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Uncommon Value: The Characteristics and Investment Performance of Contrarian Funds

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Motivated by extant theories of herding behavior, this paper empirically identifies contrarian mutual funds as those trading most frequently against the crowd. We find that contrarian funds generate superior performance both when they trade against and with the herd, indicating that they possess superior private information. Furthermore, contrarians do not trade in a particularly correlated fashion with each other, consistent with these funds having disparate information. Our fund-level contrarian measure is largely unrelated to existing measures of fund strategy uniqueness, as both contrarian and herding funds score highly on such measures. Building on our finding of superior alphas for contrarian funds, we construct a stock-level contrarian score that reflects the aggregate stock selection information possessed by contrarian managers. This stock-level contrarian score significantly predicts stock returns after controlling for measures of stock-level herding, as well as a battery of return-predictive investment signals documented in prior studies.

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1. Introduction

Academic researchers have long been interested in whether institutional investors trade together in a "herd-like" manner (e.g., Lakonishok et al. 1992, Grinblatt et al. 1995, Wermers 1999, Sias 2004). Although many papers document similarities in the trades of institutional investors, much less attention is paid to the strategies and performance of institutions that are "contrarian investors"—those who trade independently from herds.

Interestingly, among U.S. equity mutual funds, many well-known managers with sustained superior performance use investment strategies that are explicitly or implicitly contrarian—for example, Peter Lynch at Fidelity, Bill Miller at Legg Mason, John Neff at Wellington Management, and John Templeton at Franklin Templeton. On the other hand, there exists significant anecdotal evidence that managers making daring moves against the crowd often fail spectacularly.[1]

Whether contrarian funds outperform depends on the economic rationale for their contrarian behavior. Scharfstein and Stein (1990), perhaps the most well-known model of reputation-based herding, predict that managers with reputational concerns may find it optimal to herd with other managers in their investment decisions, even if this involves ignoring their own private information, to avoid the risk of failing alone. However, even with reputational concerns, herding is less attractive for those managers with superior private information not available to the herd. Thus, contrarians under this theory may, for example, buy technology stocks during 2002, while not buying them during 1999; they may buy financials during 2008, while not buying them during 2006; in both cases, they take actions that are uncommon. Such reputation-based herding models would predict contrarian funds—those with uncommon actions—to outperform their peers, due to contrarians possessing private information that is independent from that of the crowd.[2]

However, contrarian investing may lead to a very different outcome if herds behave according to

[1] For example, two prominent contrarian fund managers recently lost their jobs due to significant losses from betting on banking stocks during 2008 and Chinese stocks during 2011 (see Luxenberg 2013).

[2] Specifically, a nonherding equilibria obtains in Scharfstein and Stein (1990) when "smart" project managers possess information that is independent from each other, and that is unavailable to "dumb" managers.

information-based theories (e.g., Bikhchandani et al. 1992), where funds herd because they believe the crowd to possess a "common truth." In this case, it is possible that contrarian traders are those who are overconfident and, thus, overweight their private information signals and underweight useful public information signals (Daniel et al. 1998). If it is overconfidence that leads fund managers to deviate from the crowd, contrarian funds are likely to underperform, on average, as predicted by Daniel et al. 1998. Furthermore, excessive risk taking may motivate some managers to deviate from the herd; Brown et al. (1996) and Chevalier and Ellison (1997) show that some fund managers "gamble" toward the end of the year to game the convexity in the flow-performance relation. In these cases, we would expect contrarians to consist of managers who are prone to agency problems and who tend to underperform, as documented in Huang et al. (2011).

In this study, we systematically analyze the characteristics and performance of contrarian funds. Currently, no widely accepted contrarian designation exists in the fund industry or in the academic literature. In addition, funds often game their self-designated investment objectives.[3] In light of these concerns, we propose a new approach to identifying contrarians by examining the *trades* of fund managers, rather than their tendency to *hold* particular types of stocks (e.g., value stocks or past losers). That is, we analyze "contrarianism," not based on any particular self-designated investment style, such as "deep value" or "bear market," but based on its most rudimentary characteristic: the tendency of a manager to trade differently from herds of mutual funds. Our method is very simple: each quarter we assign a "contrarian index" to individual funds that ranges from -5 (extreme herding behavior) to $+5$ (extreme contrarian behavior), based on their flow-adjusted and trade-size weighted tendency to trade against the herd, as well as the strength of the herd against which they trade.

Our contrarian index is intended to capture the tendency of funds to trade independently from the crowd during the same quarter—the finest granularity of trade information allowed by our data—to minimize the number of public information events (e.g., earnings announcements) that occur during the measurement period. In this manner, we capture contrarians as those funds that trade differently in the same information environment.

We compute the contrarian index of each actively managed U.S. domestic equity mutual fund during each quarter from 1995 to 2012. We find a wide dispersion of this index across funds: the average contrarian index of the bottom quintile ("herding" funds) is -1.99, whereas that of the top quintile (contrarian funds) is 0.40. To understand whether this variation results from an intentional pursuit of economically significant contrarian strategies by some funds, rather than an occasional straying from the herd, we conduct two analyses. First, we perform a bootstrap analysis under the assumption that funds do not intentionally make herding or contrarian trades. Across 2,000 bootstraps, we find zero outcomes where the average value of the contrarian index for the top (bottom) quintile funds exceeds (drops below) the observed value of 0.40 (-1.99). Second, the contrarian index of individual funds is highly persistent over time, even after controlling for simple deep-value or price-contrarian strategies. Thus, the contrarian index identifies an economically meaningful group of funds with a persistent tendency to be different from the crowd.

Furthermore, funds with a greater contrarian index tend to have recent success; they have higher past alphas and greater inflows, and are more likely to be rated as Morningstar "five-star funds," which suggests that contrarian fund managers may have reduced career concerns and may even be overconfident. Interestingly, the trades of contrarian funds exhibit low commonality among themselves—i.e., contrarian managers do not tend to form their own (smaller) herd. Besides trading against herding funds, contrarian managers pursue strategies that are distinctive from each other, suggesting that they do not mechanically trade together against the same stocks chased by herds.

Importantly, we show that our notion of contrarian investing is quite different from some existing measures of fund "strategy activeness" and "reliance on public information" (*RPI*) (Kacperczyk et al. 2005, Kacperczyk and Seru 2007, Cremers and Petajisto 2009). First, there exists an important conceptual difference between our contrarian index and strategy activeness measures. We measure contrarianism based on the extent to which a fund trades against the herd, not on whether a fund loads on a set of return-predictive factors or deviates from its benchmark, as the above-mentioned strategy activeness measures are designed to capture. Indeed, we find that funds with the greatest levels of strategy activeness include both extreme contrarian funds and extreme herding funds. That is, herding funds, on average, deviate together away from their benchmarks, whereas contrarian funds also deviate from their benchmarks, but in unique ways, as their strategies bear little resemblance to each other. As a consequence, our contrarian index captures uncommon strategies in a way that is largely unrelated to what is captured by the strategy activeness measures in past literature. Second, we find that both herding and contrarian funds tend to have a slightly higher *RPI*, as defined by Kacperczyk and Seru (2007). Therefore,

[3] Sensoy (2009) points out that there is a great deal of gaming in self-designations by fund management companies for their own benefit, often nullifying the meaning of their investment-objective statements.

the fund skill information embedded in our contrarian index is not subsumed by *RPI*, either.

Perhaps most revealing about the motivation of contrarian funds is that these funds (ranked in the top contrarian index quintile) significantly outperform herding funds (those ranked in the bottom quintile) over the following four quarters, based on Daniel et al. (1997) (hereafter, DGTW) characteristic-adjusted holdings-based returns and Carhart (1997) four-factor net return alphas. The fact that contrarian funds outperform herding funds suggests that contrarianism among fund managers is unlikely to be mainly driven by overconfidence or excessive risk taking, where it is herding funds that collectively possess superior information.

How do contrarian fund managers achieve these superior returns? To address this question, we further analyze the performance of their trades. We find that contrarian funds not only outperform with their contrarian trades, they also outperform *when they trade with the crowd*. This evidence indicates that contrarian managers do not simply benefit from, mechanically, the price pressure caused by herding funds (e.g., Dasgupta et al. 2011a, b; Brown et al. 2014). Rather, they appear to possess superior private information, as they trade independently and may end up trading with or against the crowd, depending on whether their information conforms to that of other funds.

Lastly, we examine whether the superior performance of contrarian funds translates into a successful stock-picking signal. That is, if each contrarian fund has unique stock-picking skills, then the aggregate investment by contrarian funds in a particular stock should be a superior investment signal, not only relative to the aggregate investment by herding funds, but also relative to the investment of a single contrarian fund. To test this hypothesis, we implement the approach of Wermers et al. (2012) to construct a stock-level "contrarian score"—which measures the relative degree to which a stock is held by contrarian funds versus herding funds. We find that this stock-level contrarian score significantly predicts stock returns during the subsequent four quarters. This result holds when we control for stock-level herding, as well as a battery of return-predictive signals already documented in existing studies.

Our study is the first academic paper on the motivation and performance of contrarian investing. Using detailed portfolio holdings information, we uniquely identify a group of funds that outperform the crowd through their uncommon investing behavior. As such, our study is related to existing evidence that most mutual funds (i.e., the "crowd") are unable to outperform their benchmarks, even before expenses (see, e.g., Barras et al. 2010, Fama and French 2010). Also, we show that contrarian investing is distinct from strategy activeness and weak reliance on public information and, thus, represents a new and important characteristic that is common among skilled fund managers.

Furthermore, we contribute to the literature through an intuitive and systematic trade-based approach to measuring contrarianism as an investment strategy. This trade-based, rather than holdings-based, approach has its foundations in extant theories of herding, where funds herd either because they infer that other funds are acting on superior information or because they discard their private information (e.g., due to career concerns).

Finally, we emphasize that the contrarian funds we identify employ strategies not only different from the herd, but also different from each other. Therefore, the contrarian behavior that we document is not merely the mechanical opposite of herding behavior. Our paper is, thus, distinct from existing studies that focus on institutional herding. Moreover, since contrarian funds appear to invest independently from each other, our findings suggest that the trades of contrarian funds, as a group, may bring diverse sources of private information into stock prices.

2. Data and Methodology

2.1. Mutual Fund Sample

Our sample of mutual funds includes U.S. active domestic equity funds that exist in both the Thomson-Reuters mutual fund holdings data and the Center for Research in Security Prices (CRSP) mutual fund database during 1995 to 2012. Funds in these two data sets are matched via the MFLINKS file (available from Wharton Research Data Services). We focus on this relatively recent period since recent research indicates that the fraction of the market portfolio represented by mutual funds has expanded so quickly that trading by herds during this recent period results in a sizable price-pressure effect, followed by reversals in stock returns (Dasgupta et al. 2011b, Brown et al. 2014).[4] This provides a motivation to study whether there exist funds that do not engage in herding behavior and trade independently, and, thus, do not suffer from the detrimental effects of herding.

