Is anti-herding always a smart choice? Evidence from mutual funds

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Abstract: Recent empirical studies document a negative relation between herding behaviour and the skill of mutual fund managers. We explore this relationship further by focusing on fund managers' contrarian buy and sell behaviour against the market. Our study reveals an asymmetry in the performance of mutual funds with contrarian buy behaviour and contrarian sell behaviour. The contrarian-buy behaviour reflects skill by positively predicting the cross-section of next period's mutual fund returns, while the contrarian-sell behaviour reflects a lack of skill associated with a negative prediction. These findings are robust to various risk-adjusted performance measures. Contrarian-buy funds outperform momentum-buy funds by 3% per year, while contrarian-sell funds underperform momentum-sell peers by about 4%. These findings are robust across different sizes and styles of mutual funds. Further analysis indicates that the asymmetric effect is reversed during recessions and disappears when market sentiment is high. We also study how mutual fund characteristics relate to contrarian buy and sell practices. We find that mutual funds with larger size, higher flow, lower tracking error, and no manager ownership are more likely to buy against the crowd but sell with the crowd.

Keywords: Mutual funds, Herding, Contrarian trading, Buy and sell asymmetry

1. Introduction

Recent empirical studies report a negative relation between herding behaviour and the skill of mutual fund managers (Jiang & Verardo, 2018; Koch, 2017; Wei, Wermers, & Yao, 2015).[1] We pursue this line of research further by focussing on the buy-sell asymmetry, recognising institutional investors often exhibit asymmetric motivations in their buy and sell decisions (Keim & Madhavan, 1995). Chan and Lakonishok (1993) argue that "Since an institutional investor typically does not hold the market portfolio, the choice of a particular issue to sell, out of the limited alternatives in a portfolio, does not necessarily convey negative information … In contrast, the choice of one specific issue to buy, out of the numerous possibilities on the market, is likely to convey favourable firm-specific news" (p. 185).

In addition to information-motivated trades, behavioural trades may also exhibit asymmetric behaviour. The disposition effect, for instance, might cause investors to realise the gain and ride it out but not act as promptly in containing their losses (Cici, 2012). Furthermore, Chan and Lakonishok (1995) document that the price impact of institutional trading is asymmetric. The stock price increases for buys and stays high, and it decreases for sells but rebounds later.

If contrarian trading behaviour can be viewed as skilled behaviour of mutual funds, one would expect that both contrarian-buy and contrarian-sell behaviour would generate superior returns. However, mutual funds may also engage in trades due to liquidity constraints, for example, in situations where they are under time pressure to meet demands for redemptions, that are not triggered by information. Thus, it is not always clear whether contrarian traders would experience asymmetry between their buy and sell signals.

We fill a gap in the literature by investigating investors' contrarian behaviour in the mutual fund industry with a focus on the buy and sell asymmetry. The mutual fund industry is an ideal setting for this study as mutual funds tend to herd with other institutional investors or financial intermediaries in general. Moreover, mutual funds must disclose their holdings quarterly, enabling us to access their trading decisions.

Previous studies show that mutual funds that trade against

[1] Wei et al. (2015) provide evidence that mutual funds with lower holdings of herding stocks have better performance. Koch (2017) shows that unlike leaders, contemporaneous herding managers and followers do not outperform, and if anything, they exhibit poor performance. Jiang and Verardo (2018) introduce a dynamic measure of mutual fund following the crowd and demonstrate the underperformance of herding funds.

previous actions of other institutions are contrarian funds and demonstrate skill (Jiang & Verardo, 2018; Wei et al., 2015). However, herding behaviour of mutual funds may be misclassified if a wrong crowd is chosen to compare the fund's trades against. As such, we measure a fund's tendency for contrarian behaviour against contemporary stock performance - a proxy for collective trading of all market participants.

Using quarterly holdings data of U.S. mutual funds from 1993 to 2022, we construct portfolios of funds based on different levels of contrarian-buys and contrarian-sells. For each fund in each quarter, we calculate the contrarian-buy index (*CB)* as the increases of fund holdings in each quarter multiplied by the return of every stock in the same quarter and the contrarian-sell index (*CS)* as the decreases of fund holdings in each quarter multiplied by the return of every stock in the same quarter.

On average, we find that *CB* positively relates to fund performance, while *CS* negatively relates to fund performance. In particular, mutual funds in the top *CB* decile outperform those in the bottom *CB* decile by 3% per year, whereas mutual funds in the highest *CS* decile underperform those in the bottom *CS* decile by 4.08% per year. Such differences in performance cannot be explained by the different risk exposures or style factors of mutual funds. For example, the highest *CB* decile continues to outperform the lowest decile by 4.08% a year after accounting for the risk exposures of the Fama-French five factors. In contrast, mutual funds in the highest *CS* decile continue to underperform those in the bottom decile by 4.56% per year on a risk-adjusted basis. The return gaps between *CB* and *CS* portfolios remain similar across different fund size groups and different fund styles.

Using panel regressions, we show that *CB* positively predicts Fama-French five-factor alphas, while *CS* predicts these alphas negatively. These predictive relationships cannot be explained by fund characteristics that have been shown to predict mutual fund performance in prior studies. We further analyse these predictive relationships that *CB* and *CS* exhibit by carrying out several robustness tests.

First, we examine the relation between contrarian behaviour and mutual fund skill in the presence of buy and sell asymmetry by delaying the start of the sample period to May 2004. This coincides with the time the Securities and Exchange Commission (SEC) required mutual funds to disclose their holdings quarterly, hence providing the opportunity to obtain more accurate holdings information. Results for this subsample provide evidence as strong as those for the full sample period.

