Chapter 19
Against the 'Wisdom of Crowds': The Investment Performance of Contrarian Funds

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19.1 Introduction

In an article published in the *Financial Analysts Journal* (Treynor, 1987), Jack Treynor wrote about a series of "bean jar" experiments he conducted with students in his investments courses at the University of Southern California. In the first set of experiments, he asked students to independently estimate the number of beans contained in a full jar. While most students' individual estimates missed the actual number by a wide margin, surprisingly, the average estimates were pretty close to being correct. In the second set of experiments, he first provided students with advice on properties of the jar, such as the air space at the top of the jar, and materials of the jar. While such information supposedly could help improve the accuracy of students' estimates, the resulting average estimates, alas, had much larger errors than those from the first set of experiments. It seems his advice did nothing more than cause common errors among students!

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Treynor's first set of experiments was made famous by the popular book of James Surowiecki (2004) as early evidence of the "wisdom of crowds." A substantial part of Treynor's FAJ article, however, was about the second set of experiments, and their implications for potential shared errors in the stock market. He remarked that investors may be persuaded to give up their independent information and, instead, rely on certain common sources of information, such as published analyst research reports, and that this may actually do damage to market efficiency. In the FAJ article, he further contemplated a strategy to take advantage of such investor behavior, by waiting "until propagation [of the research among investors] is complete, or almost complete, and then copper it." However, he also cautioned about the considerable challenges for doing so given the difficulty of estimating the "shared error."

Treynor's notion of investors giving up their independent opinions to follow influential common advice is also known as "herding," and those who attempt to trade against herds are known as "contrarians." In this article, we examine contrarian investment behavior in the mutual fund industry, and uncover interesting empirical findings related to the characteristics and performance of contrarian funds. In particular, we find that there are mutual funds that systematically act in a contrarian fashion, as contemplated by Treynor (1987), and which are capable of delivering outperformance even after we take into account the different types of risks to which they are exposed.[1]

Prior to our study, academic researchers have focused their attention primarily on the herds—investors who follow each other in pursuing similar trades. These studies include, for example, Lakonishok, Shleifer, and Vishny (1992), Wermers (1999), Sias (2004), Dasgupta, Prat, and Verardo (2011a), and Brown, Wei, and Wermers (2014). The collective wisdom drawn from these studies is that, in less recent times (e.g., prior to the mid-1990s), mutual fund herding was relatively weak, and does not substantially distort stock prices; however, in more recent years, herding has become more prevalent, and herds tend to cause a significant price impact, followed by a return reversal.[2]

These strong results for funds that herd bring about an important question: do funds that do not herd, or that even "anti-herd," (actively invest against the crowd),exhibit different strategies and performance from their more conventional counterparts? For example, given the time-trend of increasing price impact caused by trades of herds, it is natural to wonder if sophisticated investors have emerged in recent years who choose to deviate from the crowd and take advantage of the

[1]We note that Treynor created a methodology to rate investment funds in Treynor (1965) and Treynor and Mazuy (1966), and the Fama–MacBeth (1973) regressions that we use for identifying the relation between "contrarianism" and "the abnormal returns of stocks" by contrarian funds build on this work.

[2]There is also a debate on whether herds indeed irrationally give up their own opinion and rely too much on certain influential common information sources. For example, Sias (2004) argues that herds merely infer information from each other's trades.

temporary price dislocations created by herds. Further, are contrarians “smarter” than herding funds in researching stock fundamentals? We address those questions in this article.

Anecdotal evidence suggests that some household names in the investment industry are contrarian investors. For example, in Wikipedia (which arguably represents the “wisdom of the crowd”), the entry for “contrarian investing” includes the “notable contrarian investors” Warren Buffett, Marc Faber, David Dreman, and John Neff. Successful mutual fund managers such as Peter Lynch, Bill Miller, and John Templeton have also been known to have strong contrarian elements in their investment themes. While such anecdotes are interesting, we would like to know whether a successful track-record belongs to only a rare few, or whether contrarian investing, in general, is rewarded. Also, by parsing through their positions and trades, as we do in this article, we hope to learn about the characteristics of a successful contrarian, as well as the specific sources of contrarian investor performance.