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, although mutual funds are only required to report

[4] Indeed, Wermers (1999) and Brown et al. (2014) do not find mutual fund herding to be price destabilizing prior to the mid-1990s. Similarly, Dasgupta et al. (2011b) show that persistent institutional trading leads to long-term return reversals mainly in the post-1994 period.

their holdings at a semiannual frequency, about 50% of mutual funds voluntarily disclose to Thomson at a quarterly frequency. Since our trade-based contrarian measure depends critically on a timely and precise measure of the direction and size of fund trades, we compute trades from changes in holdings reported for consecutive quarter ends.

Fund net returns, flows, investment objectives, and other characteristics are obtained or computed with data 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 assets 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.[5] 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 to have at least 20 reported stock holdings, at both the end of that quarter and the prior quarter. These filters are imposed to ensure that we identify funds that follow an economically important contrarian strategy. Our final sample includes 73,654 fund quarters during the period of 1995 to 2012.

2.2. Construction of Fund-Level Contrarian Index

We define contrarian funds as those that tend to trade in the opposite direction relative to mutual fund herds. Note that various papers have proposed theories of investor herding (see, e.g., Scharfstein and Stein 1990, Bikhchandani et al. 1992, Froot et al. 1992, Hirshleifer et al. 1994, Falkenstein 1996). Empirically, we can only observe mutual funds trading together without directly differentiating between various motivations for fund herding. Therefore, we follow the past literature and empirically define herding as instances of funds trading together beyond what one would expect with random and independent trading. Specifically, we obtain an empirical stock-level herding measure (HM_{it}) following Lakonishok et al. (1992):

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

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; $\bar{p}_t$, 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; and $E(|p_{i,t} - \bar{p}_t|)$ is an adjustment factor, which equals the expected value of $|p_{i,t} - \bar{p}_t|$ under the null of no herding (Lakonishok et al. 1992).[6]

We exclude stocks that are newly issued within the prior four quarters since their supply increases from zero to a large positive number, making them appear to be subject to buy-herding among funds. Next, we classify a stock as either a "buy-herd" or "sell-herd" stock, depending on whether the proportion of mutual fund buys is higher or lower than average for that quarter. The conditional buy-herding and sell-herding measures ($BHM_{i,t}$ and $SHM_{i,t}$, respectively) are calculated as follows:

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

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

The buy-herding and sell-herding measures (*BHM* and *SHM*) are then combined into a single variable, $HERD_{i,t}$. For buy-herding stocks, we rank their buy-herding measure into quintiles, and assign $HERD_{i,t}$ a value ranging from 1 to 5, with 5 for stocks in the top buy-herding quintile. We rank sell-herding stocks similarly, except that $HERD_{i,t}$, in this case, is assigned 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, whereas more negative values indicate stronger sell-herding. This nonparametric ranking procedure allows us to interpret a particular contrarian index similarly across different calendar quarters.[7] Essentially, during any quarter, an individual stock is ranked as either a buy-herding stock and assigned a positive value of *HERD* between 1 and 5, with 5 indicating strong buy-herding, or it is ranked as a sell-herding stock and assigned a negative value of *HERD* between −1 and −5, with −5 indicating strong sell-herding.

Note that mutual fund trades may be forced by fund flows (Coval and Stafford 2007, Lou 2012). Therefore, we adjust fund trades for the influence of fund flows to ensure that we capture only trades that are more likely to be based either on intentional herding or superior private information, and not on fund flows. Specifically, we impute flow-driven trading as $w_{ij,t-1} FLOW_{j,t}$, where $w_{ij,t-1}$ is the portfolio weight of fund j on stock i at the end of quarter $t-1$; $FLOW_{j,t}$ is the dollar value of net fund flow (change in total net

[5] Specifically, we exclude funds with a Thomson Reuters investment objective code of 1, 5, 6, 7, or 8. In addition, we exclude index funds that are identified through the index fund indicator in the CRSP mutual fund database and by manual inspection of fund names for keywords related to index funds.

[6] Similar to Wermers (1999), we require a stock to be traded by at least 10 funds during a given quarter in order to construct an economically meaningful measure of fund herding from Equation (1).

[7] Our results to follow, however, are not materially different if we instead use each stock's parametric *BHM* and *SHM* measures to construct *HERD*. The correlation between the contrarian indexes computed with parametric versus nonparametric herding measures is about 97%.

asset value adjusted for investment returns) of fund j in quarter t. Essentially, we assume that when a fund receives inflows (outflows), it trades to proportionally scale up (down) its positions on existing stocks in the portfolio according to their current portfolio weights.[8]

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

$$CON_{j,t} = -\sum_{i=1}^{N} \omega_{ij,t} HERD_{i,t}, \tag{4}$$

$$\omega_{ij,t} = \frac{v_{ij,t} - v_{ij,t-1} - w_{ij,t-1} FLOW_{j,t}}{\sum_{i=1}^{N} |v_{ij,t} - v_{ij,t-1} - w_{ij,t-1} FLOW_{j,t}|}, \tag{5}$$

where $v_{ij,t}$ equals the dollar value of stock i held by fund j at the end of quarter t, and N equals the total number of stocks traded by the fund. The lagged dollar value, $v_{ij,t-1}$, is calculated using the number of shares of stock i held by fund j at the end of quarter $t-1$, multiplied by the stock price at the end of quarter t. The number of shares held at $t-1$ is split adjusted using the CRSP share adjustment factor to bring it forward to the implied buy-and-hold shareholding at the end of quarter t. Thus, since $w_{ij,t-1} FLOW_{j,t}$ can be interpreted as the portion of a stock trade passively induced by fund flows, $v_{ij,t} - v_{ij,t-1} - w_{ij,t-1} FLOW_{j,t}$ measures the flow-adjusted 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, after adjusting for pro-rata trading induced by fund flows.

Note that there is a negative sign in front of the summation operator in Equation (4). By construction, if a fund makes a flow-adjusted purchase of a stock sold by herds, $HERD_{i,t}$ has a negative value and $\omega_{ij,t}$ has a positive value. This trade would contribute positively to the fund's contrarian measure, *CON*. On the other hand, if a fund makes a flow-adjusted purchase of a stock bought by herds, this trade would contribute negatively to the fund's contrarian measure *CON*. The same logic applies to flow-adjusted fund sales of stocks bought or sold by herds. Also note that the value of *CON* is bounded between -5 and 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.

We note that all of the above measures of herding and contrarianism are based on one-quarter trades (inferred from one-quarter differenced portfolio holdings). Funds not reporting holdings on a quarterly basis are not included in our computations during the period that they fail to report at that frequency. In addition, we analyze a fund's trades of a stock relative to the direction and magnitude of herding by all funds in that stock within the same quarter (rather than within a coarser period, such as the same year). Thus, the contrarian index captures trades made by contrarian funds relative to those of fund herds during the same quarter to minimize the number of information events (e.g., earnings announcements) that occur during the measurement period.[9]

Table 1 reports summary statistics for the fund contrarian index and other fund characteristics, along with those for the stock-level buy-herding and sell-herding measures. Note that the mean and the median of the contrarian index are both negative (-0.84 and -0.88). This is not surprising, given that—by the definition of herding—the majority of funds must be herding funds. In addition, the distribution of *CON* in panel B suggests significant dispersion of the herding/contrarian index among our sample of funds. Note that even the 75th percentile of *CON* is negative, at -0.33. This suggests that funds systematically pursuing strong contrarian investing constitute a relatively small group, as would be expected from the definition of contrarianism.

3. Characterizing Contrarian Funds

3.1. How Different Are Contrarian Funds? A Bootstrap Analysis

Panel A of Table 2 provides further statistics on the distribution of the contrarian index. At the end of each quarter, we sort funds by *CON* into quintiles, and compute the mean *CON* value for each quintile. Then,

[8] Lou (2012) estimates that, when mutual funds experience significant inflows, they invest approximately 62¢ per dollar of inflows in their existing holdings. When they experience significant outflows, they scale down their existing holdings dollar-for-dollar. In an unreported analysis, we show that even if we take into account the potential asymmetric impact of fund flows on fund trades, the resulting contrarian index has a correlation greater than 98% with that defined according to Equations (4) and (5); in addition, all of our findings remain qualitatively and quantitatively similar.

[9] If contrarian managers also pay attention to trading by the crowd itself, it is useful to note that, even without explicitly observing disclosed holdings by other funds until the fiscal quarter end, contrarian managers may be able to infer the trade direction of herds by obtaining institutional order flow from data vendors or inferring the overall market sentiment by vigilantly observing public signals, such as analyst recommendation revisions, trading volume, bid-ask spreads, and articles from the financial media. Moreover, brokers may "tip" preferred fund managers with information on their other clients' actions (see, e.g., Irvine et al. 2007).

Table 1 Summary Statistics

Panel A: Summary statistics on fund characteristics

	Mean	Median	Std. dev.	25th	75th
Fund_ size ($millions)	1,215	229	4,391	67	796
Total_expenses (%/year)	1.32	1.26	0.45	1.01	1.56
Turnover (%/year)	83.16	64.54	67.59	35.10	111.10
Flows (%/quarter)	1.17	−0.83	9.51	−4.02	3.92
Fund_age (years)	12.82	8.46	13.63	4.35	15.53
Raw_return (%/quarter)	2.35	2.27	4.85	−0.52	5.12
CON	−0.8374	−0.8758	0.8646	−1.3841	−0.3270

Panel B: Distributions of the stock-level herding measures and the fund-level contrarian index

	Mean	Std dev.	Min	P1	P5	P25	P50	P75	P95	P99	Max
BHM	0.0378	0.1289	−0.1371	−0.1135	−0.1060	−0.0293	0.0006	0.0824	0.2809	0.3655	0.4769
SHM	0.0376	0.1111	−0.1136	−0.1370	−0.1342	−0.0453	0.0006	0.0887	0.3193	0.3964	0.4359
CON	−0.8374	0.8646	−3.9435	−2.8706	−2.1774	−1.3841	−0.8758	−0.3270	0.6277	1.4621	2.8553

Notes. Panel A reports summary statistics for our sample of actively managed U.S. equity mutual funds from 1995 to 2012. Each quarter, we calculate the cross-sectional mean, median, standard deviation, 25th, and 75th 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. Panel B reports detailed distributions of the stock-level herding measures and the fund-level contrarian index during the 1995–2012 period.

we report the time-series average of quintile means across all sample quarters. If we consider funds in the top *CON* quintile as "contrarian funds," and those in the bottom quintile as "herding funds," herding funds have an average *CON* of −1.99, and contrarian funds have an average *CON* of 0.40. In addition, slightly more than half (53%) of trades by contrarian funds are contrarian trades, which is striking, since we would expect that a fund would trade with the herd a great majority of the time if the manager traded randomly. Since the average *CON* index for contrarian funds is significantly positive, their contrarian trades (those trades made in a direction opposite to herds) tend to be larger in value than their other trades. This is consistent with small trades being driven by motivations such as staying close to fund benchmarks, as opposed to private information.