Second, we examine whether the contrarian behaviour varies with the season. If investors' flow and mutual fund risk preferences vary with the season, we could expect a seasonal effect on this buy-and-sell asymmetry. It turns out that the asymmetric effect on contrarian behaviour is reversed in the summer. Contrarian-buy makes a negative prediction of fund performance, while contrarian-sell makes a positive prediction. This result may be due to the 'Halloween effect' that stock market returns tend to be significantly lower during summer than during winter suggesting mutual funds may be following a "Halloween strategy," also known as "Sell in May and Go Away."

Third, we examine trading asymmetries during economic booms and recessions. Kacperczyk, Nieuwerburgh, and Veldkamp (2014) find that skilled managers pick stocks in boom periods and time the market during recessions. Therefore, both the positive effect of contrarian-buy, and the negative effect of contrarian-sell would diminish during a recession. Our results confirm that market conditions impact the contrarian-buy and contrarian-sell asymmetry. During recessions, managers tend to be less contrarian and tilt towwards the market portfolio.

Fourth, we consider investor sentiment as a possible explanation for the asymmetry. According to Antoniou, Doukas, and Subrahmanyam (2013), momentum strategies work during optimistic (high sentiment) periods but not during pessimistic (low sentiment) periods. Due to the contrarian behaviour's reverse relationship with momentum, we would expect the opposite relation to hold. Our results show a reduction in this asymmetric effect when market sentiment is high, and the asymmetric effect is mainly driven by low investor sentiment.

Fifth, we consider several fund characteristics that have been shown to be associated with fund performance to gain a better understanding of which types of funds are more likely to pursue contrarian practices. In particular, we consider fund size, fund age, expense ratio, fund turnover, funds flow in the previous quarter, fund alpha, and tracking error estimated over the last three years. We also consider a few manager characteristics, including whether the fund is managed by a team, whether the manager has ownership in the fund, and the average tenure of the manager.[2] The results show that mutual funds with higher flow, larger size, lower tracking error, and no manager ownership exhibit larger *CB* and smaller *CS*.

We contribute to the literature on mutual fund performance by documenting the asymmetric effects of contrarian buy and contrarian sell measures on fund performance. Previous studies examined investors' herding regardless of their trading direction, focusing on either its impact on stock prices or mutual fund performance. Building on Jiang and Verardo (2018) findings on anti-herding behaviour and skill, we further analyse contrarian-buy and contrarian-sell behaviour. Our results show that the contrarian measures capture the skill distribution among fund managers only on the buy-side, and this effect is stronger during booms and low sentiment periods.The rest of the paper proceeds as follows. Section 2 describes the sample selection process and explains the construction of contrarian indices (both *CB* and *CS*) and fund performance measures. Section 3 presents the results on the predictability of *CB* and *CS* for mutual fund performance. Section 4 documents robustness tests. Section 5 investigates the determinants of fund contrarian indices based on several fund and manager characteristics, and Section 6 concludes.

2. Sample selection and index construction

2.1. Data and sample selection

The primary data sources in this study are the Morningstar Direct Mutual Fund Database and the Center for Research in Security Prices (CRSP) stock price data. The Morningstar Direct Mutual Fund Database includes information on fund holdings, fund returns, total net assets, investment objectives, and other fund characteristics. The data is collected from reports filed by mutual funds with the SEC and voluntary reports generated by the funds. The SEC allows mutual funds to disclose with a delay of up to 60 days. As a result, the report date and filing date (quarter-end) of holdings are often different. We follow Lou (2012) and assume that the managers do not trade between the quarter-end and the report date.

Our final sample spans the period between 1993 and 2022. We discarded balanced, bond, index, international, and sector funds and focus on U.S. domestic equity mutual funds investing in companies listed on the NYSE, NASDAQ, or AMEX stock exchanges. Our final sample includes 1942 actively managed diversified equity funds. We use the one-month US Treasury bill rate as the risk-free rate and obtain monthly market factor returns from Kenneth French's website.[3] Finally, we obtain the liquidity factor from Lubos Pastor's website.[4]

2.2. Contrarian index construction

We define the fund contrarian measure, the Contrarian Index, based on the fund holdings change during each quarter. Specifically, we first calculate the fund's contrarian level on each stock by multiplying each stock's weight change with its return during the same quarter. We also

[2] We thank an anonymous referee for the suggestion.

[3] See http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html

[4] See http://faculty.chicagobooth.edu/lubos.pastor/research.

put a negative sign for each calculation so that contrarian traded stocks by a mutual fund have a positive contrarian level score. In contrast, stocks being part of mutual fund herding have a negative contrarian level score. That is to say, a stock with negative performance has a positive contrarian-buy index when a mutual fund increases its holding. Table 1 provides an example of how a fund's contrarian level on each stock is calculated. A stock with a − 15% return and a 10% weight increase has a contrarian-buy score of 1.5%, whereas a stock with a − 15% return and a 10% weight decrease has a contrarian-sell score of −1.5%.

Second, we separate a fund's holding into buy and sell groups depending on each stock's weight change. We then calculate the Contrarian-buy Index (*CB*) and the Contrarian-sell Index (*CS*) of each fund by adding up all stock holdings in buy and sell groups.