19.2 Identifying Contrarian Funds

There are various ways to define contrarian investing. For example, if we think of contrarian investing as a deep-value investing style, we can look at how funds trade on fundamental value indicators. Alternatively, we can define contrarian funds as those buying stocks whose prices have fallen dramatically. Treynor (1987) suggests influential analyst research reports as a prominent stimulus of herding by investors; thus, one can also define contrarian investing as trading against analyst recommendations. However, perhaps the most straightforward definition of contrarian funds would be those trading against herds, which is the definition that we adopt in our study. The advantage of this approach, in our belief, is that we need not assume a particular trading strategy to define contrarian funds or the specific source of common errors that they avoid (e.g., analyst reports). Instead, we can simply identify those funds that most frequently trade against herds, and let the data tell us what strategies that they tend to follow in doing so.

To construct a fund-level contrarian measure, we first classify, for a given fund, each trade into either a “herding” trade or a “contrarian” trade during a particular quarter (we infer “trades” by examining changes in quarterly portfolio holdings data available from Thomson Reuters). A herding trade is one in the same trading direction as the majority of funds (i.e., the “crowd”), while a contrarian trade is one in the opposite direction of the majority. For example, if a fund sells a stock when the majority of the funds are buying, or if a fund buys a stock when the majority of funds are selling, such a trade is contrarian; if the fund buys or sells with the crowd, that trade is a herding trade.

However, we first need a formula that identifies when a group of funds trading a stock can be considered a herd; more to the point, we need a measure of how strong or weak a herd is. Here, we rely on a stock-level measure of herding by the pioneering paper of Lakonishok, Shleifer, and Vishny (Lakonishok et al., 1992):

$$\mathrm{HM}_{i,t} = |p_{i,t} - \overline{p}_t| - E\left(|p_{i,t} - \overline{p}_t|\right), \tag{19.1}$$

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. Note that $\overline{p}_t$, a proxy for the expected value of $p_{i,t}$, is the cross-sectional mean of $p_{i,t}$ over all stocks traded by all funds during quarter t. E($|p_{i,t} - \overline{p}_t|$) is an adjustment factor, which equals the expected value of $|p_{i,t} - \overline{p}_t|$ under the null of no herding.[3]

Intuitively, this measure defines herding as the tendency with which a group of funds exhibit similarity in trading activity, above what would have been expected as a result of random occurrences of same-side trading by funds in the same stock. Depending on the direction of herding, we can further define conditional buy-herding (BHM_{it}) and sell-herding (SHM_{it}) measures as follows:

$$\mathrm{BHM}_{i,t} = \mathrm{HM}_{i,t}\Big|p_{i,t} > \overline{p}_t \tag{19.2}$$

$$\mathrm{SHM}_{i,t} = \mathrm{HM}_{i,t}\Big|p_{i,t} < \overline{p}_t. \tag{19.3}$$

A positive value of *BHM* indicates that the majority of funds are buyers of the stock (hence, herding on the buy side), and a positive value of *SHM* indicates that the majority funds are sellers (hence, herding on the sell side).

Each quarter, we separately rank stocks into quintiles, based on the magnitude of *BHM* and *SHM*, and further assign negative signs to the quintile ranks of the *SHM* stocks. Thus, during a given quarter, BHM stocks are assigned ranks of 1 (least amount of buy herding) to 5 (most amount of buy herding), while SHM stocks are assigned ranks from −1 (least amount of sell herding) to −5 (most amount of sell herding). This way, we combine the buy-herding and sell-herding measures into a single variable, *HERD*, that takes on integer values from −5 to +5 (excluding 0), and that summarizes both the direction (buy or sell) and the strength of the herd.