To understand how aggressively contrarian funds pursue a contrarian strategy, and how different they are from herding funds, we perform a bootstrap analysis. In doing so, we draw from a distribution of trades that has the same proportion of herding and contrarian trades as in our actual sample. Specifically, the bootstrap resamples (without replacement) from the distribution of all actual trades of our sample funds during each quarter for each stock, and reassigns those randomly drawn stock trades to randomly drawn funds. Resampling without replacement preserves the herding measure to be the same in the actual and bootstrapped data for each stock quarter. We then compute the contrarian index (*CON*) for individual funds using the bootstrapped trades, and rank funds into quintiles based on their bootstrapped *CON*. Finally, we compute the mean *CON* measure for each quintile, then average over time to compare with the actual trade data.

Across these 2,000 bootstraps, the average value of *CON* is −1.48 for the bottom *CON* quintile, and 0.27 for the top *CON* quintile of funds. Notably, not a single bootstrap results in a *CON* value below −1.99 for the bottom quintile, or above 0.40 for the top quintile, as we observe in the original sample (panel A of Table 2). Thus, the distribution of *CON* in our data is extremely unlikely to result from a sample of funds randomly choosing herding versus contrarian trades; funds in these two quintiles tend to tilt significantly more heavily toward making herding or contrarian trades, respectively. Furthermore, bootstrapped statistics on the fraction of aggregate contrarian trades within each *CON* quintile lead us to the same conclusion.

Another interesting aspect of contrarians is that a significant portion of their trades (47%) is with fund herds. This suggests that contrarian funds may end up trading with or against herds based on their private information, instead of trading mechanically against them.[10] To further assess the uniqueness of investment strategies pursued by contrarian funds, we construct Lakonishok et al. (1992) herding measures limited to trades conducted by the universe of funds within each *CON* quintile. A comparison across the five groups of funds quantifies the extent to which trades by funds with a similar level of the contrarian index are correlated with each other. The results reported in

[10] In unreported analysis, we further decompose the contrarian index into two components, *CON*_buy and *CON*_sell, to separate the contribution of a fund's contrarian buy versus sell trades to its overall contrarian index. For instance, since most mutual funds do not sell stocks short, they may find it easier to trade as contrarians on the buy side. However, we find that, on average, a fund's overall contrarianism is not dominated by contrarianism on either the buy- or the sell-side of trading.

Table 2 Characteristics of Contrarian Funds

Panel A: Herding related characteristics

CON quintiles	*CON*	% *Contrarian*	*HM*	*BHM*	*SHM*
1	−1.9875	31.34	0.0810	0.0805	0.0784
2	−1.2775	37.10	0.0460	0.0449	0.0441
3	−0.8754	40.38	0.0268	0.0250	0.0256
4	−0.4442	43.81	0.0160	0.0141	0.0151
5	0.3956	52.95	0.0191	0.0168	0.0183

Panel B: Characteristics of fund holdings

CON quintiles	*Size_rank*	*B/M_rank*	*MOM_rank*	*ILLIQ_rank*	*ICI*	*Active_share*	*RPI*
1—Low	4.2568	2.5890	3.1263	1.3279	0.0993	0.8405	0.0985
2	4.2706	2.6076	3.1032	1.3167	0.0848	0.8236	0.0936
3	4.3338	2.6825	3.0533	1.3001	0.0784	0.8164	0.0909
4	4.3969	2.7534	2.9724	1.2858	0.0793	0.8150	0.0943
5—High	4.4763	2.8560	2.8580	1.2611	0.0947	0.8340	0.1043
High − Low	0.2196	0.2671	−0.2683	−0.0668	−0.0046	−0.0065	0.0058
	(8.04)	(11.19)	(−15.70)	(−4.55)	(−1.81)	(−1.43)	(3.38)

Panel C: Other fund characteristics

CON quintiles	*TNA*	*Expense_ratio*	*Turnover*	*Age*	*Past_alpha*	% *Five-star*	*Volatility_of_ret*	*Past_flow*	% *Cash_holdings*	*Volatility_of_flow*
1—Low	960	1.33	79.37	12.61	−0.05	8.05	1.85	1.03	4.70	2.79
2	1,081	1.32	92.27	12.69	−0.05	7.66	1.74	1.22	4.76	2.80
3	1,123	1.31	92.17	12.87	−0.06	8.17	1.66	1.53	4.78	2.85
4	1,224	1.31	83.98	12.81	−0.02	9.39	1.65	2.14	5.08	2.84
5—High	1,581	1.31	67.89	13.14	0.02	10.37	1.71	2.18	5.79	2.85
High − Low	621	−0.02	−11.48	0.53	0.07	2.32	−0.13	1.15	1.09	0.06
	(7.76)	(−1.68)	(−6.04)	(1.90)	(5.29)	(2.51)	(−6.20)	(4.37)	(8.58)	(1.07)

Notes. This table examines the characteristics of contrarian funds. Each quarter, we group funds into quintile portfolios according to their contrarian index (*CON*) and calculate the mean characteristics for each quintile, then average these means over all quarters. Panel A reports the average value of *CON*, the proportion of contrarian trades, the Lakonishok et al. (1992) herding measure (*HM*), and the buy-herding and sell-herding measures (*BHM* and *SHM*, respectively) computed among trades conducted by funds within each quintile. Panel B reports the average size (*Size_rank*); the book-to-market, momentum, and illiquidity quintile ranks (*B/M_rank*, *MOM_rank*, and *ILLIQ_rank*, respectively) of fund stock holdings; the industry concentration index (*ICI*), computed as the Herfindahl index of implied portfolio industry weights; active share (*Active_share*), measured as the share of portfolio holdings that differs from the best-fit benchmark index holdings; and reliance on public information (*RPI*), computed as the R-squared from regressing quarterly fund trades on lagged analyst recommendation changes of the underlying stocks in the past four quarters. In panel C, we report the average value of the following variables for each quintile: total net assets (in $millions) (*TNA*), expense ratio (in %) (*Expense_ratio*), turnover (in %) (*Turnover*), fund age (in years) (*Age*), Carhart (1997) four-factor alpha in the past 36 months (in % per month) (*Past_alpha*), the percentage of funds ranked as Morningstar five-star funds (% *Five-star*), standard deviation of the four-factor alpha in the past 36 months (in % per month) (*Volatility_of_ret*), prior-quarter flows (in %) (*Past_flow*), cash holdings as a percentage of total net assets (% *Cash_holdings*), and standard deviation of flows in the past 12 months (in % per month) (*Volatility_of_flow*). In panels B and C, differences in the reported variables between contrarian funds (quintile 5) and herding funds (quintile 1) and their associated t-statistics calculated with Newey–West robust standard errors are also reported.

panel A of Table 2 (columns 3–5) show that there is a high correlation among trades by herding funds, as the Lakonishok et al. (1992) herding measure for that group is about 8%. In contrast, the herding measure for contrarian funds is only about 2%, suggesting a much greater diversity of trades by these funds. Therefore, different contrarian funds do not trade very similarly, whether their trades are with or against the (noncontrarian) herd. In this sense, contrarians appear to be true mavericks.

3.2. Persistence of Contrarian Investing

So far, we have established that there exists a significant dispersion in the tendency of mutual funds to trade with or against the crowd during a particular quarter. Next, we examine whether contrarian investing is persistent through time. That is, we examine whether contrarianism is a relatively stable fund characteristic, rather than representing deviations from the crowd for some temporal reason, such as a change in fund strategy that results in an abrupt short-term portfolio transition.

First, we find a correlation between a fund's current- and following-quarter *CON* measures of 24% ($p < 1\%$). In addition, 29% of the funds ranked in the top *CON* quintile in the current quarter remain in the top *CON* quintile during the following quarter, whereas only 11% of current-quarter bottom quintile *CON* funds move to the top *CON* quintile during the following quarter. Furthermore, this positive autocorrelation of *CON* in adjacent quarters remains highly significant in a multivariate regression analysis that controls for fund investment styles and characteristics of fund holdings such as size, book-to-market ratio, and momentum (to control for contrarianism that results from mechanical strategies such as deep value investing).

Note that, since contrarian funds do not trade very often (reflected in their low turnover, as shown in the next subsection), a contrarian fund's high current-quarter *CON* index may not be immediately followed by a high next-quarter *CON* index, but may, instead, be correlated with how frequently the fund exhibits a high *CON* index during the next several quarters. Following this logic, we examine funds' degree of contrarian trading over the following four quarters. We find that 61% of the funds ranked in the top *CON* quintile in the current quarter are ranked in the top *CON* quintile again in at least one of the following four quarters; only 32% of current-quarter bottom *CON* quintile funds end up in the top *CON* quintile during at least one of the following four quarters.

Furthermore, when we group funds into quintiles based on their contrarian indexes (*CON*), we find that funds ranked in the top contrarian index quintile continue, on average, to exhibit a significantly higher contrarian index than those ranked in the bottom quintile, during at least the subsequent eight quarters (for brevity, these results are not tabulated in the paper).

How should we interpret this relatively persistent contrarian index? If contrarian investing occurs for a temporal reason, such as the above-mentioned short-term strategy change, then we would not expect *CON* to persist beyond one or two quarters. On the other hand, if contrarian investing is based on superior manager skills, then we would expect the *CON* measure to persist for a relatively long period of time. Specifically, Avramov and Wermers (2006) show that fund managers have skills that last for up to three to five years. However, we note that investment skills may not be the only driver of the persistence in *CON*. For example, funds with overconfident managers or managers with risk-shifting incentives may also exhibit persistence in *CON*. To develop a better understanding of the motive behind contrarian investing behavior, we next investigate the characteristics associated with contrarian and herding funds.

3.3. Characterizing the Investment Choices of Contrarian Funds

We start by conducting a detailed comparison of investment choices between contrarian funds and other funds. First, we characterize fund holdings in terms of the average quintile ranks of size, book-to-market, momentum, and the Amihud (2002) illiquidity measure of stocks held by each fund.[11] Panel B of Table 2 shows that, relative to herding funds, contrarian funds tend to invest in stocks that are slightly larger and, thus, slightly more liquid. Moreover, they appear to prefer stocks with a higher book-to-market ratio and lower past returns. However, the "tilts" of contrarian funds toward value stocks and low past-return stocks are slight, indicating that contrarians do not, on average, simply implement deep value investing or negative feedback trading—which are occasionally equated to contrarianism by fund prospectuses. Panel B also shows that, because contrarians often shy away from stocks strongly bought and held by mutual fund herds, their holdings tend to be slightly less liquid.