The Contrarian-buy Index (*CB*) is defined as the aggregation of the contrarian level for each stock bought by the mutual fund:

$$CB_{j,t} = -\sum_{i=1}^{N} \Delta\omega_{ij,t} * RET_{i,t} | \Delta\omega_{ij,t} > 0, \tag{1}$$

The Contrarian-sell Index (*CS*) is defined as the aggregation of the contrarian level for each stock sold by the mutual fund:

$$CS_{j,t} = -\sum_{i=1}^{N} \Delta\omega_{ij,t} * RET_{i,t} | \Delta\omega_{ij,t} < 0, \tag{2}$$

where $\Delta\omega_{ij,t}$ denotes the weight change of stock *i* in fund *j* at the end of quarter *t*, $RET_{i,t}$ is the return of stock *i* in quarter *t*, and *N* equals the total number of stocks traded by fund *j* in quarter *t*.

The contrarian index measures how a mutual fund adjusts its holdings based on the contemporary stock price movement, reflecting the stock's market demand and supply. The index is positive if a mutual fund has relatively more trades in the opposite direction of the stock price movement and is negative if a mutual fund is a momentum trader.

Panel A of Table 2 presents summary statistics of the contrarian indices and other fund characteristics. The average actively managed U. S. equity fund has a contrarian-buy index of 0.7% and a contrarian-sell index of −1.3%. The standard deviations for *CB* and *CS* are 5% and 2.8%, respectively, demonstrating a significant cross-sectional variation in mutual funds' contrarian behaviour. Panel B of Table 2 presents the correlation between fund contrarian indices, fund return, and fund characteristics - age, size, loads, investment style, and turnover. In general, we observe statistically significant correlations across the variables.

2.3. Performance measures

We examine the relation between the contrarian index and fund performance using different risk factor models. The dependent variable is the monthly return on fund portfolio *j* in month *t* minus the risk-free rate. The specification of the factor models is as follows.

2.3.1. Fama and French risk factor models

Our primary benchmark for evaluating fund performance are the Fama and French (1993) three-factor model and the Fama and French (2015) five-factor model. The Fama and French (1993) three factor model, which controls for market, size, and value-growth return factors, is given by:

$$R_{jt} - Rf_t = \alpha_j + \beta_{j,MKT} * (R_{MKT,t} - Rf_t) + \beta_{j,SMB} * SMB_t + \beta_{j,HML} * HML_t + u_{jt} \tag{3}$$

Specifically, $R_{MKT,t} - Rf_t$ denotes the excess return of the market portfolio over the risk-free rate; SMB_t is the return difference between diversified portfolios of small and large-capitalisation stocks; HML_t is the return difference between diversified portfolios of high and low book-to-market stocks; and u_{jt} is a zero-mean residual term.

The five-factor model of Fama and French (2015), which adds two extra factors to the Fama and French three factor model, capturing the variation in average stock returns in relation to profitability and investment.

$$\begin{aligned} R_{jt} - Rf_t = &\alpha_j + \beta_{i,MKT} * (R_{MKT,t} - Rf_t) + \beta_{j,SMB} * SMB_t + \beta_{j,HML} * HML_t \\ &+ \beta_{j,RMW} * RMW_t + \beta_{j,CMA} * CMA_t + u_{jt} \end{aligned} \tag{4}$$

where RMW_t is the return difference between diversified portfolios of stocks with robust and weak profitability, and CMA_t is the return difference between diversified portfolios of the stocks of low and high investment firms.

We also present results for the single-factor CAPM given by:

$$R_{jt} - Rf_t = \alpha_j + \beta_{j,MKT} * (R_{MKT,t} - Rf_t) + u_{jt} \tag{5}$$

2.3.2. Ferson-Schadt conditional measure

Ferson and Schadt (1996) argue that traditional unconditional factor models might be unreliable due to not incorporating the common time variation of expected returns and risks. Such confounding variations in risk and risk premia of mutual funds could be mistakenly regarded as reflecting superior information or market timing ability. Thus, a managed portfolio strategy that can be replicated using readily available public information should not be judged as having superior information. The specification of the conditional model follows Wermers (2003) and Kacperczyk, Sialm, and Zheng (2005), who add interaction terms between the excess market returns and four macro-economic variables to the Fama-French factor model:

$$\begin{aligned} R_{jt} - Rf_t = &\alpha_j + \beta_{j,MKT} * (R_{MKT,t} - Rf_t) + \beta_{j,SMB} * SMB_t + \beta_{j,HML} * HML_t \\ &+ \beta_{j,RMW} * RMW_t + \beta_{j,CMA} * CMA_t \\ &+ \sum_{k=1}^{4} \beta_{j,k} \left[z_{k,t-1} * (R_{MKT,t} - Rf_t) \right] + u_{jt} \end{aligned} \tag{6}$$

where $z_{k,t-1}$ is the demeaned value of the lagged macro-economic variable *k*. Consistent with previous studies, we consider the following four macro-economic variables: the one-month Treasury bill yield, the dividend yield of the S&P 500 Index, the Treasury yield spread (long- minus short-term bonds), and the quality spread in the corporate bond market (low- minus high- grade bonds). The intercept of the model, α_j, is the conditional measure of fund performance.

2.3.3. Pastor-Stambaugh liquidity factor measure

Our measure of the mutual fund contrarian behaviour could reflect behaviour to provide liquidity. Existing literature shows that traders can benefit from bearing liquidity risk. We control for liquidity risk using the Pastor-Stambaugh model (Pástor & Stambaugh, 2003). Specifically, we add a liquidity factor as an additional control variable to the Fama-French five-factor model and estimate the following model:

Table 1
Example of A Stock's contrarian level calculation.