We then measure the extent to which fund j conducts contrarian versus herding trades by computing the weighted average of the *HERD* measure across all stocks traded by that fund during a particular quarter, where the weights are proportional to the dollar values of the trades, and are denoted as ω_{ijt},

$$\mathrm{CON}_{jt} = -\sum_{i=1}^{N} \omega_{ijt}\mathrm{HERD}_{it}. \tag{19.4}$$

[3]This value is calculated assuming, under the null of no herding in stock-quarter i,t, that funds trade randomly and independently of each other. With this assumption, $p_{i,t}$ can be assumed to follow a binomial distribution with parameters (n, $\overline{p}_t$), where $n =$ the number of funds that trade stock i during quarter t.

We term this measure the fund-level "contrarian index" or *CON*. Note that ω_{ijt} has a positive (negative) value for buy (sell) trades, whereas $HERD_{it}$ has a positive (negative) value for buy-herding (sell-herding) stocks. The value of CON is, thus, positively correlated with the (dollar) proportion of contrarian trades, and negatively correlated with the proportion of herding trades executed by a fund. In summary, a highly positive contrarian index identifies a contrarian fund, while a highly negative contrarian index identifies a herding fund.

The following example helps to illustrate the economic meaning of our definition. If almost all mutual funds are buying IBM and selling Cisco during a particular quarter, then a fund that sells IBM and buys Cisco during that quarter would be assigned a very high contrarian index. Note that this definition of contrarianism does not necessarily imply that contrarians are all alike, and form a small herd of their own. For example, some contrarians might sell IBM without buying Cisco, while others might buy Cisco without selling IBM.

19.3 Distribution and Characteristics of Contrarian/Herding Funds

Table 19.1 displays the cross-sectional distribution of the contrarian index. One eye-catching pattern is that the majority of funds have negative contrarian index (*CON*) values. The average value of the index across funds is –0.84, and even the 75th percentile is negative, at –0.33. This suggests that most funds are herds, while funds systematically pursuing strong contrarian investing constitute a relatively small group. This is not surprising, as, by definition, the majority of funds must be those that herd.

One important issue is whether the contrarian index is capable of capturing certain systematic differences in fund investment strategies, as opposed to being a mere statistical fluke. We address this issue using two different approaches. First, we ask what the distribution of *CON* would have looked like in an alternative world, where there were no intentional herding funds and no intentional contrarians. To answer this question, we randomly assign the trades observed in our data to sample funds—that is, keeping the actual trades in the data, but reshuffling the identities of which funds execute the trades. We find that, after reshuffling, the resulting contrarian indexes of individual funds exhibit a much smaller variability, relative to what are observed in the actual data. That is, we find far fewer funds heavily engaging in herding or contrarian trading in the randomized data. Thus, the distribution of the contrarian index in our data is extremely unlikely to result from random trading activities among our sample of funds, where some funds just happened to trade against the crowd frequently (by chance alone).

Second, we find that the contrarian index is quite persistent over time. Funds with high contrarian indices in one quarter tend to continue to have high contrarian indices for at least the following eight subsequent quarters. Therefore, the classi-

Table 19.1 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 fication of funds into herding versus contrarian funds based upon our contrarian index likely reflects the purposeful pursuit of different investment strategies by some funds.

What types of funds are likely to be contrarian funds? Do they behave any differently from prior-examined funds that pursue unique strategies? In Table 19.2, we first characterize the holdings of contrarian funds. Specifically, each quarter, we sort funds into quintile portfolios based upon their contrarian indexes, then report the average characteristics of the stock holdings of each portfolio of funds. The specific holdings-based fund characteristics we report include the average size, B/M, momentum, and illiquidity quintile ranks of fund stock holdings. Table 19.2 shows that, relative to herding funds, contrarian funds tend to invest in stocks with a larger market capitalization, a higher book-to-market ratio, lower past returns, and having slightly lower liquidity. While some of these characteristics of fund holdings are consistent with various alternative definitions of "contrarianism" based upon self-designated investment styles frequently shown on fund prospectuses, we note that contrarian funds do not substantially tilt toward value stocks and low past-return stocks. Our definition of a contrarian investment strategy is, therefore, not equivalent to simple deep value investing or negative stock price feedback trading.

