same category to form the categorical variable. However, a stock-quarter observation is excluded from our sample if during the quarter more than 9 individual characteristics for the stock are missing, or more than 5 categorical variables for the stock are missing.

There are a fairly large number of missing values for individual variables in the data. If untreated, missing observations would significantly reduce the sample size for multivariate regressions involving these variables as joint regressors. A reason for combining individual stock characteristics into nine categorical variables is to alleviate the missing observation problem in multivariate regressions. In addition, variables within the same category tend to have similar nature and exhibit high correlations. Combining them into a single variable alleviates the multi-colinearity problem in regressions. Finally, when implementing multivariate regressions, we further use the multiple imputation procedure to address the missing observation problem.

Table 1: Summary Statistics

This table reports summary statistics for our sample of actively managed US equity mutual funds from 1995 to 2008. Each quarter, we calculate the cross-sectional mean, median, standard deviation, 25^{th} and 75^{th} percentile values of fund size (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**	**25^{th}**	**75^{th}**
Fund Size	1158	204	4221	61	720
Total Expense	1.33%	1.27%	0.46%	1.01%	1.58%
Turnover	82.60%	63.77%	67.80%	34.51%	109.76%
Flows	1.10%	-0.61%	10.16%	-4.03%	4.25%
Fund Age	11.97	7.31	13.80	3.55	14.61
Raw Return	1.95%	1.82%	4.95%	-1.05%	4.81%
CON	-0.7520	-0.7611	0.8714	-1.2874	-0.2306

Table 2: Characteristics of Contrarian Funds

This table examines the characteristics of contrarian funds. Each quarter, we group funds into quintile portfolios according to their contrarian indexes (*CON*) and calculate average characteristics for each quintile. Panel A reports the average value of *CON*, proportion of contrarian trades, the LSV (1992) herding measure (HM), and the buy (BHM) and sell-herding (SHM) measures within each fund quintile. Panel B reports the average size, B/M and momentum quintile ranks of fund stock holdings, Industry Concentration Index (ICI) computed as a Herfindahl index of portfolio industry weights, Active Share measured as the share of portfolio holdings that differs from the benchmark index holdings, and R^2 computed as the *R*-square from regressing monthly fund returns on the Carhart (1997) four factors, using past 12 months of data. Time-series averages of the contrarian index and fund characteristics of each quintile portfolio are reported. In Panel B, differences 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

CON Quintile	CON	% Contrarian	HM	BHM	SHM
1	-1.9327	31.34%	0.0940	0.0898	0.0915
2	-1.1805	37.10%	0.0473	0.0438	0.0442
3	-0.7614	40.38%	0.0257	0.0207	0.0237
4	-0.3423	43.81%	0.0156	0.0124	0.0120
5	0.4553	52.95%	0.0225	0.0190	0.0186

Panel B: Characteristics of Investment Styles

CON Quintile	Size Rank	B/M Rank	MOM Rank	ICI	Active Share	R^2
1	4.4299	2.5309	3.1157	0.0576	0.7700	0.8944
2	4.3691	2.5611	3.1019	0.0503	0.7720	0.9067
3	4.3125	2.6619	3.0447	0.0494	0.7780	0.9043
4	4.2711	2.7418	2.9895	0.0510	0.7910	0.8958
5	4.2997	2.8572	2.8717	0.0590	0.8120	0.8801
5-1	-0.1302	0.3262	-0.2439	0.0014	0.0411	-0.0143
t-stat	(-3.86)	(15.42)	(-14.29)	(0.88)	(5.73)	(-3.93)

Table 3: Determinants of Contrarian Index

This table reports results of panel regressions of contrarian index (*CON*) on fund characteristics. The explanatory variables include four-factor alpha in the past 36 months, flows in the prior quarter, the dummy variable indicating whether a fund has a Morningstar star ranking of 5, standard deviation of monthly four-factor adjusted returns during the past 36 months, stand deviation of monthly flows during the past 12 months, the logged value of fund size as proxied by total net asset value, expenses, turnover ratio and the logged value of fund age plus one. Quarter dummies are included in all regressions to control for time fixed effects. The corresponding t-statistics reported in parentheses are based on standard errors clustered by funds.