Since contrarian funds often invest differently from the crowd and may deviate more from their style benchmarks, we further examine differences between our contrarian index and three measures of fund activeness: industry concentration index (*ICI*), *Active_share*, and reliance on public information (*RPI*). Following Kacperczyk et al. (2005), a fund's industry concentration index (*ICI*) measures the Herfindahl index of its implied industry-level portfolio weights. According to Cremers and Petajisto (2009), *Active_share* measures the share of portfolio holdings that differs from the closest-fit benchmark index holdings.[12] *RPI* is the *R*-squared from regressing quarterly trades by a given fund, across all stocks, on lagged analyst recommendation changes of these stocks during the past four quarters (see Kacperczyk and Seru 2007). The aforementioned prior studies argue that funds with higher *ICI* and *Active_share* or lower *RPI* employ more active investment strategies and rely more on private information, and, thus, tend to outperform.

The results in panel B suggest that the relations between *CON* and the *ICI* and *RPI* are weak and are often U-shaped: both herding funds and contrarian funds tend to have a greater *ICI* and slightly higher *RPI* relative to the average fund.[13] The relation between *CON* and *Active_share* is also nonmonotonic. Furthermore, the dispersion of these three strategy activeness measures tends to be fairly small across *CON* quintiles: the difference in these measures is less than 1% between the top and the bottom quintiles, suggesting that extreme herding and contrarian funds tend to be

[11] Since trading volume is not comparable between NYSE/AMEX and Nasdaq stocks, we rank all CRSP stocks into quintiles, each quarter, according to their Amihud (2002) illiquidity measures, relative to all stocks traded on their respective markets.

[12] We thank Martijn Cremers for providing the *Active_share* measure for all funds during our sample period. We construct the *ICI* following Appendix B of Kacperczyk et al. (2005).

[13] In unreported analyses, we find that, although both herding and contrarian funds tend to have a higher RPI measure, trades of herding funds tend to be made in the same direction as past analyst recommendation changes, whereas those of contrarian funds tend to be in the opposite direction. This finding is consistent with the evidence in Brown et al. (2014) that mutual fund herds tend to follow analyst recommendations.

very similar in terms of the extent to which they deviate from their benchmarks or trade on public information. Therefore, trading independently from the crowd (i.e., contrarianism) and deviating from benchmarks (i.e., strategy activeness) or public investment signals are two very different fund characteristics.

3.4. Differences in Fund Characteristics

Panel C of Table 2 reports a number of additional fund characteristics for funds in different *CON* quintiles to further illustrate the incentives and fund attributes that are associated with contrarian investing. These characteristics include fund size, expense ratio, turnover, age, past fund performance, and past flows. We measure fund size (total net assets), expense ratio, turnover, and age using information from the CRSP mutual fund database at the end of, or during, the year prior to the fund ranking date.[14]

The panel shows that funds ranked in the top contrarian quintile tend to be larger, older, and have lower turnover, relative to funds in the bottom quintile. The fact that they have larger size and lower turnover indicates that contrarian funds may be more patient traders that have better access to capital to implement longer term investments. However, we note that the relation of the contrarian index, *CON*, with many of these fund characteristics is nonmonotonic.

To understand why contrarian funds are more likely to be on the opposite side of the crowd, we examine whether managers of these funds face different incentives. We note that herding by mutual fund managers may be motivated by nonfundamental information-related incentives, such as short-term career concerns (Scharfstein and Stein 1990 and Chevalier and Ellison 1999). Managers with good recent performance and correspondingly high inflows likely have lower career concerns, and may even become overconfident and underweight public information when they deviate from the crowd (Daniel et al. 1998). Alternatively, managers with poor recent performance and corresponding outflows may engage in risk shifting and trade away from the crowd as well (Brown et al. 1996, Chevalier and Ellison 1997). To determine the primary motivation of contrarian managers, we compare the recent performance and flows of herding versus contrarian funds.

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 overall Morningstar star performance ranking (which is based on the fund's 3-, 5-, and 10-year peer-adjusted past performance). We focus on comparing the percentage of funds having five-star rankings—the highest overall Morningstar ranking—across *CON* quintiles. If the career concerns and/or overconfidence hypotheses, as opposed to the risk-shifting hypothesis, hold, we would expect that managers of funds with higher risk-adjusted performance or that have five-star rankings are more likely to be contrarians. Also, we would expect funds with higher prior-quarter inflows to be more likely to engage in contrarian strategies because such funds may have more flexibility in making investment choices without having to sell stocks. We measure monthly fund flows as the percentage change in total net asset value adjusted for investment returns.

The results reported in panel C show that funds in the top *CON* quintile (contrarian funds) have past four-factor alphas that exceed those in the bottom quintile (herding funds) by seven basis points per month (0.84% per year). In addition, contrarian funds are more likely to be ranked as five-star funds by Morningstar, which is deemed a very significant accomplishment for a fund manager by the industry. They also appear to have lower performance volatility, as measured by the standard deviation of past alphas. Consistent with the well-documented phenomenon of flows chasing past performance, contrarian funds attract larger inflows during the prior quarter, relative to herding funds (2.18% versus 1.03%), while the volatility of these flows is only slightly higher for contrarians. Correspondingly, the cash holdings of contrarian funds account for 5.79% of their total net assets, 1.09% higher than that of herding funds. This difference is economically large, given that the average mutual fund cash holding is 5.02% across the five groups of funds. The higher inflows of contrarian funds give them additional liquidity with which to implement their strategies, which sometimes take longer to pay off than other strategies.

Overall, managers of contrarian funds tend to have better recent performance and higher inflows than peers. Therefore, their contrarian behavior is unlikely a result of risk shifting. Rather, they may be more inclined to deviate from their peers because of lower immediate reputational concerns or perhaps even overconfidence. These alternative sources of contrarianism, however, have different implications for future fund performance. We therefore examine the future performance of contrarians in the next section.

4. Performance of Contrarian Funds

4.1. Performance Analysis Based on Fund Holdings and Returns

We start by analyzing fund holdings, as holdings-based measures enable us to more precisely determine, compared to regression-based approaches, whether

[14] The percentage cash holdings information (PER_CASH) is missing from 1998 to 2002 in the CRSP mutual fund database. We fill in the missing value with the average of the 1997 and 2003 values for each fund.

Table 3 Performance of Contrarian Funds

	Portfolio raw returns				
CON quintiles	Quarter 1	Quarter 2	Quarter 3	Quarter 4	Cumulative
1—Low	2.77	2.19	2.05	2.06	9.31
2	2.58	2.51	2.19	2.21	9.78
3	2.72	2.44	2.33	2.33	10.06
4	2.70	2.54	2.50	2.46	10.49
5—High	2.88	2.66	2.66	2.70	11.21
High − Low	0.11	0.46	0.62	0.63	1.90
	(0.34)	(1.68)	(2.14)	(1.97)	(2.00)

	DGTW-adjusted abnormal returns					Carhart (1997) four-factor alphas of fund returns				
CON quintiles	Quarter 1	Quarter 2	Quarter 3	Quarter 4	Cumulative	Quarter 1	Quarter 2	Quarter 3	Quarter 4	Cumulative
1—Low	0.09	−0.17	−0.16	−0.12	−0.33	−0.44	−0.58	−0.62	−0.58	−2.12
	(0.76)	(−1.11)	(−1.17)	(−0.68)	(−1.10)	(−2.24)	(−2.74)	(−3.30)	(−2.56)	(−2.68)
2	0.02	0.08	−0.11	−0.05	−0.03	−0.50	−0.39	−0.49	−0.48	−1.80
	(0.18)	(0.53)	(−0.77)	(−0.34)	(−0.09)	(−2.49)	(−2.04)	(−2.63)	(−2.26)	(−2.36)
3	0.09	0.05	−0.01	0.01	0.16	−0.42	−0.36	−0.41	−0.35	−1.49
	(0.71)	(0.39)	(−0.05)	(0.08)	(0.56)	(−2.24)	(−2.01)	(−2.06)	(−1.96)	(−2.09)
4	0.05	0.07	0.05	0.07	0.27	−0.25	−0.19	−0.19	−0.23	−0.83
	(0.45)	(0.65)	(0.44)	(0.65)	(0.84)	(−1.32)	(−1.04)	(−1.07)	(−1.24)	(−1.19)
5—High	0.21	0.19	0.16	0.22	0.82	−0.08	−0.09	−0.02	0.07	−0.07
	(1.84)	(1.69)	(1.46)	(1.81)	(1.92)	(−0.43)	(−0.53)	(−0.09)	(0.34)	(−0.09)
High − Low	0.12	0.37	0.32	0.34	1.14	0.36	0.50	0.61	0.64	2.05
	(0.94)	(2.81)	(2.34)	(1.85)	(2.39)	(2.09)	(2.86)	(3.78)	(2.78)	(3.20)

Notes. At the end of each quarter t, we sort funds into quintile portfolios based on their contrarian indexes and compare their performances. We report raw returns and DGTW-characteristic-adjusted abnormal returns computed based on fund portfolio holdings, as well as Carhart four-factor alphas of reported net fund returns. Returns are reported in percentage (quarterly percentages are not annualized). 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.

fund performance can be attributed to fund 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 during each of the subsequent four quarters ($t+1$ to $t+4$), along with the four-quarter cumulative return. Since Table 2 indicates that holdings of herding funds and contrarian funds differ systematically in some return predictive stock characteristics, we also compute their DGTW-characteristic-adjusted returns. The characteristic-adjusted return for a given stock is the buy-and-hold stock return during a quarter, in excess of the return to its value-weighted characteristic benchmark portfolio. The characteristic benchmark portfolios are constructed following DGTW, except that we measure size, book-to-market ratio, and momentum characteristics at the end of each quarter, rather than once per year. This more frequent update of the benchmark portfolio allows a better control for changes in stock characteristics (e.g., in case contrarian managers are simply implementing short-term momentum strategies). Finally, to see whether there exist any performance differences between contrarian and herding funds in terms of their reported after-fee returns, we compare the Carhart (1997) four-factor alpha of funds with high versus low CON indexes.

In Table 3, we form quarterly *CON* quintiles and report their quarter-by-quarter raw returns, DGTW-adjusted returns, and Carhart (1997) four-factor alphas, along with their four-quarter cumulative returns.[15] The table shows that stock portfolios held by contrarian funds (i.e., the top *CON* quintile) significantly outperform herding funds (i.e., the bottom *CON* quintile) in risk-adjusted after-fee returns during each of the following four quarters. The four-factor alphas of contrarian funds are significantly higher than those for the herding funds by 0.36%, 0.50%, 0.61%, and 0.64% per quarter during quarters $t+1$ to $t+4$, respectively, and by 2.05% over the full year; all performance differences are statistically significant.[16] Similar patterns are present in fund holdings-based raw returns and DGTW-adjusted returns, reflecting the significantly higher stock-selection skills of contrarian fund managers. In

[15] To evaluate funds' Carhart (1997) four-factor alphas over a four-quarter horizon, we adopt an overlapping portfolio approach. Each quarter, we consider four portfolios with the same *CON* index quintile ranking, but formed during each of the prior four quarters. We then combine the four portfolios in equal weights into a single portfolio and hold it during the next quarter. Lastly, we compute four-factor alphas from the resulting time series of portfolio returns, and annualize the four-factor alpha. This portfolio formation procedure is similar to the overlapping momentum portfolio procedure of Jegadeesh and Titman (1993).