To further illustrate the fund characteristics associated with contrarian investing, we report fund size, expense ratio, turnover, age, past fund performance, and past flows in Table 19.2. Consistent with the idea that contrarian funds tend to be long-term investors with reduced short-term career concerns, the results indicate that contrarian funds tend to be large funds with a low portfolio turnover ratio. They also have higher risk-adjusted performance and higher Morningstar star performance ratings. Moreover, they tend to have lower performance volatility, suggesting that they are unlikely to be those with merely good recent performance—who could be expected to be able to afford to that deviate from the crowd occasionally without much risk. Consistent with their good past performance and low performance volatility, contrarian funds appear to attract much larger investor inflows than other funds.

Lastly, we contrast the contrarian index with several measures of fund strategy uniqueness examined in the literature. By construction, contrarian funds are those that deviate from the crowd, which suggest that they may be those funds that tend to deviate more from their style benchmarks. We, therefore, examine differences between our contrarian index and three prior-documented measures of fund strategy uniqueness: Industry Concentration Index (ICI; Kacperczyk, Sialm, & Zheng, 2005), Active Share (Cremers & Petajisto, 2009), and Reliance on Public Information (RPI; Kacperczyk & Seru, 2007).

Table 19.2 shows that both funds with a very low contrarian index (i.e., herding funds) and those with a very high contrarian index (i.e., contrarian funds) tend to have a greater *ICI* and *RPI*. This is not surprising, as both herding funds and contrarian funds need to take extreme positions, and, therefore, deviate from their benchmarks, even though the motivation behind their departure from the benchmarks is very different. For example, in unreported analyses, we show that, while herding funds tend to have a high *RPI* measure (as analyst recommendations

Table 19.2 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_ref*), 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 are an important catalyst of herding), contrarian funds tend to trade in the opposite direction of analyst recommendations, resulting in a higher negative correlation of their trades with analyst recommendations and, thus, a higher *RPI*.[4] Lastly, the relation between the contrarian index and Active Share is also non-monotonic. In summary, we conclude that contrarianism is different from prior measures of deviation from benchmarks or fund strategy uniqueness.

19.4 Performance of Contrarian and Herding Funds

While contrarian behavior could be driven by superior private information in the context of Treynor (1987), it may also be driven by overconfidence. That is, certain fund managers might overweight their private information and underweight useful commonly observed information, due to overconfidence (Daniel, Hirshleifer, & Subrahmanyam, 1998). Under this scenario, contrarian funds would tend to underperform. Moreover, contrarian funds are likely to underperform, as well, if their departure from herds result from fund manager incentives to gamble on fund performance, as illustrated in the risk-shifting literature (Brown, Harlow, & Starks, 1996; Chevalier & Ellison, 1997; and Huang, Sialm, & Zhang, 2011).

We, therefore, compare the performance of contrarian and herding funds to gain insight into the motivation behind contrarianism. We employ three different performance measures. The first is reported net fund return, after deducting fund expenses. The second is the characteristic-adjusted abnormal return, using a method developed by Daniel, Grinblatt, Titman, and Wermers (1997). Briefly, this method calculates the abnormal returns of each stock held by a fund, then portfolio weights this abnormal return across stocks held by the fund. The abnormal return is the return of that stock, in excess of the return of an appropriate benchmark portfolio. The benchmark portfolio for a stock is the value-weighted portfolio of stocks with similar characteristics—in terms of market capitalization, book-to-market equity ratio, and price momentum—to the stock being examined. The third performance measure is the risk-adjusted fund performance based on the four-factor model of Carhart (1997). The risk-adjusted fund performance, or the "four-factor alpha," is the intercept from regressing fund returns onto four factors—the market minus T-bills factor, size, and book-to-market factors, and, additionally, a price momentum factor.

Table 19.3 shows that contrarian funds—funds ranked in the top quintile by their contrarian index—are able to generate much better performance than herding funds (those ranked in the bottom quintile). The net fund return, characteristic-adjusted return, and four-factor alpha of the contrarian funds are 2.88 %, 0.21 %, and −0.08 %, respectively, during the quarter after fund ranking. By contrast,

[4]Note that RPI is the correlation, either positive *or negative*, between fund trading and public information.