	Weight Change	
Stock Return	10% (Buy)	−10% (Sell)
15% (Positive)	−1.5% = −(15%)*10%	1.5% = −(15%)*(−10%)
−15% (Negative)	1.5% = −(−15%)*10%	−1.5% = − (−15%)*(−10%)

$$R_{j,t} - Rf_t = \alpha_j + \beta_{j,MKT} * (R_{MKT,t} - Rf_t) + \beta_{j,SMB} * SMB_t + \beta_{j,HML} * HML_t + \beta_{j,RMW} * RMW_t + \beta_{j,CMA} * CMA_t + \beta_{j,LIQ} * LIQ_t + u_{j,t} \tag{7}$$

where LIQ_t denotes the value in month t of the stock market liquidity measure of Pástor and Stambaugh (2003). The liquidity factor is the value-weighted return on the 10–1 portfolio from a sort based on historical liquidity betas.

2.3.4. Market timing

A mutual fund manager with market timing ability could also engage in opposite trading with the market; hence our contrarian measure could simply be a reflection of timing ability. Treynor and Mazuy (1966) introduced a quadratic term of market return to capture market timing. We extend the Fama-French five-factor model with the squared market excess return to control for market timing:

$$R_{j,t} - Rf_t = \alpha_j + \beta_{j,MKT} * (R_{MKT,t} - Rf_t) + \beta_{j,SMB} * SMB_t + \beta_{j,HML} * HML_t + \beta_{j,RMW} * RMW_t + \beta_{j,CMA} * CMA_t + \beta_{j,TM} * (R_{MKT,t} - Rf_t)^2 + u_{j,t} \tag{8}$$

where $(R_{MKT,t} - Rf_t)^2$ is the square of market excess return in month t.

3. Predicting mutual fund performance using the contrarian index

In this section, we present the empirical results. We start by analysing the portfolio performance in deciles of the *CB* index and the *CS* index. We then investigate how the *CB* index and *CS* index relate to fund performance using a panel regression approach. We further examine how fund size, investment styleinteract with the observed performance relation.

3.1. Portfolio evidence

This section uses portfolio-based analysis to gauge the relative performance of funds with different contrarian levels. At the end of each quarter, we sort all mutual funds into ten groups based on their contrarian-buy index and contrarian-sell index. We then compute equal-weighted returns for each decile over the next period. We also estimate the risk-adjusted returns of these portfolios as intercepts from time-series regressions of the asset pricing models discussed in the previous section.[5]

Table 3 presents the portfolio results across different models. Panel A reports results related to *CB*, and Panel B shows the results of *CS*. Fund returns are measured in each month of quarter $t + 1$. The first row of both panels reports the mean value of the contrarian-buy index and contrarian-sell index for each decile portfolio, measured at the end of quarter t. Funds in decile 10 exhibit a strong tendency to buy (sell) against the market trades, with an average of *CB* (*CS*) reaching 10% (1%). In contrast, funds in decile one exhibit a strong tendency to trade in the same direction as the other market participants, with negative values reaching −5% (−5%).

The results in panel A show that the funds with the highest tendency of contrarian buy (decile 10) outperform the funds with the highest tendency of momentum buy (decile 1) by 0.25% per month, which implies an annualised rate of 3%. This performance differential between contrarian-buy funds and momentum-buy funds cannot be attributed to the propensity to take risks or different investment styles. The difference in alphas from the CAPM, Fama and French three-factor, Fama and French five-factor, Pastor and Stambaugh, Ferson and Schadt and Treynor and Mazuy models are even larger, ranging from 0.28% to 0.34% per month, all of which are statistically significant.

In contrast, the results for the contrarian-sell index in panel B show that the cross-sectional differences in fund contrarian-sell behaviour predict negative mutual fund performance differences. Funds with the highest contrarian-sell tendency (decile 10) underperform the funds with the highest momentum-sell tendency (decile 1) by 0.34% per month, which implies an annual difference of 4.08%. These differences are significant across all asset pricing models we employ.[6]

3.2. Size effect

Due to the presence of diseconomies of scale in money management, Berk and Green (2004) show that funds with larger sizes have fewer investment opportunities to exploit, and thus have lower performance relative to a passive benchmark. In this section, we investigate whether the predictive effect of contrarian indices depends on fund size. We separate mutual funds into different size portfolios and compare the performance of contrarian and herding funds within each size portfolio.

To gauge the impact of fund size on the relationship between contrarian trading and fund performance, we first sort funds into quintiles based on their Total Net Asset (*TNA*) value at the end of the previous quarter. Quintile 1 represents the smallest funds group, and quintile 5 represents the group of the largest funds. We further sort the mutual funds within each size quintile into two equally sized groups according to their Contrarian-buy or Contrarian-sell Index. Mutual funds in the smallest size quintile have an average *TNA* of 40.5 million, while funds in the largest size quintile on average manage 6251 million.

[5] Following the suggestion of an anonymous reviewer, we used the number of contrarian buys and the number of contrarian sells for each fund in each quarter as an alternative measure of contrarian behaviour capturing trading activity. We present these results in Table A1 in the appendix. The results show a positive relationship between mutual fund contrarian buying and mutual fund performance, while contrarian selling exhibits a negative predictive relationship with mutual fund performance. These findings are consistent with the results presented in Table 3 for decile buy and sell portfolio performance. We obtain similar results using predictive panels regressions. We report these results in Table A2 in the appendix. These results are consistent with the results reported in Table 6 below.

[6] We also compared the monthly return averages of different investment strategies, such as market index funds. Our results presented in Table A3 show that buy portfolios have positive returns while contrarian sell portfolios underperform other trading strategies. We thank an anonymous reviewer for the suggestion.

Table 2
Summary statistics.