Dependent Variable	**Contrarian Index**	
Intercept	-0.5587	-0.6062
	(-16.43)	(-17.14)
Alpha	11.4754	11.0761
	(6.64)	(6.30)
Past Flow	0.9067	0.8140
	(17.29)	(15.05)
Star Fund	0.0435	0.0457
	(1.90)	(2.00)
Volatility of Ret		-1.3936
		(-1.26)
Volatility of Flow		2.0188
		(7.12)
Size	0.0000	0.0000
	(3.61)	(4.03)
Expense	5.2536	6.1325
	(2.82)	(4.03)
Turnover	-0.0222	-0.0279
	(-1.72)	(-2.09)
Fund Age	-0.0012	-0.0005
	(-1.81)	(-0.72)
Time Dummy	Yes	Yes
Clustering by Funds	Yes	Yes
***R*-Square**	0.066	0.068
Number of Obs	41606	41407

Table 4: Holdings-Based Performance of Contrarian Funds

Each quarter t, we compute the buy-and-hold hypothetical return of a fund's equity portfolio for each of the subsequent four quarters (t+1 to t+4) along with the four-quarter cumulative returns. We then sort funds into quintile portfolios based upon their contrarian indexes and report the average quarterly and four-quarter cumulative returns for each of the quintile portfolios. Panel A reports results with raw returns while panel B reports results with DGTW (1997) characteristic-adjusted abnormal returns. Returns are reported in percentage. We also report the performance of a zero cost portfolio that buys quintile 5 (contrarian) funds and sells quintile 1 (herding) funds. t-statistics calculated with Newey-West robust standard errors are in parentheses.

Panel A: Raw Returns

CON	**Horizon**				
Quintile	Qtr 1	Qtr 2	Qtr3	Qtr 4	Cumulative
1—Low	1.92	1.84	1.73	1.79	7.58
	(1.39)	(1.34)	(1.22)	(1.23)	(2.11)
2	1.84	2.01	1.94	2.03	8.14
	(1.37)	(1.44)	(1.40)	(1.43)	(2.24)
3	1.98	2.07	2.17	2.20	8.71
	(1.48)	(1.53)	(1.57)	(1.55)	(2.42)
4	1.96	2.05	2.18	2.36	8.85
	(1.51)	(1.53)	(1.60)	(1.70)	(2.51)
5—High	2.11	2.32	2.50	2.59	9.92
	(1.65)	(1.71)	(1.84)	(1.87)	(2.79)
High-Low	0.20	0.48	0.76	0.80	2.35
	(0.63)	(1.72)	(2.55)	(2.66)	(2.69)

Panel B: DGTW Adjusted Abnormal Returns

CON	**Horizon**				
Quintile	Qtr 1	Qtr 2	Qtr3	Qtr 4	Cumulative
1—Low	-0.01	-0.15	-0.24	-0.24	-0.61
	(-0.09)	(-0.78)	(-1.63)	(-1.32)	(-1.96)
2	-0.03	0.00	-0.09	-0.07	-0.16
	(-0.19)	(-0.03)	(-0.63)	(-0.45)	(-0.54)
3	0.07	0.03	0.01	-0.01	0.11
	(0.50)	(0.17)	(0.05)	(-0.04)	(0.29)
4	0.04	0.02	0.00	0.14	0.24
	(0.35)	(0.16)	(-0.03)	(1.00)	(0.69)
5—High	0.22	0.22	0.16	0.21	0.87
	(1.73)	(1.49)	(1.10)	(1.53)	(1.91)
High-Low	0.23	0.37	0.40	0.45	1.48
	(1.81)	(2.35)	(2.56)	(2.57)	(3.15)