Table 19.3 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 the corresponding numbers for herding funds are 2.77 %, 0.09 %, and −0.44 %, respectively. The differences between contrarian funds and herding funds in these three sets of performance measures are 0.11 %, 0.12 %, and 0.36 % per quarter.

The table also shows that performance differences remain significant for several quarters after the initial fund ranking. For example, the cumulative net return of contrarian funds is 11.21 % during the four quarters after the fund ranking, significantly higher than that of herding funds, 9.31 %.

Recall that Table 19.2 indicates that contrarian funds differ from herding funds in terms of fund size, turnover, and investor flows, as well as characteristics of fund holdings. Some of these characteristics have previously been documented to be correlated with fund performance.[5] To more robustly test whether managers of contrarian funds are truly more skilled, we perform a multivariate regression of fund performance on the contraian index, with added control variables included for these fund characteristics that may be related to fund performance. In addition, since we know that contrarian funds tend to have higher measures of strategy activeness, we also wish to control for these factors, to see whether the contrarian index has any explanatory power for performance beyond that of prior-documented measures of strategy activeness (or uniqueness). The dependent variable of this panel regression is the cumulative Carhart (1997) four-factor adjusted return for a fund over the four quarters after we measure that fund's contrarian index (and other fund characteristics).

While we do not present a table (this can be found as Table 5 in Wei, Wermers, and Yao, 2015), we find that the results from this model are consistent with the aforementioned results using our simple approach of ranking funds in Table 19.3. That is, contrarian funds consistently deliver better performance than herding funds, controlling for their differing characteristics. 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.[6] Moreover, the significant return predictive power of the contrarian index remains strong after we add control variables for industry concentration, Active Share, and *RPI*, measures of strategy activeness or uniqueness that have been shown to help predict fund alphas. Thus, the success of contrarian funds is not limited to a few well-known cases, but appears to be a general phenomenon. More interestingly, the outperformance of contrarian funds suggests that contrarian managers do not appear to simply be overconfident. Given their greater past performance and inflows, and, thus, lower short-term career concerns, their contrarian trading strategies are likely motivated by their reliance on superior private information.

[5]For example, Chen, Hong, Huang, and Kubik (2004) document decreasing returns-to-scale among mutual funds.

[6]Recall that buying stocks (selling stocks) with a lower buy-herding (sell-herding) measure means that the fund tends to trade against the crowd; i.e., the fund is more contrarian in its trading behavior.

19.5 What Does It Take to Be A Successful Contrarian? Parsing Through Fund Trades

What is the source of outperformance by contrarian funds? Prior studies (e.g., Dasgupta et al., 2011a and Dasgupta, Prat, & Verardo, 2011b; Brown et al., 2014) show that fund herding results in a significant short-term price impact that tends to reverse in the long-run. Is it that contrarian funds simply profit from the temporary price pressure effect of herding? If so, it seems that many investors could potentially mimic their success by simply taking the opposite position of mutual fund herds. On the other hand, if contrarian funds profit from their superior information, they should outperform, regardless of whether they trade with or against herds.

To answer this question, we parse through fund trades to examine what types of trades contribute to contrarian fund outperformance. We break down all fund trades into 40 (5x2x4) groups. First, we classify funds, by their contrarian index, into quintiles. Then, within each contrarian index quintile, we group fund trades, by direction, into buy and sell trades. Finally, within each fund quintile rank and trade direction category, we further break trades into four types, depending on the contrarian/herding nature of the trades. Type 1 consists of contrarian trades of strongly herded stocks, Type 2 for contrarian trades of weakly herded stocks, Type 3 for herding trades of strongly herded stocks, and Type 4 for herding trades of weakly herded stocks. A stock is considered a "strong herding stock" if either its buy-herding measure (BHM) or sell herding (SHM) 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. We then report the quarter-by-quarter performance of the resulting 40 trade portfolios (5 fund quintiles, 2 trade directions, and 4 trade types) during the following four quarters.