[16] Note that the four-factor alphas reported in Table 3 are generally smaller than the DGTW-adjusted returns since the former is computed based on funds' reported after-fee returns, which also include trading costs.

§4.3, we will further explore this issue in a multivariate regression framework, to control for prior-documented differences in fund characteristics (beyond the size, book-to-market, and momentum characteristics of their holdings) that proxy for skill (e.g., *RPI* or *Active_share*).

4.2. Performance Analysis Based on Fund Trades

We now turn to an analysis of the performance of fund trades, which enables us to determine *which* trades made by contrarian funds contribute to their performance advantage, relative to herding funds. Here, we are interested in determining the fraction of contrarian fund outperformance that derives from simply being on the opposite side of fund herds to benefit from the price-pressure effects of fund herding (see, e.g., Dasgupta et al. 2011a, b; Brown et al. 2014), and the fraction that derives from contrarian trading independently based on their private information. To achieve this end, we first classify all the trades made by a fund in a given quarter into the following four types:

(1) *Type* 1. A contrarian trade of a strong herding stock.

(2) *Type* 2. A contrarian trade of a weak herding stock.

(3) *Type* 3. A herding trade of a strong herding stock.

(4) *Type* 4. A herding trade of a weak herding stock.

First, a stock is considered a strong herding stock if either its buy-herding measure or sell-herding measure is ranked in the top two *BHM* or *SHM* quintiles, respectively, among all stocks during the same quarter; otherwise the stock is considered a weak herding stock.[17] Second, consistent with our classification implied by Equation (4), a trade made by a fund is defined as a "contrarian trade" if the fund buys a stock with a negative *HERD*, or sells a stock with a positive *HERD*, after adjusting for pro-rata trading driven by fund flows. Thus, based on both the level of herding by all funds in a stock and a fund's trade direction in the stock, a trade (of a stock in one of the top two *BHM* or *SHM* quintiles during that quarter) can be classified into one of the above four types. Note that a fund may make all four types of trades, although contrarian funds, by construction, tend to make more type 1 and 2 trades than herding funds.

Prior studies (e.g., Dasgupta et al. 2011a, b; Brown et al. 2014) find that institutional herding results in significant temporary stock price pressure that persists for one to two quarters, then exhibits reversals. Thus, some of the performance difference between contrarian and herding funds in their type 1 trades may potentially be attributed to fund herding-related return reversals. Specifically, contrarian trades in the opposite direction of fund herding may generate negative abnormal returns initially because of price pressure, but positive abnormal returns in the long run because of reversals. Thus, if the type 1 trades by contrarian funds are profitable, abnormal returns may show up with some delay. In contrast, any performance difference in type 2 and 4 trades (trading of weak herding stocks) between contrarian and herding funds is more likely to reflect differences in their private information, and is less likely influenced by the price pressure associated with fund herding. These trades may generate profits either in the short run or in the long run, depending on the nature of such information. Lastly, if contrarian funds show superior performance relative to herding funds in their type 3 trades (herding trades of strong herding stocks), this would strongly suggest that they invest based on their superior private information, as opposed to mechanically trading against the crowd—since herding, in general, results in poor performance in the long run.

To implement this trade-based analysis, at the end of each quarter, t, we classify funds into quintiles based on their contrarian index, *CON*. Then, for each fund quintile, we separately examine the performance of the aforementioned four types of trades. As buy and sell trades may exhibit different performance and reflect different stock selection abilities, we look at these two trade directions separately. In essence, we form eight portfolios for each contrarian quintile of funds: four based on the four types of buy trades described above, and four based on the four types of sell trades. For each fund, we value weight each trade for a given quarter by the dollar value of the trade. We then examine the equal-weighted average performance of each of these trade portfolios across all funds in the same *CON* quintile, and present time-series averages and t-statistics of these quarterly equal-weighted averages. We analyze the performance of fund trades in each of the following four quarters to better capture the timing differences in the profits across the four types of trades.

We report the quarter-by-quarter performance of the resulting 40 portfolios (five fund quintiles, two trade directions, and four trade types) along with their four-quarter cumulative performance (during $t+1$ to $t+4$) in Table 4. The numbers reported are the quarterly rebalanced DGTW characteristic–adjusted returns during each of the subsequent four quarters, along with the performance spread between contrarian and herding funds. As a robustness check, we have also examined the Carhart four-factor alphas of individual trade-based portfolios, although we only report the performance spread for brevity.

We first focus on the performance of buy trades. The results in the left panel of Table 4 indicate that the buy trade portfolios of contrarian funds (top *CON*

[17] Our results are qualitatively similar if we only consider stocks in the top *BHM* or *SHM* quintiles as strong herding stocks.

Table 4 Trade-Based Performance of Contrarian Funds

		Buy trades					Sell trades				
	CON	Quarter 1	Quarter 2	Quarter 3	Quarter 4	Cumulative	Quarter 1	Quarter 2	Quarter 3	Quarter 4	Cumulative
Type 1 trades	1—Low	0.06	−0.30	0.01	0.31	0.09	0.26	−0.24	−0.65	−0.50	−1.00
Contrarian trades of		(0.22)	(−1.08)	(0.04)	(1.04)	(0.17)	(0.83)	(−0.77)	(−1.96)	(−1.29)	(−1.62)
strong herding stocks	2	−0.18	0.11	0.12	0.44	0.74	0.20	−0.15	−0.24	−0.63	−0.82
		(−0.66)	(0.38)	(0.45)	(1.48)	(1.71)	(0.66)	(−0.47)	(−0.71)	(−1.49)	(−1.48)
	3	0.04	0.24	0.49	0.75	1.58	0.48	0.05	−0.44	−0.33	−0.24
		(0.16)	(1.02)	(1.77)	(2.77)	(3.07)	(1.66)	(0.15)	(−1.66)	(−1.00)	(−0.59)
	4	−0.10	−0.02	0.36	0.27	0.56	0.49	0.00	−0.38	−0.10	0.04
		(−0.46)	(−0.09)	(1.50)	(1.21)	(1.07)	(1.59)	(0.00)	(−1.53)	(−0.33)	(0.08)
	5—High	−0.11	0.13	0.55	0.75	1.57	0.64	−0.04	−0.05	−0.41	0.13
		(−0.55)	(0.61)	(2.17)	(3.07)	(2.18)	(2.39)	(−0.12)	(−0.18)	(−1.51)	(0.27)
DGTW	High − Low	−0.18	0.43	0.54	0.44	1.48	0.38	0.21	0.60	0.09	1.13
		(−0.57)	(1.75)	(1.78)	(1.69)	(1.73)	(1.55)	(0.92)	(2.57)	(0.33)	(2.00)
Carhart	High − Low	−0.12	0.70	0.84	0.69	1.96	0.60	0.42	0.69	0.00	1.61
		(−0.29)	(2.38)	(2.22)	(1.96)	(1.92)	(1.91)	(1.36)	(2.37)	(0.00)	(2.21)
Type 2 trades	1—Low	−0.17	−0.21	−0.06	0.38	−0.17	0.19	0.02	0.11	0.16	0.60
Contrarian trades of		(−0.67)	(−0.87)	(−0.26)	(1.54)	(−0.44)	(0.81)	(0.09)	(0.57)	(0.65)	(1.15)
weak herding stocks	2	−0.21	−0.12	0.01	0.14	−0.09	0.31	0.15	0.13	0.13	0.85
		(−0.95)	(−0.51)	(0.06)	(0.67)	(−0.23)	(1.41)	(0.55)	(0.58)	(0.60)	(1.28)
	3	−0.23	−0.12	−0.10	0.53	0.03	0.14	0.12	0.03	−0.11	0.27
		(−1.14)	(−0.63)	(−0.45)	(2.77)	(0.07)	(0.69)	(0.55)	(0.15)	(−0.47)	(0.59)
	4	−0.22	0.08	0.02	0.50	0.41	0.19	0.10	0.03	0.19	0.62
		(−1.11)	(0.40)	(0.08)	(2.33)	(0.89)	(0.99)	(0.52)	(0.19)	(0.90)	(1.39)
	5—High	0.23	0.29	0.27	0.55	1.31	0.20	0.28	0.11	0.12	0.78
		(1.38)	(1.36)	(1.22)	(2.37)	(2.23)	(1.06)	(1.31)	(0.60)	(0.53)	(1.55)
DGTW	High − Low	0.40	0.50	0.33	0.17	1.47	0.01	0.26	0.00	−0.04	0.18
		(1.89)	(2.58)	(1.32)	(0.69)	(2.43)	(0.04)	(1.02)	(0.02)	(−0.22)	(0.44)
Carhart	High − Low	0.78	0.74	0.65	0.57	2.74	0.47	0.37	0.27	0.24	1.43
		(3.01)	(2.68)	(2.34)	(1.69)	(3.53)	(1.81)	(1.29)	(1.09)	(0.80)	(2.20)