Table 5: Trade Based Performance of Contrarian Funds

Each quarter we sort funds into quintile portfolios based upon their contrarian indexes. Within each fund, we break down fund trades into 4 types: 1) a contrarian trade on a strong-herd stock, 2) a contrarian trade on a weak-herd stock, 3) a herding trade on a strong-herd stock, 4) a herding trade on a weak-herd stock. We then measure DGTW (1997) characteristic-adjusted abnormal returns of each type of trades in each of the following four quarters along with their four-quarter cumulative abnormal returns. Panel A reports results for buy trades while Panel B reports results for sell trades. Returns are reported in percentage. We also report the performance of a 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: Performance of Buy Trades

Trade		Horizon				
Type	**Quintile**	**Qtr 1**	**Qtr 2**	**Qtr3**	**Qtr 4**	**Cumulative**
1		-0.13	-0.05	-0.03	0.51	0.23
	1—Low	(-0.27)	(-0.11)	(-0.06)	(0.93)	(0.27)
(Contrarian		-0.31	0.37	0.38	0.94	1.60
Trade/Strong Herd Stock)	2	(-0.87)	(0.91)	(0.86)	(1.85)	(1.89)
		-0.48	-0.26	0.82	0.82	1.20
	3	(-1.21)	(-0.60)	(1.99)	(1.83)	(1.93)
		-0.11	-0.45	0.51	0.42	0.86
	4	(-0.32)	(-1.59)	(1.35)	(1.31)	(1.61)
		-0.14	0.26	0.99	0.90	2.65
	5—High	(-0.36)	(0.64)	(-2.61)	(2.29)	(2.85)
		-0.01	0.31	1.02	0.39	2.42
	High-Low	(-0.01)	(0.84)	(2.54)	(1.03)	(2.10)
2		-0.55	-0.36	0.16	0.14	-0.54
	1—Low	(-1.87)	(-1.10)	(0.64)	(0.56)	(-1.25)
(Contrarian		-0.15	-0.04	-0.16	0.28	0.11
Trade/Weak Herd Stock)	2	(-0.56)	(-0.15)	(-0.73)	(1.11)	(0.20)
		-0.04	0.05	0.22	0.51	0.75
	3	(-0.20)	(0.19)	(0.86)	(1.91)	(1.23)
		-0.03	-0.21	0.15	0.43	0.45
	4	(-0.16)	(-0.70)	(0.65)	(1.88)	(0.71)
		0.31	0.06	0.41	0.70	1.77
	5—High	(1.32)	(0.22)	(1.31)	(2.50)	(2.11)
		0.85	0.41	0.25	0.55	2.31
	High-Low	(3.49)	(1.28)	(0.87)	(1.92)	(2.50)

Trade Type	Quintile	Horizon				
		Qtr 1	Qtr 2	Qtr3	Qtr 4	Cumulative
3 (Herding Trade/Strong Herd Stock	1—Low	-0.15	-0.74	-0.89	-0.91	-2.52
		(-0.40)	(-1.73)	(-2.46)	(-1.90)	(-3.02)
	2	0.16	-0.10	-0.54	-0.89	-1.16
		(0.47)	(-0.23)	(-1.42)	(-2.19)	(-1.55)
	3	0.14	0.11	-0.61	-0.86	-0.90
		(0.38)	(0.31)	(-1.73)	(-2.32)	(-1.12)
	4	0.15	-0.03	-0.35	-0.53	-0.27
		(0.43)	(-0.10)	(-1.07)	(-1.56)	(-0.44)
	5—High	0.57	-0.34	-0.26	0.06	0.53
		(1.72)	(-0.93)	(-0.69)	(0.14)	(0.80)
	High-Low	0.72	0.41	0.64	0.97	3.04
		(2.41)	(1.04)	(1.83)	(2.35)	(3.26)
4 (Herding Trade/Weak Herd Stock)	1—Low	-0.01	-0.14	-0.12	-0.43	-0.63
		(-0.03)	(-0.41)	(-0.51)	(-1.71)	(-1.47)
	2	0.01	-0.11	0.00	-0.25	-0.31
		(0.04)	(-0.37)	(-0.02)	(-1.09)	(-0.52)
	3	0.31	0.11	0.02	-0.19	0.24
		(1.43)	(0.42)	(0.11)	(-0.71)	(0.46)
	4	0.32	0.20	0.11	0.29	0.98
		(1.20)	(0.76)	(0.55)	(1.10)	(1.62)
	5—High	0.37	0.32	0.39	0.24	1.56
		(1.33)	(1.20)	(1.37)	(1.08)	(2.09)
	High-Low	0.37	0.46	0.52	0.68	2.19
		(1.37)	(1.24)	(1.75)	(2.48)	(3.22)