Panel A: Fund Characteristics

	Mean	Median	P25	P75	Std. Dev
Age (years)	2.517	2.584	2.11	2.983	0.769
Alpha (%)	−0.041	−0.049	−0.214	0.106	0.336
Fee (%)	1.148	1.11	0.87	1.37	0.482
Flow (%)	0.817	−1.221	−3.804	2.594	11.852
Size (in millions)	1754.91	271.59	62.23	1068.51	3860.32
TE (%)	1.314	1.168	0.855	1.602	0.737
Turnover (%)	66.574	50.66	26	88	60.015
Fret (%)	0.724	1.079	−1.821	3.711	5.154
CB	0.007	0.008	−0.013	0.03	0.05
CS	−0.013	−0.011	−0.026	0.001	0.028

Panel B: Correlation Matrix

Variable	*Age*	*Alpha*	*CB*	*CS*	*Fee*	*Flow*	*Fret*	*Size*	*TE*	*Turnover*
Age	1									
Alpha	−0.146***	1								
CB	−0.007***	0.02***	1							
CS	−0.031***	−0.022***	−0.699***	1						
Fee	−0.207***	−0.012***	−0.014***	0.034***	1					
Flow	−0.25***	0.27***	0.1***	−0.077***	0.049***	1				
Fret	0.007***	−0.012***	−0.004*	0.007***	0.012***	−0.006***	1			
Size	0.417***	−0.119***	0.004**	−0.051***	−0.543***	−0.111***	−0.007***	1		
TE	−0.217***	0.156***	−0.03***	0.04***	0.373***	0.07***	0.002	−0.088***	1	
Turnover	−0.16***	−0.04***	−0.016***	−0.001	0.229***	0.023***	0	−0.228***	0.248***	1

This table presents descriptive statistics for the sample of actively managed equity mutual funds used in this paper. The sample consists of 1942 mutual funds from 1993Q1 to 2022Q4 in the U.S. market. Panel A reports the summary statistics of fund characteristics. *CB* is the Contrarian-buy Index constructed from the fund holdings increase of each quarter multiplying each stock's return during the same quarter, while *CS* is the Contrarian-sell Index constructed from the fund holdings decrease of each quarter multiplying the return of each stock during the same quarter. *Age* is the natural log of fund age in years. *Alpha* is the fund's three-factor alpha estimated over the previous three years. *Fee* is the fund expense ratio. *Flow* is the fund flow in the previous quarter. *Size* is the dollar value of the previous quarter-end TNAs. Tracking Error (*TE*) is the standard deviation of the fund's three-factor residual estimated over the previous three years. *Turnover* is the fund's turnover ratio. *Fret* is the fund return determined each month by taking the change in monthly net asset value. Panel B reports the contemporaneous correlations between the main variables used in the paper. ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively.

Table 4 reports the size effect results based on contrarian buy (Panel A) and contrarian sell (Panel B). Consistent with Chen, Hong, Huang, and Kubik (2004), we show that small funds outperform large funds. For example, small funds have monthly abnormal returns of 0.05% for low *CB* and 0.17% for high *CB* using the Fama-French five-factor model, while funds in the largest-sized group have abnormal returns of −0.08% for low *CB* and 0.06% for high *CB*. Table 4 also presents the effect of different contrarian levels within each size group. Panel A shows a positive performance difference for *CB* within each size quintile. Specifically, the abnormal return of the difference between high *CB* groups and low *CB* groups ranges from 0.12% to 0.17% per month, using the Fama-French five-factor model. In contrast, Panel B shows a negative performance difference for *CS* within each size quintile. The abnormal returns of the difference between high *CS* and low *CS* groups are significantly negative, ranging from −0.23% to −0.14% per month using the Fama and French five-factor model. Similar to *CB*, these *CS* effects do not differ significantly across different size groups.

3.3. Style portfolios

Funds tend to focus on stock characteristics, for example, value versus growth, and different styles of mutual funds may have an effect on fund performance. For instance, Wermers (2000) provides evidence that growth-oriented funds tend to have better performance than value-oriented funds. This section investigates whether our main results of interest are related to funds' different investment styles. We sort the mutual funds sample into three groups based on investment styles, namely, growth, blend, and value. We further divide each group into two sub-groups, according to contrarian indices. We obtain six portfolios of mutual funds for either *CB* or *CS* according to their styles and contrarian tendency.

Table 5 summarises the abnormal returns of different performance measures for the style portfolios that we constructed. Consistent with the findings in previous studies (Chen, Jegadeesh, & Wermers, 2000; Daniel, Grinblatt, Titman, & Wermers, 1997; Wermers, 2000), we observe that growth style mutual funds outperform other funds across all performance measures. For example, Table 5 Panel A shows that growth-oriented mutual funds outperform value-oriented mutual funds by 0.17% and 0.16% per month for the low *CB* group and high *CB* group, respectively, using the Fama and French (2015) five-factor model.

Consistent with our earlier findings, mutual funds with a higher contrarian buy tendency generate higher abnormal returns given the same fund style. In contrast, mutual funds with a higher contrarian sell tendency produce lower abnormal returns within style categories. Consider the abnormal return based on the Fama and French (2015) five-factor model as an example. Growth mutual funds with the most contrarian buy tendency have an abnormal return of 0.05% per month, while the least contrarian buy growth mutual funds have an abnormal return of −0.07% per month. The high *CB* growth mutual funds outperform the low *CB* growth mutual funds by 0.12% per month, which is significant at the 5% level. The difference between the high and low groups is slightly larger and significantly positive for value-oriented mutual funds.

On the other hand, growth mutual funds with the most contrarian-sell tendency have an abnormal return of −0.06% per month, while the least contrarian-sell growth mutual funds have an abnormal return of 0.05% per month. The return gap between high *CS* and low *CS* growth-oriented funds is −0.1% per month. Overall, our findings suggest that the *CB* and *CS* effects on abnormal returns under different style groups are similar to our main results, with the difference between high groups and low groups of contrarian buy tendency being strongest for value-oriented style mutual funds.