		Buy trades					Sell trades				
	CON	Quarter 1	Quarter 2	Quarter 3	Quarter 4	Cumulative	Quarter 1	Quarter 2	Quarter 3	Quarter 4	Cumulative
Type 3 trades	1—Low	0.26	−0.42	−0.63	−0.67	−1.46	−0.60	−0.10	0.46	0.56	0.38
Herding trades of		(0.80)	(−1.17)	(−2.18)	(−1.81)	(−2.42)	(−2.70)	(−0.42)	(1.65)	(2.10)	(0.87)
strong herding stocks	2	0.21	−0.03	−0.44	−0.51	−0.76	−0.19	−0.05	0.24	0.29	0.38
		(0.73)	(−0.07)	(−1.58)	(−1.50)	(−1.38)	(−0.83)	(−0.27)	(0.88)	(1.38)	(0.99)
	3	0.21	0.03	−0.26	−0.40	−0.36	−0.10	−0.14	0.42	0.44	0.63
		(0.75)	(0.10)	(−1.06)	(−1.30)	(−0.81)	(−0.51)	(−0.67)	(2.00)	(1.91)	(1.31)
	4	0.23	0.01	−0.22	−0.19	−0.16	−0.13	0.06	0.30	0.60	0.87
		(0.79)	(0.03)	(−0.94)	(−0.66)	(−0.40)	(−0.70)	(0.40)	(1.41)	(2.95)	(2.25)
	5—High	0.46	0.17	−0.08	0.10	0.72	−0.01	0.22	0.47	0.49	1.34
		(1.94)	(0.83)	(−0.35)	(0.37)	(1.42)	(−0.03)	(1.20)	(2.15)	(2.30)	(2.74)
DGTW	High − Low	0.21	0.59	0.55	0.77	2.18	0.60	0.32	0.01	−0.08	0.95
		(0.90)	(2.32)	(2.17)	(2.55)	(3.17)	(2.46)	(1.34)	(0.03)	(−0.27)	(1.57)
Carhart	High − Low	0.51	0.88	1.05	1.01	3.44	0.63	0.61	0.28	0.28	1.96
		(1.54)	(2.85)	(3.00)	(2.78)	(4.07)	(2.33)	(2.27)	(0.96)	(0.75)	(2.64)
Type 4 trades	1—Low	0.23	−0.20	−0.14	−0.34	−0.32	−0.25	−0.15	0.11	0.40	0.12
Herding trades of		(1.02)	(−0.72)	(−0.63)	(−1.52)	(−0.67)	(−1.11)	(−0.60)	(0.52)	(1.76)	(0.25)
weak herding stocks	2	0.24	0.21	−0.09	−0.10	0.33	−0.05	0.14	−0.20	0.35	0.28
		(1.16)	(0.89)	(−0.43)	(−0.52)	(0.67)	(−0.26)	(0.86)	(−0.99)	(1.74)	(0.65)
	3	0.20	0.20	0.04	0.03	0.58	0.03	0.20	−0.01	0.37	0.75
		(1.05)	(0.82)	(0.20)	(0.14)	(1.26)	(0.15)	(0.99)	(−0.06)	(1.70)	(1.29)
	4	0.27	0.15	−0.04	0.26	0.71	−0.04	0.03	−0.04	0.26	0.22
		(1.43)	(0.76)	(−0.18)	(1.37)	(1.48)	(−0.22)	(0.17)	(−0.21)	(1.09)	(0.41)
	5—High	0.46	0.09	0.27	0.34	1.25	−0.08	0.29	0.14	0.54	0.97
		(2.27)	(0.47)	(1.30)	(1.55)	(2.19)	(−0.37)	(1.45)	(0.70)	(2.64)	(1.83)

Table 4 (Continued)

		Buy trades					Sell trades				
	CON	Quarter 1	Quarter 2	Quarter 3	Quarter 4	Cumulative	Quarter 1	Quarter 2	Quarter 3	Quarter 4	Cumulative
DGTW	High − Low	0.23	0.29	0.42	0.68	1.57	0.17	0.44	0.03	0.15	0.86
		(0.95)	(1.20)	(1.89)	(2.33)	(2.85)	(0.70)	(1.74)	(0.13)	(0.68)	(1.63)
Carhart	High − Low	0.52	0.67	0.91	0.92	2.89	0.63	0.55	0.15	0.38	1.69
		(1.70)	(2.26)	(3.25)	(2.57)	(3.66)	(2.69)	(1.93)	(0.59)	(1.22)	(2.62)

Notes. Each quarter we sort funds into quintile portfolios based on their contrarian indexes. Within each fund, we break down fund trades into four types: (1) contrarian trades of strong herding stocks, (2) contrarian trades of weak herding stocks, (3) herding trades of strong herding stocks, (4) herding trades of weak herding stocks. We then measure the average quarterly and four-quarter cumulative DGTW-adjusted abnormal returns of each type of trade within each quintile portfolio. Returns are reported in %/quarter. We also report the performance difference in DGTW-adjusted abnormal returns and Carhart (1997) four-factor alphas between quintile 5 (contrarian) funds and quintile 1 (herding) funds; t-statistics calculated with Newey–West robust standard errors are in parentheses.

quintile) significantly outperform those of the herding funds (bottom *CON* quintile) during the following four-quarter period across all four types of buy trades. First, contrarian funds outperform herding funds by 2.18% per year when the contrarians buy with the herd (i.e., type 3 trades), which is quite strong evidence of superior contrarian fund skills, since prior research finds that the average strong buy-herding stock exhibits negative and significant abnormal returns in the long run. Specifically, whereas herding funds experience significantly negative returns for their herding trades of strong-herding stocks during quarters $t+3$ and $t+4$ (when the initial price pressure of fund herding reverses), contrarian funds generate zero abnormal returns on those trades, indicating that, when contrarians trade with the herd, herding is associated with a permanent price impact. As a result, contrarians outperform herding funds by 0.55% and 0.77%, respectively, during these two quarters on type 3 buy trades. Therefore, it appears that contrarians trade on the same side as the crowd for certain stocks when their own private information conforms to that of the crowd (i.e., when the crowd is correct).

Type 1 trades, buys of strong sell-herding stocks by contrarians, also exhibit superior abnormal returns relative to herding funds, albeit after some delay. Specifically, the significant abnormal returns associated with type 1 trades conducted by contrarian funds do not appear until quarter $t+3$. This finding is consistent with the above-noted initial price-pressure effect of fund herding. Although contrarians appear to benefit from the reversal pattern associated with fund herding, in an untabulated analysis, we find that type 1 trades are not more frequent than the other types of trades made by contrarian funds, which indicates that exploiting return reversals is not the primary source of profits for contrarian funds.

Contrarians also outperform in their contrarian buys or herding buys of weak herding stocks (i.e., types 2 and 4 trades), where any price-pressure effect is likely small. Specifically, contrarian funds earn a significantly positive DGTW-adjusted return of 1.31% (1.25%) per year from their contrarian (herding) buys of weak sell- (buy-) herding stocks, outperforming similar trades of herding funds by about 1.47% (1.57%) per year. Since there should not be any significant abnormal returns associated with price-pressure effects with simply being on the opposite side of a weak herd of funds, contrarian funds' outperformance on types 2 and 4 trades are again likely attributed to their superior information relative to herds. Carhart alphas exhibit similar patterns to the DGTW-adjusted returns discussed above.

Overall, our findings on the abnormal trading returns of contrarian funds and the patterns of these returns over time suggest that contrarian funds do not just mechanically trade against the crowd, as about half of their trades are in the same direction as fund herds (as indicated in §3.1), and they outperform even when trading in the same direction as herds. That is, although contrarian funds are more likely to trade away from the crowd compared to herding funds, contrarians often end up trading with herds (if their private information conforms with that of herds), and they earn abnormal returns from this private information advantage as well as from (apparently incidentally) benefiting from the return reversals associated with fund herding.

In the right panel of Table 4, we report the performance of sell trades. Here, there exist very small performance differences between contrarian funds and herding funds among type 2 and type 3 sell trades, whereas stocks sold by contrarian funds actually earn higher returns than stocks sold by herding funds in their type 1 and type 4 trades. In addition, unlike buy trades, returns to sell trades do not follow a particular time pattern. This result is consistent with the findings of previous studies (e.g., Chen et al. 2000, Wermers et al. 2012) that stocks sold by skilled funds tend to have *higher* returns than stocks sold by funds deemed unskilled. Since mutual funds do not short sell stocks, the stocks they sell to finance purchases of other attractive stocks must be from their existing holdings. Although the stocks contrarian funds sell may be expected to underperform those they buy given their superior overall performance, as illustrated in Table 3, such stocks may not necessarily underperform those held or sold by herding funds if the latter funds are less skillful in selecting stocks to begin with.[18] In addition, sell trades of contrarian funds may be driven by liquidity needs (to meet investor flows) as well as to fund even more attractive stock purchases.

4.3. Multivariate Regression Analyses of Fund Performance

In the prior two subsections, we have shown that the stock holdings and trades of contrarian funds significantly outperform those of herding funds. To more precisely determine the source of their outperformance, it is important to control for differences in fund characteristics. As indicated in Table 2, contrarian and herding funds tend to have different size, age, turnover, and flow characteristics; some of which have been previously documented as being related to fund performance. In addition, we are interested in learning whether the contrarian index has standalone performance-predictive power beyond that of existing measures of strategy activeness, since, at first blush, one might suspect that contrarianism is equivalent to a fund actively deviating from its benchmark (although our Table 2 results indicated otherwise). Therefore, we implement multivariate regressions to examine the relation between reported net fund returns and the contrarian index, controlling for other factors that may be related to fund performance, including proxies for strategy activeness and reliance on public information.

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 prior 36 months to estimate the expected fund return for a particular quarter. Such rolling-window estimations allow for time variation in the factor loadings of individual funds. Finally, we implement a panel regression of cumulative four-factor adjusted returns during 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 robust standard errors clustered by funds to account for serial correlation induced by overlapping observations of fund performance. We also include quarter fixed effects.

The results in Table 5 show that a larger contrarian index leads to significantly greater abnormal fund performance during the following four quarters, controlling for differences in fund characteristics, such as fund size, age, expense ratio, turnover, and prior-quarter fund flows. Specifically, a fund that buys (sells) stocks that have a buy- (sell-) herding measure that is one-quintile lower exhibits almost a 0.19% per year higher four-factor alpha during the following year. 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 used to measure fund alphas. Therefore, we further include the average size, book-to-market, and momentum quintile ranks of the fund portfolios as control variables. The inclusion of these controls does not substantially change the coefficient on *CON*.

Since contrarian funds, by design, pursue investment decisions that deviate from the crowd, it is possible, as mentioned above, that their superior performance may at least partially derive from certain prior-documented aspects of strategy activeness. Previous studies show that funds employing more active strategies deliver significantly better risk-adjusted performance. We therefore further control for portfolio industry concentration (*ICI*), *Active_share*, and *RPI*. As shown in models (3) and (4), the performance-predictive effect of the contrarian index remains strong with these additional controls, even though *ICI* and *Active_share* significantly predict fund alphas in the direction indicated by past research.

Overall, our results of §4 indicate that contrarian managers, on average, are motivated by reduced career concerns due to recent superior performance and greater fund inflows. They do not appear to be overconfident, as their subsequent performance is also superior.

5. Stock-Level Contrarian Score and the Cross Section of Stock Returns

The empirical results of §§3 and 4 indicate that contrarian funds hold and buy stocks that outperform those held and bought by herding funds, respectively, suggesting that they possess superior information about stock fundamentals. Chen et al. (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), since funds tend to hold some of their

[18] Brown et al. (2014) show that buy-herding creates a weaker price impact than sell-herding, perhaps because funds can only sell what they already hold, due to their short-sale constraint. Specifically, funds with poor returns face investor redemption pressure in common, and, in response, sell poorly performing stocks that they likely hold in common. Therefore, it is not surprising that contrarian sell trades are less likely to benefit from price-pressure effects when they are selling against a herd that is buying.