Panel B: Performance of Sell Trades

Trade Type	Quintile	Horizon				
		Qtr 1	Qtr 2	Qtr3	Qtr 4	Cumulative
1 (Contrarian Trade/Strong Herd Stock)	1—Low	0.03	-0.78	-1.30	-1.30	-2.89
		(0.05)	(-1.67)	(-2.68)	(-2.65)	(-3.66)
	2	-0.11	-0.47	-0.97	-1.21	-2.58
		(-0.27)	(-1.28)	(-2.36)	(-2.36)	(-3.53)
	3	0.25	0.18	-0.73	-0.85	-0.87
		(0.55)	(0.57)	(-1.75)	(-2.09)	(-1.38)
	4	0.36	-0.11	-0.36	-0.53	-0.31
		(0.78)	(-0.29)	(-0.89)	(-1.26)	(-0.45)
	5—High	0.65	0.24	-0.62	-0.60	-0.18
		(1.32)	(0.55)	(-1.51)	(-1.40)	(-0.25)
	High-Low	0.62	1.02	0.69	0.70	2.71
		(1.40)	(2.49)	(1.92)	(1.64)	(3.29)

Trade		Horizon				
Type	**Quintile**	**Qtr 1**	**Qtr 2**	**Qtr3**	**Qtr 4**	**Cumulative**
2	1—Low	-0.10	-0.20	0.00	-0.23	-0.37
		(-0.34)	(-0.62)	(-0.02)	(-0.71)	(-0.66)
(Contrarian Trade/Weak Herd Stock)	2	0.11	-0.03	-0.01	-0.07	0.11
		(0.47)	(-0.10)	(-0.03)	(-0.27)	(0.20)
	3	0.13	0.34	-0.28	-0.08	0.09
		(0.51)	(1.22)	(-1.28)	(-0.31)	(0.15)
	4	0.30	0.21	0.04	-0.10	0.67
		(1.43)	(0.75)	(0.18)	(-0.41)	(1.06)
	5—High	0.22	0.18	0.03	0.00	0.46
		(1.07)	(0.57)	(0.12)	(0.01)	(0.68)
	High-Low	0.32	0.38	0.03	0.24	0.83
3		-0.81	-0.22	0.88	0.78	0.99
	1—Low	(-2.48)	(-0.67)	(2.21)	(2.06)	(1.42)
(Herding Trade/Strong Herd Stock		-0.19	-0.26	0.39	0.71	0.87
	2	(-0.60)	(-0.85)	(1.05)	(2.46)	(1.49)
		-0.12	0.05	0.59	0.90	1.58
	3	(-0.42)	(0.19)	(1.76)	(3.38)	(2.61)
		-0.23	0.03	0.41	0.68	1.29
	4	(-0.92)	(0.10)	(1.22)	(2.15)	(1.91)
		0.01	-0.05	0.62	0.68	1.90
	5—High	(0.04)	(-0.14)	(1.64)	(2.11)	(2.53)
		0.82	0.17	-0.27	-0.10	0.91
	High-Low	(2.21)	(0.47)	(-0.98)	(-0.27)	(1.09)
4	1—Low	-0.33	0.02	-0.01	0.16	-0.06
		(-1.37)	(0.07)	(-0.04)	(0.62)	(-0.12)
(Herding Trade/Weak Herd Stock)	2	0.16	0.05	-0.01	0.35	0.67
		(0.69)	(0.24)	(-0.06)	(1.46)	(1.27)
	3	0.08	0.19	0.10	0.71	1.16
		(0.37)	(0.81)	(0.43)	(2.64)	(1.81)
	4	-0.15	-0.06	-0.09	0.38	0.11
		(-0.61)	(-0.28)	(-0.40)	(1.51)	(0.18)
	5—High	0.43	-0.07	0.25	0.69	1.47
		(1.78)	(-0.28)	(0.91)	(2.72)	(2.34)
		0.75	-0.08	0.26	0.53	1.53
	High-Low	(3.13)	(-0.27)	(1.03)	(2.06)	(3.18)