Table 19.4 displays the quarter-by-quarter, as well as cumulative abnormal returns (characteristic-adjusted returns described earlier; for robustness, the four-factor alphas of the return difference between contrarian and herding funds is also presented) during the 4 quarters after trading, of the 40 different types of trades. Let us focus on the buy trades first. Contrarian funds outperform herding funds on Type-1 buys, i.e., contrarian buys of stocks strongly sold by herds. Consistent with the documented short-term price impact of institutional herding, contrarian fund Type-1 buys initially do not outperform during the first quarter, but significantly outperform starting from the second quarter.

Interestingly, contrarian funds also outperform (relative to the same types of trades by herding funds) in the other three types of buy trades—contrarian buys of weakly herded stocks (Type 2), and herding buys on strongly and weakly herded stocks (Type 3 and 4). For example Contrarians also outperform in their contrarian buys of weak herding stocks (i.e., type-2 trades), where the profit from riding on the reversals of the price-pressure effect is likely small. More interestingly, contrarian fund buy trades outperform those of herding funds, even when they trade with herds (Types 3 and 4 trades). Specifically, while herding funds experience significantly negative returns in their herding trades of strong-herding stocks during quarters

Table 19.4 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 strong herding stocks		(0.22)	(−1.08)	(0.04)	(1.04)	(0.17)	(0.83)	(−0.77)	(−1.96)	(−1.29)	(−1.62)
	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 weak herding stocks		(−0.67)	(−0.87)	(−0.26)	(1.54)	(−0.44)	(0.81)	(0.09)	(0.57)	(0.65)	(1.15)
	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)

(continued)

Table 19.4 (continued)

		Buy trades					Sell trades				
	CON	Quarter 1	Quarter 2	Quarter 3	Quarter 4	Cumulative	Quarter 1	Quarter 2	Quarter 3	Quarter 4	Cumulative
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 strong herding stocks		(0.80)	(−1.17)	(−2.18)	(−1.81)	(−2.42)	(−2.70)	(−0.42)	(1.65)	(2.10)	(0.87)
	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 weak herding stocks		(1.02)	(−0.72)	(−0.63)	(−1.52)	(−0.67)	(−1.11)	(−0.60)	(0.52)	(1.76)	(0.25)
	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)
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

$t + 3$ and $t + 4$ (when the initial price pressure of fund herding reverses), contrarian funds generate zero abnormal returns on those trades. Therefore, contrarians trade on the same side as the crowd for certain stock when their own private information conforms to that of the crowd. In this case, herding is associated with a permanent price impact.

These findings suggest that, although, by construction, contrarian funds are more likely to trade away from the crowd; they do not just mechanically trade against the crowd. In fact, contrarians often end up trading with herds, as a significant portion of their trades are in the same direction as herds (Table 19.2). Therefore, the success of contrarian funds is not merely due to taking advantage of the price-pressure effect of herding (i.e., their contrarian trades). They are likely to have profited from their own source of information, even though such information may or may not conform to that of the crowd.

Next, we turn to the performance of the sell trades. The exhibit shows that there exist very small performance differences between contrarian funds and herding funds among Type-2 and Type-3 sell trades, although 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, Jegadeesh, & Wermers, 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 generally do not short-sell stocks, the stocks they sell to finance purchases of other attractive stocks must come from their existing holdings. While the stocks contrarian funds sell may be expected to underperform those they buy given their superior overall performance, 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. 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.

Overall, the trade-based analysis reveals that contrarian managers do not simply benefit from, mechanically, the price-pressure caused by fund herding. 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. Such private information, rather than overconfidence or gambling incentives, is likely to be the source of their contrarian trading behavior and consequently their outperformance.

19.6 Extracting Stock Selection Information From Contrarian Fund Holdings

Following the observation that contrarian funds may possess superior private information, we further extract such information and aggregate it into a stock selection signal. To do so, we adopt an approach developed by Wermers et al.