Table 5 Multivariate Analysis of the Performance of Contrarian Funds

Dependent variable:	*Carhart four-factor adjusted fund returns* (in %)					
	(1)	(2)	(3)	(4)	(5)	(6)
Intercept	0.9141	−1.6915	−0.0192	−5.6244	−0.9883	−2.5147
	(2.47)	(−1.65)	(−0.02)	(−4.75)	(−0.86)	(−2.02)
CON	0.1881	0.2045	0.2180	0.1767	0.2017	0.1727
	(3.69)	(4.15)	(4.31)	(3.58)	(3.78)	(3.21)
Size_rank		−0.1725	−0.1876	0.2105	−0.1872	0.0436
		(−1.86)	(−2.04)	(1.91)	(−1.93)	(0.39)
B/M_rank		0.4963	0.1057	0.4169	0.3163	0.0622
		(4.15)	(0.88)	(3.54)	(2.51)	(0.49)
MOM_rank		0.5891	0.3908	0.4613	0.4582	0.2510
		(2.99)	(1.99)	(2.38)	(2.04)	(1.16)
Fund_size	−0.1181	−0.1144	−0.1118	−0.1005	−0.0677	−0.0675
	(−3.12)	(−2.96)	(−2.83)	(−2.59)	(−1.66)	(−1.62)
Fund_age	0.0329	0.1023	0.1190	0.0855	0.0768	0.1146
	(0.39)	(1.17)	(1.34)	(0.98)	(0.84)	(1.25)
Total_expenses (%)	−0.4748	−0.4825	−0.7555	−0.6544	−0.4673	−0.7274
	(−2.85)	(−2.88)	(−4.34)	(−3.87)	(−2.45)	(−3.81)
Turnover	−0.2459	−0.2519	−0.2466	−0.2561	−0.2558	−0.2301
	(−2.45)	(−2.19)	(−2.12)	(−2.25)	(−2.04)	(−1.88)
Flows	0.6043	0.2446	0.3362	0.0047	−0.0209	0.0286
	(1.20)	(0.47)	(0.62)	(0.01)	(−0.04)	(0.05)
ICI			3.5758			2.7382
			(5.72)			(3.95)
Active_share				3.7018		2.3432
				(8.56)		(4.96)
RPI					0.8547	−0.9430
					(1.40)	(−1.51)
R-squared	0.0517	0.0528	0.0528	0.0617	0.0558	0.0611
No. of observations	59,985	57,407	57,407	50,329	57,401	42,257

Notes. 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 after the contrarian index is measured. The explanatory variables include contrarian index (*CON*); average size (*Size_rank*); the book-to-market and momentum quintile rankings of fund holdings (*B/M_rank* and *MOM_rank*, respectively); the logged value of fund size as proxied by total net asset value (*Fund_size*); the logged value of 1 plus fund age (*Fund_age*), total expenses (*Total_expenses*); turnover ratio (*Turnover*); and prior quarter fund flows (*Flows*); industry concentration index (*ICI*), computed as the Herfindahl index of portfolio industry weights; *Active_share*, measured as the share of portfolio holdings that differs from the benchmark index holdings; and reliance on public information (*RPI*), computed as the *R*-squared from regressing quarterly fund trades on lagged analyst recommendation changes of the underlying stocks in the past four quarters. 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.

stocks for noninformation related reasons (such as tracking the benchmark). Accordingly, we shift our focus from contrarian fund performance to returns of individual stocks that are held in common by contrarian funds. Intuitively, 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. Therefore, we aggregate information across funds to extract the information content of fund holdings/trades at the stock level in this section. This transformation from the fund-level contrarian index to a stock-level contrarian measure allows us to further explore the source of contrarian outperformance.

5.1. The Contrarian Score of Individual Stocks

Our approach of extracting the stock selection information of contrarian funds follows the efficient aggregation of fund holdings approach in Wermers et al. (2012). A salient feature of this approach is that it aggregates information across all funds with varying degrees of contrarianism, rather than focusing on a small subset of funds with extreme contrarianism (e.g., as per Chen et al. 2000).

Specifically, we construct a stock-level contrarian score by adopting the fund-level contrarian index as the fund skill proxy in Wermers et al. (2012). We start with the assumption 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:

$$S_{j,\,t+1} = \sum_{i=1}^{N} x_{ij,\,t}\alpha^{S}_{i,\,t+1},$$

where $S_{j,\,t+1}$ is the fund j's stock selection ability in period $t+1$ $(j = 1, \ldots, M)$; $\alpha^{S}_{i,\,t+1}$ is the stock alpha in period $t+1$ $(i = 1, \ldots, N)$; and $x_{ij,\,t}$ is the portfolio weight of fund j on stock i at the end of period t (beginning of period $t+1$). We then follow their assumption that $S_{j,t+1}$ can be measured, with noise, by information available at the end of period t. In our case, such information is the fund contrarian index $CON_{j,t}$:

$$CON_{j,t} = S_{j,t+1} + e_{j,t+1},$$

where $e_{j,t+1}$ is the information noise, or an error term. Combining the two expressions above, we have

$$CON_{j,t} = \sum_{i=1}^{N} x_{ij,t}\alpha^S_{i,t+1} + e_{j,t+1}.$$

In matrix form, this can be further expressed as (dropping the time subscript):

$$\mathbf{CON} = \mathbf{X}\boldsymbol{\alpha} + \mathbf{e},$$

where **CON** is the $M \times 1$ vector of $CON_{j,t}$, **X** is the $M \times N$ matrix of fund portfolio weights $x_{ij,t}$, $\boldsymbol{\alpha}$ is the $N \times 1$ vector of stock alphas, $\alpha^S_{i,t+1}$, and **e** is the $M \times 1$ vector of the noise term, $e_{j,t+1}$.

In the above expression, $\boldsymbol{\alpha}$ can be viewed as an unknown parameter vector, and can be estimated from the observed **CON** and **X**. Wermers et al. (2012) point out that because of a dimensionality problem (i.e., the fund number M is typically smaller than the stock number N), the usual ordinary least squares estimator cannot be implemented. They suggest an alternative estimator based on the generalized inversion. In our setting, the generalized inverse approach leads to the following estimator:

$$\boldsymbol{\alpha}_{\mathbf{CON}} = (\mathbf{V}\mathbf{D}^{+}\mathbf{V}')\mathbf{X}'\mathbf{CON}, \tag{6}$$

where **V** consists of the K eigenvectors of $\mathbf{X}'\mathbf{X}$ corresponding to the K largest eigenvalues; $\mathbf{D}^+$ is an N by N diagonal matrix whose first K diagonal elements are the inverse of the largest K eigenvalues of $\mathbf{X}'\mathbf{X}$, with the remaining $N-K$ diagonal elements being zeros. Following Wermers et al. (2012), K is set to $M/2$. We term $\boldsymbol{\alpha}_{\mathbf{CON}}$ the stock-level contrarian score.

The variable $\boldsymbol{\alpha}_{\mathbf{CON}}$ can be interpreted as the aggregate stock selection information for individual stocks extracted from portfolio holdings of funds with varying degrees of contrarianism. That is, if contrarianism is a proxy for fund manager skills, a stock is predicted to outperform if it is held heavily by contrarian funds and held lightly by herding funds, but not if it is held heavily by both.

The fund-level contrarian index vector **CON** used in (6) is the rolling four-quarter average of the quarterly **CON** vector (averaged over $t-3$ to t, where t is the quarter at the end of which α_{CON} is estimated), with the requirement that a fund have a valid CON observation during at least one of the two most recent quarters ($t-1$ and t).[19] The stock-level contrarian score $\alpha_{\mathbf{CON}}$ is estimated every quarter for individual stocks. Computed each quarter, then averaging over time, the mean of the estimated $\alpha_{\mathbf{CON}}$ is -0.52, and the median is -0.23, with the 25th and 75th percentiles being -1.16 and 0.12, respectively. The negative mean and median of $\alpha_{\mathbf{CON}}$ result from the negative mean and median of the key model input, fund-level contrarian index CON. In addition, the cross-sectional standard deviation (averaged across quarters) is 1.67.

5.2. Contrarian Score and Stock Characteristics

Before we evaluate the return-predictive power of the contrarian score, we first examine the characteristics of stocks picked by contrarian funds (i.e., those with high contrarian scores) to understand the nature of the stock selection ability of contrarian funds. In Table 2, we found that contrarian funds strongly prefer high book-to-market stocks and stocks that are past losers. To obtain a broader view of the holding preferences of contrarian funds, we now examine the relation between the contrarian score and an extensive list of return-predictive stock characteristics.

We first examine the relation between α_{CON} and the stock-level herding measure. As discussed earlier, by construction, α_{CON} is higher if a stock is held with larger weights by contrarian funds. Since the portfolio weights of a fund are the result of its trades in the past, α_{CON} of a stock should be higher if contrarian funds buy more of it, and lower if contrarian funds sell more of it. Furthermore, since, by definition, contrarian funds tend to buy stocks with a high sell-herding measure and sell stocks with a high buy-herding measure, α_{CON} should be negatively correlated with BHM and positively correlated with SHM. In other words, α_{CON} is expected to be negatively correlated with the stock-level herding measure, $HERD$, introduced earlier, which combines a stock's quintile rank of BHM or SHM, and takes a value between 5 (for extreme buy-herding stocks) and -5 (for extreme sell-herding stocks).

During each quarter t, we sort stocks into deciles, based on the contrarian score, and compute their $HERD$ measures during each of the preceding four quarters ($t-3$ to t). As expected, the results reported in the first four columns of Table 6 show that the contrarian score is significantly negatively correlated with the herding intensity, $HERD$, measured during the current quarter, t, as well as during the past three quarters ($t-3$ to $t-1$).

Next, we examine the relation between α_{CON} and an extensive set of stock return predictors known

[19] As shown in §4.2, trades by contrarian funds often deliver profits with a delay of a few calendar quarters. Taking a rolling average has the effect of including fund actions from earlier quarters, rather than focusing narrowly on the most recent quarter.