Table 3
Decile portfolios: contrarian index and fund performance.

Panel A: Contrarian-buy Index.

CB rank	1	2	3	4	5	6	7	8	9	10	D10-D1
CB	−0.05	−0.02	−0.01	0	0.01	0.01	0.02	0.03	0.05	0.1	0.15
Average	0.7	0.71	0.87	0.82	0.83	0.89	0.84	0.91	0.87	0.94	0.25*
	(2.73)	(2.95)	(3.71)	(3.49)	(3.52)	(3.94)	(3.68)	(3.94)	(3.74)	(3.88)	(1.95)
CAPM α	−0.23	−0.19	−0.01	−0.06	−0.06	0.03	−0.03	0.04	−0.01	0.05	0.28**
	(−3.23)	(−3.29)	(−0.2)	(−1.17)	(−1.33)	(0.72)	(−0.61)	(0.8)	(−0.13)	(0.71)	(2.42)
FF3 α	−0.24	−0.2	−0.03	−0.08	−0.07	0.01	−0.04	0.03	−0.01	0.05	0.29**
	(−3.39)	(−3.52)	(−0.66)	(−1.54)	(−1.7)	(0.36)	(−1.02)	(0.64)	(−0.26)	(0.77)	(2.5)
FF5 α	−0.26	−0.22	−0.08	−0.11	−0.09	0	−0.04	0.01	−0.02	0.08	0.34***
	(−3.5)	(−3.84)	(−1.54)	(−2.17)	(−1.93)	(0)	(−0.97)	(0.23)	(−0.45)	(1.24)	(2.79)
FS α	−0.26	−0.21	−0.07	−0.11	−0.08	−0.01	−0.04	0.02	−0.02	0.09	0.34***
	(−3.54)	(−3.67)	(−1.46)	(−2.04)	(−1.83)	(−0.14)	(−0.92)	(0.32)	(−0.48)	(1.34)	(2.87)
PS α	−0.26	−0.22	−0.08	−0.12	−0.09	−0.01	−0.05	0	−0.03	0.06	0.32***
	(−3.5)	(−3.9)	(−1.66)	(−2.31)	(−2.13)	(−0.25)	(−1.15)	(0.07)	(−0.62)	(1)	(2.64)
Timing α	−0.21	−0.18	−0.1	−0.08	−0.07	−0.01	−0.02	−0.01	0.01	0.13	0.34***
	(−2.53)	(−2.7)	(−1.65)	(−1.27)	(−1.4)	(−0.11)	(−0.48)	(−0.17)	(0.26)	(1.72)	(2.97)

Panel B: Contrarian-sell Index.

CS rank	1	2	3	4	5	6	7	8	9	10	D10-D1
CS	−0.05	−0.03	−0.02	−0.02	−0.01	−0.01	0	0	0	0.01	0.06
Average	1.06	0.84	0.88	0.87	0.87	0.81	0.8	0.77	0.77	0.72	−0.34***
	(4.23)	(3.6)	(3.81)	(3.79)	(3.74)	(3.52)	(3.44)	(3.28)	(3.31)	(2.87)	(−2.97)
CAPM α	0.16	−0.03	0.01	0	−0.01	−0.07	−0.08	−0.11	−0.1	−0.2	−0.36**
	(1.85)	(−0.56)	(0.2)	(−0.02)	(−0.29)	(−1.69)	(−1.75)	(−2.04)	(−1.62)	(−2.66)	(−2.41)
FF3 α	0.16	−0.04	0	−0.02	−0.03	−0.07	−0.09	−0.13	−0.12	−0.2	−0.36**
	(2.23)	(−0.71)	(−0.02)	(−0.53)	(−0.66)	(−1.85)	(−2.06)	(−2.58)	(−1.99)	(−2.76)	(−2.53)
FF5 α	0.17	−0.05	−0.02	−0.05	−0.05	−0.08	−0.09	−0.15	−0.16	−0.22	−0.38**
	(2.27)	(−0.79)	(−0.39)	(−1.18)	(−1.13)	(−1.96)	(−1.83)	(−2.76)	(−2.68)	(−2.87)	(−2.41)
FS α	0.16	−0.04	−0.01	−0.05	−0.05	−0.08	−0.08	−0.14	−0.15	−0.22	−0.38**
	(2.15)	(−0.61)	(−0.17)	(−1.1)	(−1.15)	(−2.06)	(−1.77)	(−2.54)	(−2.57)	(−2.91)	(−2.37)
PS α	0.15	−0.06	−0.03	−0.06	−0.06	−0.09	−0.08	−0.15	−0.16	−0.22	−0.38**
	(2.12)	(−1.05)	(−0.65)	(−1.52)	(−1.43)	(−2.2)	(−1.81)	(−2.88)	(−2.68)	(−2.9)	(−2.33)
Timing α	0.16	−0.03	0.01	−0.06	−0.07	−0.09	−0.03	−0.1	−0.17	−0.15	−0.31**
	(1.85)	(−0.41)	(0.22)	(−1.29)	(−1.51)	(−1.9)	(−0.59)	(−1.69)	(−2.43)	(−1.71)	(−2.11)