Table 6: 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 four-quarter cumulative Carhart (1997) four-factor abnormal fund returns, net of expense ratio. The explanatory variables include contrarian index, average size, BM and momentum quintile rankings of fund holdings, the logged value of fund size as proxied by total net asset value, the logged value of 1 plus fund age, total expenses, turnover ratio, prior quarter fund flows, the interaction term between the contrarian index and prior quarter fund flows, R^2 computed as the *R*-square from regressing monthly fund returns on the Carhart (1997) four factors, using past 12 months of data, and Active Share measured as the share of portfolio holdings that differs from the benchmark index holdings. Quarter dummies are included in all regressions to control for time fixed effects. The corresponding t-statistics reported in parentheses are based on standard errors clustered by funds.

Dependent Variable	**Carhart 4-Factor Adjusted Fund Returns (in %)**				
	(1)	(2)	(3)	(4)	(5)
Intercept	2.9215	-4.7639	1.5778	3.8864	1.6358
	(5.45)	(-4.05)	(1.10)	(1.65)	(1.14)
CON	0.2709	0.3011	0.2753	0.2996	0.2742
	(4.25)	(5.14)	(4.72)	(3.94)	(4.71)
Size Rank		0.1937	0.2437	-0.0119	0.2038
		(1.70)	(1.90)	(-0.07)	(1.81)
BM Rank		0.9547	0.7550	0.9396	0.7594
		(7.36)	(5.81)	(5.89)	(5.84)
Mom Rank		1.4050	1.2652	-0.8798	1.2699
		(5.90)	(5.51)	(-3.51)	(5.52)
Fund Size	-0.1080	-0.1421	-0.1260	-0.1513	-0.1249
	(-2.38)	(-3.11)	(-2.78)	(-2.42)	(-2.76)
Fund Age	0.0543	0.1597	0.1791	0.0499	0.1797
	(0.57)	(1.67)	(1.89)	(0.42)	(1.90)
Total Expenses	-27.0877	-27.9123	-40.9539	-71.6907	-40.9107
	(-1.21)	(-1.43)	(-2.11)	(-2.82)	(-2.10)
Turnover	-0.2665	-0.1400	-0.3549	0.2018	-0.3530
	(-2.16)	(-2.74)	(-2.57)	(1.07)	(-2.55)
Flows	0.0011	-1.1153	-1.1455	-1.1036	-0.0151
	(0.00)	(-1.67)	(-1.73)	(-1.35)	(-0.02)
CON*Flows					1.8964
					(2.91)
R^2			-5.7446	-5.4826	-5.7903
			(-7.20)	(-3.42)	(-7.23)
Active Share				2.4682	
				(3.46)	
Time Dummy	Yes	Yes	Yes	Yes	Yes
Clustering by Funds	Yes	Yes	Yes	Yes	Yes
***R*-Square**	0.05	0.062	0.066	0.114	0.067
Number of Obs	40552	39623	39617	22775	39617

Table 7: Contrarian Scores and the Cross Section of Stock Returns

Each quarter, we sort stocks into equal-weighted deciles based on the contrarian score α_{CON} and report the decile portfolio performance in the following four quarters. D1 is the decile with the lowest α_{CON} and D10 is the decile with the highest α_{CON}. In addition, the column "JT4" reports the performance of the portfolios using the four-quarter overlapping portfolio approach of Jegadeesh and Titman (1993). The performance measures include raw returns, DGTW (1997) characteristic-adjusted returns, and alphas from the Carhart (1997) four-factor model.