(2012) to construct a stock-level contrarian score from fund holdings and the fund contrarian index. This contrarian score measures the relative degree to which a stock is held by contrarian funds versus herding funds. Intuitively, if a stock is held heavily by contrarian funds and held lightly by herding funds, this score is high. But, if a stock is held equally by contrarian funds and herding funds, the score is neutral. Intuitively, since contrarian funds possess superior investment skills, their investment choices as extracted from their portfolio holdings can be used to locate stocks with superior future returns.

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). In our setting, the generalized inverse approach in Wermers et al. (2012) leads to the following stock-level contrarian score:

$$\alpha_{CON} = \left(\mathbf{V}'\mathbf{D}^{+}\mathbf{V}\right)\mathbf{X}'\mathbf{CON}, \tag{19.5}$$

where **CON** is the M X 1 vector consisting of elements CON_{jt} (the fund-j contrarian index score at the end of quarter t), **X** is the M X N matrix of fund portfolio weights, x_{ijt}, **V** is the first K eigenvectors of $\mathbf{X}'\mathbf{X}$, corresponding to the K largest eigenvalues. $\mathbf{D}^{+}$ is a M X M diagonal matrix whose first K diagonal elements are the inverse of the largest K eigenvalues of $\mathbf{X}'\mathbf{X}$, with the remaining M-K diagonal elements being zeros. Following Wermers et al. (2012), K is set to M/2. The higher a stock’s contrarian score, α_{CON}, the more heavily the stock is held by contrarian funds, as oppossed to herding funds. If contrarian funds possess superior investment skills, we would expect stocks with a higher α_{CON} score to earn higher abnormal returns in the future.

Before we examine this prediction, we compare the stock-level contrarian score with various quantitative stock selection factors, in order to understand whether contrarian fund investment strategies are systematically related to certain stock characteristics that also help to predict stock returns. Table 19.5 shows that stocks with higher contrarian scores have stronger value-oriented characteristics, fewer investment and financing activities, higher operating efficiency, more intangible investments, and greater illiquidity. Further, they have lower earnings momentum, higher uncertainty, and lower profitability. By and large, these results are consistent with the view that contrarian funds prefer value stocks and shy away from glamorous, profitable, or liquid stocks.

Lastly, we conduct regression analyses to examine how much price-pressure, public valuation signals, or private information each contribute to the superior performance of stocks preferred by contrarian funds. Specifically, we perform Fama–MacBeth regressions of DGTW-adjusted abnormal returns of stocks, during each of the four quarters after we measure the contrarian score, on their contrarian score, controlling for the price-pressure effect associated with herding, and the various valuation signals that are correlated with the contrarian score. We show, in Table 19.6, that the contrarian score significantly predicts stock returns during the subsequent four quarters after signal construction. The return-predictive power of the contrarian score is robust to controlling for the price impact of herding funds,

Table 19.5 Contrarian Score, Herding Intensity, and Quantitative Stock Characteristics

	HERD	HERD	HERD	HERD										
	(Q 0)	(Q−1)	(Q−2)	(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 (denoted as Q0), we sort stocks into deciles based on their contrarian score α_{CON}. For each decile we calculate the average herding index (*HERD*) for the four quarters from quarter $t-3$ (denoted as Q–3) to quarter t (denoted as Q0), 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, Yao, and Zhao (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

Table 19.6 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 as well as well-known quantitative stock selection factors. These stock-level results further confirm our conjecture that the stock selection information possessed by contrarian funds is private, and goes beyond the mere exploitation of price-pressure caused by herds or publicly available quantitative signals.

19.7 Conclusions

A short article by Treynor (1987) offers insights on potential mispricing caused by investors' herding behavior, and muses on strategies to take advantage of such mispricing. The findings of our recent study echo his insights. We identify contrarian and herding mutual funds and examine their characteristics, performance, and trades. We find that contrarian funds outperform herding funds by a significant margin. The success of the contrarian funds depends in part on their contrarian trades against herds. However, it appears that contrarian funds also possess private stock selection information. Thus, merely mimicking their contrarian trades will not make one as successful.

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