Panel A presents the performance of decile portfolios sorted on the fund's contrarian-buy index (*CB*), the average tendency of mutual funds to buy against the market sell. We sum up the *CB* of each stock a fund bought to get the *CB* of the fund during that quarter. The decile portfolios are formed at the end of each quarter from 1993Q1 to 2022Q4 and held for one quarter. The monthly return series spans the period from January 1993 to March 2023. Decile 10 is the portfolio of funds with the highest average *CB*. Panel B presents decile portfolios' performance sorted on the fund's contrarian-sell index (*CS*), the average tendency of mutual funds to sell against the market buy. *CS* is constructed by multiplying the fund's holdings decrease of each quarter times the stock's return during the same quarter. We sum up the *CS* of each stock a fund sold to get *CS* of the fund during that quarter. Decile 10 is the portfolio of funds with the highest average *CS*. We consider risk-adjusted returns based on the capital asset pricing model (CAPM), the Fama and French (1993) three-factor model (FF3), Fama and French (2015) five-factor model (FF5), the Ferson and Schadt (1996) conditional model (FS), the Pástor and Stambaugh (2003) five-factor model (PS), and the Treynor and Mazuy (1966) market-timing model (Timing). This table reports average returns and alphas (α) in monthly percentages. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively, for the return differentials between deciles 10 and 1 (D10-D1).

3.4. Multivariate regression analysis

In this section, we investigate the relation between contrarian indices and fund performance through predictive panel regressions. A drawback of portfolio analysis is that it cannot control for multiple fund characteristics, which may impact fund performance, simultaneously. For example, Berk and Green (2004) argue that diseconomies of scale make it more difficult for larger funds to deploy investment opportunities than smaller funds. Smaller funds tend to be more active (Cremers & Petajisto, 2009) and industry-concentrated (Kacperczyk et al., 2005). It is thus possible that fund size may have a negative relationship with fund performance and that the contrarian strategy matters only because it correlates with size. Compared to the portfolio approach, a multivariate regression approach mitigates confounding issues by simultaneously controlling for mutual fund characteristics.

The dependent variable in the regression model is the Fama-French five-factor (FF5) performance measure. We use monthly mutual fund returns over the past three years to estimate the FF5 model's coefficients. Next, we calculate the fund's expected return by multiplying the estimated coefficients with the corresponding factors in the following month. The abnormal return of a fund in each month is determined by subtracting the expected return from the actual fund return.

We then regress the monthly abnormal return of each fund on the contrarian indices along with other fund characteristics - fund size, age, expense ratio, turnover, net flows, tracking error, and past return alpha. We use lagged explanatory variables to mitigate potential endogeneity issues. Due to the right skewness of some fund characteristics (e.g., age and size), we take the natural logarithms of those variables. Previous studies also show that mutual fund flows affect asset prices and predict fund performance (Wermers, 2003; Zheng, 1999). We include lagged mutual fund net flows as an additional control variable.

Table 6 presents the multivariate regression results. We find that fund contrarian buy behaviour and contrarian sell behaviour have opposite predictions on fund performance. Column 1 shows the Contrarian-buy Index (*CB*) positively predicts fund performance with a significant positive coefficient. In terms of economic significance, one standard deviation increase in *CB* is expected to increase monthly abnormal returns by 3.45 (=0.69*5) basis points or 0.41 percentage

Table 4
Size portfolios.

Panel A: Contrarian-buy Index.

Size Quintile	Contrarian Buy	Average	CAPM	FF3	FF5	FS	PS	Timing
Quintile 1	Low	0.79***	0.15**	0.12**	0.05	0.05	0.03	0.03
		(3.17)	(2.17)	(2.29)	(0.88)	(1.03)	(0.62)	(0.55)
	High	0.88***	0.24***	0.22***	0.17***	0.15***	0.16***	0.19***
		(3.54)	(3.41)	(4.16)	(3.1)	(2.84)	(2.89)	(3.04)
	High-Low	0.08	0.09	0.1*	0.12**	0.1*	0.12**	0.16**
		(1.48)	(1.6)	(1.75)	(2.1)	(1.74)	(2.13)	(2.34)
Quintile 2	Low	0.69***	0.03	0.01	−0.03	−0.02	−0.04	−0.03
		(2.71)	(0.5)	(0.27)	(−0.53)	(−0.48)	(−0.71)	(−0.57)
	High	0.82***	0.18**	0.17***	0.14***	0.14***	0.13**	0.17***
		(3.29)	(2.49)	(3.29)	(2.69)	(2.73)	(2.47)	(2.72)
	High-Low	0.13**	0.15**	0.15**	0.17**	0.17**	0.16**	0.2**
		(1.96)	(2.24)	(2.29)	(2.44)	(2.41)	(2.39)	(2.5)
Quintile 3	Low	0.67***	0.02	0	−0.05	−0.05	−0.06	−0.04
		(2.66)	(0.29)	(−0.09)	(−1.09)	(−1.18)	(−1.25)	(−0.84)
	High	0.79***	0.15**	0.13***	0.1**	0.09*	0.09*	0.11**
		(3.17)	(2.21)	(2.86)	(2.07)	(1.93)	(1.88)	(2.04)
	High-Low	0.12**	0.13**	0.14**	0.15**	0.15**	0.15**	0.16**
		(1.96)	(2.14)	(2.28)	(2.43)	(2.36)	(2.39)	(2.22)
Quintile 4	Low	0.62**	−0.05	−0.06	−0.06	−0.05	−0.06	−0.04
		(2.4)	(−0.9)	(−1.15)	(−1.08)	(−0.89)	(−1.17)	(−0.6)
	High	0.76***	0.11*	0.1**	0.1**	0.1**	0.09**	0.08
		(3.04)	(1.87)	(2.27)	(2.2)	(2.12)	(1.98)	(1.52)
	High-Low	0.14**	0.16**	0.16**	0.16**	0.15**	0.15**	0.12
		(1.99)	(2.3)	(2.29)	(2.2)	(2)	(2.11)	(1.42)
Quintile 5	Low	0.59**	−0.06	−0.07*	−0.08**	−0.08**	−0.09**	−0.08*
		(2.39)	(−1.6)	(−1.78)	(−2.06)	(−2)	(−2.23)	(−1.7)
	High	0.7***	0.05	0.05	0.06*	0.07*	0.05	0.08*
		(2.85)	(1.33)	(1.43)	(1.7)	(1.75)	(1.43)	(1.73)
	High-Low	0.11**	0.11**	0.12**	0.15***	0.15***	0.14**	0.16**
		(1.99)	(2.06)	(2.23)	(2.63)	(2.57)	(2.54)	(2.39)

Panel B: Contrarian-sell Index.