	Net Return					**DGTW-Adjusted Return**					**Carhart Four-factor Alpha**				
	Qtr+1	Qtr+2	Qtr+3	Qtr+4	JT4	Qtr+1	Qtr+2	Qtr+3	Qtr+4	JT4	Qtr+1	Qtr+2	Qtr+3	Qtr+4	JT4
D1	1.78	2.02	2.04	2.14	1.75	-0.17	-0.09	-0.28	-0.31	-0.20	-0.54	-0.41	-0.36	-0.23	-0.35
D2	1.94	2.17	2.41	2.48	1.89	-0.07	-0.11	-0.16	-0.04	-0.15	-0.30	-0.16	-0.14	-0.05	-0.13
D3	2.16	2.11	2.43	2.69	2.06	0.09	-0.22	-0.07	0.08	-0.03	0.11	-0.28	-0.21	-0.10	-0.02
D4	2.27	2.49	2.23	2.34	2.03	0.20	0.15	-0.32	-0.25	-0.06	-0.02	0.07	-0.41	-0.40	-0.09
D5	2.20	2.18	2.37	2.61	2.05	-0.01	-0.18	-0.15	-0.10	-0.13	-0.12	-0.25	-0.38	-0.06	-0.15
D6	2.37	2.47	2.58	2.50	2.20	0.10	0.19	0.12	0.10	0.14	-0.01	0.28	0.46	0.24	0.25
D7	2.37	2.40	2.62	2.86	2.35	0.20	0.16	-0.04	0.15	0.10	0.02	-0.08	-0.10	0.07	0.01
D8	2.30	2.08	2.29	2.66	2.12	0.44	0.18	0.08	0.07	0.00	0.10	0.06	0.07	0.06	0.07
D9	2.37	2.56	2.61	2.52	2.40	0.19	0.18	0.09	0.01	0.12	0.05	0.09	0.02	0.03	0.05
D10	2.45	2.75	2.73	2.65	2.31	0.41	0.44	0.32	0.14	0.29	0.38	0.47	0.38	0.27	0.41
D10-D1	0.67	0.72	0.69	0.51	0.56	0.57	0.53	0.60	0.45	0.49	0.91	0.89	0.75	0.50	0.76
t-stat	(2.17)	(2.08)	(2.15)	(1.96)	(2.15)	(2.41)	(2.18)	(2.58)	(2.17)	(2.75)	(2.87)	(2.92)	(2.57)	(1.77)	(3.03)

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

In each quarter t, we sort stocks into deciles based on the contrarian score α_{CON}. For each quintile we calculate the average herding index (HERD) for the four quarters from quarter t-3 to quarter t, as well as nine categorical stock characteristic measures. HERD is herding intensity based on the quintile ranks of buy-herd and sell-herd measures. VAL is a value investment measure. INVFIN is a measure of investment and financing activities. EQAL is an earnings quality measure. EFF is an operating efficiency measure. INTAG is an intangible investment measure. EMOM is an earnings momentum measure. PROF is a profitability measure. UNCT is an uncertainty 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 B. The underlying variables are signed so that a higher value of the variable is associated with higher subsequent stock returns based on existing literature. We also report the difference in herding intensity and stock characteristics between the top and bottom stock deciles. t-statistics calculated with Newey-West robust standard errors are in parentheses.