Table 6 Contrarian Score, Herding Intensity, and Quantitative Stock Characteristics

	HERD (Q 0)	*HERD* (Q − 1)	*HERD* (Q − 2)	*HERD* (Q − 3)	*GIV*	*VAL*	*INVFN*	*EQAL*	*EFF*	*INTAG*	*EMOM*	*PROF*	*UNCT*	*ILLIQ*
D1—Low	0.58	0.63	0.59	0.47	−0.08	45.71	42.32	49.45	48.79	49.76	55.62	59.92	57.44	27.27
D2	0.54	0.60	0.52	0.45	0.02	47.00	43.70	48.77	49.66	50.42	52.88	54.80	54.23	35.48
D3	0.51	0.49	0.49	0.40	0.06	47.80	45.08	48.91	50.11	50.53	50.72	51.38	51.92	41.35
D4	0.29	0.42	0.41	0.38	0.04	48.28	46.51	49.18	50.32	50.72	49.19	48.75	49.68	46.47
D5	0.21	0.23	0.30	0.35	0.06	48.65	48.22	49.34	50.58	51.04	48.53	46.88	48.02	51.23
D6	0.01	0.15	0.27	0.26	0.07	49.59	50.88	49.08	49.93	50.41	47.78	44.80	46.59	58.08
D7	−0.13	0.14	0.26	0.29	0.03	53.06	54.93	49.34	48.72	47.79	47.77	43.82	45.65	67.03
D8	−0.20	0.11	0.29	0.21	0.07	49.02	49.80	49.39	50.36	51.85	46.45	45.15	45.65	54.26
D9	−0.12	0.02	0.07	0.16	0.08	49.03	48.16	49.91	50.01	52.35	47.27	49.62	49.02	42.18
D10—High	−0.32	−0.24	−0.15	−0.07	0.19	50.70	49.02	50.72	49.08	51.80	48.58	59.65	53.95	28.55
High − Low	−0.90	−0.87	−0.74	−0.55	0.27	4.98	6.71	1.27	0.29	2.04	−7.04	−0.27	−3.48	1.27
	(−13.29)	(−16.88)	(−17.85)	(−13.78)	(2.77)	(5.51)	(8.34)	(1.67)	(0.76)	(3.43)	(−11.28)	(−0.48)	(−5.51)	(2.67)

Notes. In each quarter t, we sort stocks into deciles based on the contrarian score α_{CON}. For each decile we calculate the average herding index (*HERD*) for the four quarters from quarter $t-3$ to quarter t, as well as 10 categorical stock characteristic measures. *HERD* is a stock's signed herding intensity measure based on its quintile ranks of buy-herd and sell-herd measures. *GIV* is the generalized inverse alpha of Wermers et al. (2012). *VAL* is a value investment measure. *INVFIN* is a measure of investment and financing activities. *EQAL* is a measure of earnings quality. *EFF* is a measure of operating efficiency. *INTAG* is a measure of intangible investment. *EMOM* is a measure of earnings momentum. *PROF* is a measure of profitability. *UNCT* is a measure of uncertainty. *ILLIQ* is a measure of illiquidity. These measures are constructed by averaging over the percentile ranks of the underlying variables, the details of which are provided in §A.1 of the appendix (where 100% means the highest rank). The underlying variables of these categorical measures are signed so that a higher value of each categorical measure is associated with higher subsequent stock returns as suggested in the existing literature. We also report differences in herding intensity and stock characteristics between the top and bottom stock deciles along with their corresponding t-statistics (in parentheses) calculated with Newey–West robust standard errors.

in the existing literature. The first is the generalized inverse alpha (*GIV*) of Wermers et al. (2012), which is constructed similarly to Equation (6), but with the rolling lagged 12-month four-factor alpha of the fund in place of its contrarian index, *CON*.[20] If funds with high past alphas have superior stock-selection information, then stocks with high ownership by high-alpha funds are likely to outperform. In addition to this aggregate return-predictive measure, we consider a total of 18 fundamental valuation characteristics. Based on their nature, these 18 variables can be grouped into nine categories: (1) value (*VAL*), (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 nine categorical variables are signed so that they are positively related to future stock returns, according to the existing literature. We combine variables in each group, for a given stock quarter, by a simple average of their cross-sectional percentile ranks to obtain the nine categorical variables. Stocks are then cross-sectionally ranked into percentiles in each quarter (where 100% means the highest rank), based on each of these nine categorical variables. Details for constructing the 18 individual firm characteristics and the nine categorical variables are provided in §A.2 of the appendix. A higher rank of a categorical variable is a predictive indicator of a higher stock return, according to past research.

The results in Table 6 suggest that, interestingly, the stock-level contrarian score is positively correlated with the generalized inverse alpha, which, according to Wermers et al. (2012), aggregates the fundamental stock selection information possessed by skilled fund managers. In addition, stocks with higher contrarian scores have stronger value-oriented characteristics, fewer investment and financing activities, more intangible investments, lower earnings momentum, and higher uncertainty.[21] By and large, these results are consistent with the view that contrarian funds prefer value stocks and shy away from glamour stocks. On the other hand, there appears to be no significant difference in earnings quality, efficiency, or profitability, between stocks in the top and bottom contrarian-score deciles. Furthermore, we note nonlinearities in the relation between α_{CON} and certain stock characteristics. For example, α_{CON} exhibits a somewhat inverse U-shaped relation with *INVFN*, *EFF*, and *ILLIQ*, whereas a somewhat U-shaped relation with *EMOM*, *PROF*, and *UNCT*. This further suggests that the stock selection information possessed by contrarian fund managers and captured

[20] Specifically, $\mathbf{GIV} = (\mathbf{VD}^{+}\mathbf{V}')\mathbf{X}'\mathbf{A}$, where $\mathbf{A}$ is a vector of estimated fund alphas.

[21] 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 negative relation between the contrarian score and *UNCT* means that stocks with higher contrarian scores have higher idiosyncratic volatility and dispersion, i.e., higher uncertainty.

by α_{CON} cannot be a simple manifestation of the return predictive information contained in these fundamental valuation characteristics.

5.3. Sources of Superior Performance: Price Pressure, Public Valuation Signals, or Private Information?

To further investigate the potential sources of contrarian abnormal returns, 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 valuation signals. The dependent variable is the DGTW-characteristic-adjusted stock return during each of the four quarters after portfolio formation ($t+1$ to $t+4$). 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 includes stock-level herding measures (*HERD*) during each of the past four quarters ($t-3$ to t). The second set of controls includes the 10 fundamental valuation variables we consider in Table 6.[22] These variables have been shown in the existing literature to predict stock returns, and they form the basis of many popular quantitative stock selection models. During each quarter t, we perform four sets of cross-sectional regressions, with the dependent variable measured during that quarter, and the independent variables measured during each of the previous four quarters ($t-4$ to $t-1$). To obtain a summary measure of return-predictability of α_{CON} over the entire four quarters following portfolio formation, we adopt the Jegadeesh and Titman (1993) approach to computing the four-quarter average coefficients (JT4). That is, we average the four sets of coefficients on the same explanatory variable across these four regressions and then compute their time-series averages and corresponding time-series t-statistics.

Table 7 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 0.0090, which is highly statistically significant. Specifically, a one standard deviation increase in the contrarian score of a stock is associated with an increase in stock abnormal return

Table 7 Contrarian Score and Stock Returns: Controlling for Herding and Return-Predictive Stock Characteristics

Explanatory variables	(1)	(2)	(3)	(4)
α_{CON}	0.0090	0.0072	0.0063	0.0049
	(8.46)	(7.22)	(6.05)	(3.36)
HERD (Q 0)		−0.0439		−0.0481
		(−2.42)		(−2.22)
HERD (Q − 1)		−0.0721		−0.0794
		(−4.35)		(−4.34)
HERD (Q − 2)		−0.0639		−0.0680
		(−4.15)		(−3.91)
HERD (Q − 3)		−0.0399		−0.0557
		(−2.53)		(−2.96)
GIV			3.3926	3.6866
			(4.24)	(3.74)
VAL			−0.0055	−0.0062
			(−1.55)	(−1.81)
INVFN			−0.0026	−0.0041
			(−0.77)	(−1.21)
EQAL			0.0039	0.0038
			(3.46)	(3.37)
EFF			0.0346	0.0343
			(9.67)	(9.67)
INTAG			0.0219	0.0216
			(5.31)	(5.28)
EMOM			0.0005	0.0023
			(0.25)	(1.15)
PROF			−0.0159	−0.0171
			(−2.80)	(−3.06)
UNCT			0.0095	0.0097
			(2.68)	(2.70)
ILLIQ			0.0135	0.0141
			(3.54)	(3.76)
R-squared	0.0004	0.0024	0.0243	0.0255

Notes. This table reports coefficients from quarterly Fama–MacBeth regressions of individual stocks' DGTW-characteristic-adjusted stock returns in each of the four quarters after portfolio formation (quarter + 1, quarter + 4) on α_{CON}. Coefficients reported in the table, following the "JT4" overlapping portfolio approach, are those averaged over four different regressions with stock returns (the dependent variable) in the same quarter, but the explanatory variables measured 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 (quarter − 3, quarter 0), the generalized alpha from Wermers et al. (2012), and nine categorical stock characteristics measured at the portfolio formation quarter (quarter 0). To avoid a significant reduction of sample size, missing quantitative stock characteristics are replaced by simulated values using a multiple imputation procedure and time-series t-statistics reported in parentheses are adjusted to account for such simulated regressors; R-squared is the average adjusted R-squared of the Fama–MacBeth regressions.

of 1.50% per quarter. When herding indexes (*HERD*) for the past four quarters ($t-3$ to t) are included as control variables, the coefficient for the contrarian score is reduced to 0.0072, but is still highly significant. The change in the coefficient for the contrarian score suggests that about 20% of the return-predictive information contained in the contrarian score is related

[22] As noted in §A.1 of the appendix, a fairly large number of stocks have some missing fundamental variables in a given quarter. To avoid a large reduction of sample size in multivariate regressions, we implement a multiple imputation procedure to "fill in" missing categorical stock fundamental variables. Specifically, in each quarter, we use simulated variables to replace missing categorical 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 et al. (2012).

to the price pressure effect of mutual fund herding. When we include the *GIV* and the nine fundamental stock characteristics as control variables, the coefficient for the contrarian score remains significant, at 0.0063, which suggests that over a four-quarter horizon, about 30% 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.[23] Overall, a little over half of the return predictive power of the contrarian score is attributable to neither herding induced price pressure nor established quantitative valuation signals.

Therefore, neither the price-pressure effect associated with herding 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 a major source of contrarian profits. In addition, our evidence suggests that the level of contrarian funds holding or trading a given stock is a useful orthogonal signal to other prior-known quantitative signals.

6. 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 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, suggesting that contrarian managers tend to have lower career concerns. 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 and strategy activeness. In addition, contrarian funds outperform not only when they trade with the herd, but also when they trade against the herd.

We extract the stock selection information contrarian funds possess based on the degree a stock is held by contrarian funds versus herding funds and convert such information into a stock-level contrarian score. A one standard deviation increase in a stock's contrarian score will, on average, increase its (DGTW) characteristic-adjusted abnormal returns by 1.50% per quarter during the following four quarters. This 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.

[23] Note that the t-statistics for the coefficient estimates of the contrarian score are related to the information ratio (IR) of an investment portfolio with portfolio weights proportional to the contrarian score (after rescaling the weights to sum up to zero). Given 72 quarters in our sample period, a t-statistic of 3.36 for the contrarian score (in model (4)) implies a quarterly information ratio of 0.396. This IR is only slightly lower than that of the generalized inverse alpha (*GIV*). The high information ratio of the contrarian score demonstrates its economic significance in helping predict stock returns.

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Appendix. Stock Characteristic Measures

A.1. 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 brackets $[\cdot]$.

1. *Value* (*VAL*):

(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 four-quarter EPS changes. The standard deviation is measured using four-quarter EPS changes during past eight quarters, with a minimum of four 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.

A.2. 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, and 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 18 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 nine 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 nine out of 18 individual characteristics for the stock are missing, or more than five out of nine 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 multicolinearity problem in regressions. Finally, when implementing multivariate regressions, we further use a multiple imputation procedure to address the missing observation problem at the categorical variable level.

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