	VAL	INVFN	EQAL	EFF	INTAG	EMOM	PROF	UNCT	ILLIQ	HERD (Q 0)	HERD (Q-1)	HERD (Q-2)	HERD (Q-3)
D1	45.40	41.46	50.01	48.32	49.65	55.78	58.01	60.05	24.50	0.51	0.61	0.56	0.55
D2	46.51	43.22	49.03	49.04	50.95	52.87	54.15	54.02	31.64	0.52	0.63	0.60	0.53
D3	47.17	44.64	49.46	49.79	51.28	50.35	51.58	50.21	38.41	0.45	0.63	0.55	0.45
D4	47.89	45.96	48.82	50.37	52.01	48.82	49.47	47.03	44.59	0.24	0.43	0.46	0.44
D5	48.27	48.59	49.21	50.48	52.26	47.96	46.68	44.38	52.43	0.07	0.31	0.39	0.38
D6	52.28	54.05	49.19	48.98	48.65	47.72	45.33	45.90	64.31	-0.34	0.12	0.28	0.22
D7	53.24	53.72	49.24	50.04	48.76	46.74	45.22	44.48	65.44	-0.17	0.21	0.33	0.31
D8	48.46	48.28	49.22	50.97	52.10	47.56	46.78	44.98	50.81	0.03	0.20	0.33	0.31
D9	48.46	46.78	48.99	50.36	52.34	47.66	49.61	48.80	40.97	0.00	0.18	0.23	0.30
D10	49.71	47.24	50.52	49.79	51.87	49.05	54.58	56.96	28.15	-0.15	-0.08	0.00	0.03
D10-D1	4.31	5.79	0.50	1.47	2.22	-6.73	-3.44	-3.09	3.66	-0.66	-0.69	-0.56	-0.52
t-stat	(5.47)	(9.51)	(0.81)	(3.43)	(3.05)	(-11.73)	(-6.21)	(-3.97)	(4.89)	(-8.39)	(-8.98)	(-7.78)	(-9.24)

Table 9: Contrarian Score and Stock Returns: Controlling for Herding and Fundamental-Related Stock Characteristics

This table reports coefficients from quarterly Fama-MacBeth regressions. The dependent variable is the DGTW (1997) characteristic-adjusted stock return of each stock in each of the four quarters after portfolio formation (Qtr+1, Qtr+4). Coefficients reported in the table, following the "JT4" overlapping portfolio approach, are those averaged over four different regressions with the stock returns (the dependent variable) in the same quarter, but the explanatory variables used in separate regressions over each of the past four quarters. The main explanatory variable is cross-sectional percentile rank of the contrarian score for individual stocks, α_{CON}. The control variables include the adjusted herding intensity measure HERD in the most recent four quarters (Qtr-3, Qtr 0), and nine fundamental stock characteristics measured at the portfolio formation quarter (Qtr 0). To avoid a significant reduction of sample size, missing quantitative stock characteristics are replaced by simulated values using the multiple imputation procedure and time series t-statistics reported in parentheses are adjusted to account for such simulated regressors. Adj. *R*-square is the average adjusted *R*-square of the Fama-MacBeth regressions.

Explanatory variables	**(1)**	**(2)**	**(3)**	**(4)**
$\boldsymbol{\alpha_{CON}}$	0.0088	0.0067	0.0063	0.0049
	(6.08)	(4.89)	(4.16)	(3.36)
HERD (Qtr 0)		-0.0501		-0.0481
		(-1.89)		(-2.22)
HERD (Qtr -1)		-0.0897		-0.0794
		(-3.81)		(-4.34)
HERD (Qtr -2)		-0.0873		-0.0680
		(-3.97)		(-3.91)
HERD (Qtr 3)		-0.0721		-0.0557
		(-3.23)		(-2.96)
VAL			-0.0096	-0.0114
			(-1.70)	(-2.12)
INVFN			-0.0045	-0.0066
			(-0.94)	(-1.38)
EQAL			0.0035	0.0034
			(2.21)	(2.22)
EFF			0.0303	0.0302
			(6.13)	(6.15)
INTAG			0.0261	0.0257
			(4.29)	(4.27)
EMOM			-0.0016	0.0009
			(-0.59)	(0.32)
PROF			-0.0061	-0.0076
			(-0.72)	(-0.92)
UNCT			0.0090	0.0080
			(1.54)	(1.68)
ILLIQ			0.0076	0.0098
			(1.61)	(1.71)
***R*-Square**	0.0009	0.0033	0.0289	0.0304