Size Quintile	Contrarian Sell	Average	CAPM	FF3	FF5	FS	PS	Timing
Quintile 1	Low	0.9***	0.26***	0.24***	0.17***	0.17***	0.16***	0.2***
		(3.59)	(3.39)	(4.37)	(3.16)	(2.96)	(2.89)	(3.07)
	High	0.76***	0.12*	0.09*	0.03	0.04	0.02	0.02
		(3.08)	(1.88)	(1.76)	(0.59)	(0.69)	(0.41)	(0.37)
	High-Low	−0.14**	−0.14**	−0.15**	−0.14**	−0.13**	−0.14**	−0.17**
		(−2.16)	(−2.15)	(−2.39)	(−2.27)	(−2.01)	(−2.16)	(−2.38)
Quintile 2	Low	0.83***	0.18**	0.16***	0.15***	0.15***	0.13**	0.15**
		(3.24)	(2.32)	(3.14)	(2.73)	(2.72)	(2.47)	(2.43)
	High	0.68***	0.04	0.02	−0.04	−0.03	−0.04	−0.02
		(2.74)	(0.62)	(0.34)	(−0.69)	(−0.64)	(−0.79)	(−0.32)
	High-Low	−0.15**	−0.14*	−0.14**	−0.18**	−0.18**	−0.17**	−0.17**
		(−2.01)	(−1.84)	(−2.04)	(−2.48)	(−2.43)	(−2.35)	(−2)
Quintile 3	Low	0.82***	0.17**	0.16***	0.12**	0.11**	0.11**	0.13**
		(3.23)	(2.29)	(3.18)	(2.33)	(2.14)	(2.09)	(2.17)
	High	0.65***	0	−0.02	−0.06	−0.07	−0.07	−0.05
		(2.59)	(−0.04)	(−0.5)	(−1.31)	(−1.35)	(−1.39)	(−0.97)
	High-Low	−0.17**	−0.17**	−0.18***	−0.18***	−0.17**	−0.17**	−0.18**
		(−2.51)	(−2.46)	(−2.78)	(−2.68)	(−2.54)	(−2.55)	(−2.32)
Quintile 4	Low	0.79***	0.13*	0.13**	0.14**	0.13**	0.12**	0.11*
		(3.07)	(1.81)	(2.38)	(2.44)	(2.35)	(2.22)	(1.66)
	High	0.6**	−0.07	−0.08	−0.09*	−0.08	−0.09*	−0.06
		(2.35)	(−1.24)	(−1.58)	(−1.74)	(−1.53)	(−1.8)	(−1.03)
	High-Low	−0.19**	−0.2**	−0.21**	−0.23***	−0.21**	−0.22***	−0.17*
		(−2.24)	(−2.25)	(−2.55)	(−2.7)	(−2.49)	(−2.58)	(−1.74)
Quintile 5	Low	0.72***	0.07	0.07*	0.07	0.06	0.05	0.06
		(2.9)	(1.51)	(1.67)	(1.55)	(1.5)	(1.25)	(1.29)
	High	0.57**	−0.08**	−0.09**	−0.08**	−0.08*	−0.09**	−0.07
		(2.31)	(−2)	(−2.14)	(−2.04)	(−1.93)	(−2.13)	(−1.44)
	High-Low	−0.15**	−0.15**	−0.15**	−0.15**	−0.14**	−0.14**	−0.13*
		(−2.25)	(−2.24)	(−2.47)	(−2.33)	(−2.19)	(−2.18)	(−1.77)

Panel A presents the performance of portfolios sorted on both mutual fund size and contrarian-buy index (*CB*). We first sort the sample into five equally sized portfolios according to the mutual funds' lagged TNA. Decile 5 is the portfolio of funds with the largest average TNA. We further divide each size portfolio into two groups based on the lagged contrarian-buy Index. *CB* is the average tendency of mutual funds to buy against the market sell, which is constructed by multiplying the fund holdings change of each quarter times the stock's return during the same quarter. We sum up the *CB* of each stock fund bought to get the *CB* of the fund during that quarter. Panel B presents the performance of portfolios sorted on both mutual fund size and the Contrarian-sell Index (*CS*). We first sort the sample into five equally sized portfolios according to the mutual funds' lagged TNA. Decile 5 is the portfolio of funds with the largest average TNA. We further divide each size portfolio into two groups based on the lagged *CS*. *CS* is the average tendency of mutual funds to sell against the market buy, which is constructed by multiplying the fund holdings change of each quarter times the stock's return during the same quarter. We sum up the *CS* of each stock fund sold to get the *CS* of the fund during that quarter. The monthly return series spans from January 1993 to March 2023. We consider risk-adjusted returns based on the capital asset pricing model (CAPM), the Fama and French (1993) three-factor model (FF3), Fama and French (2015) five-factor model (FF5), the Ferson and Schadt (1996) conditional model (FS), the Pástor and Stambaugh (2003) five-factor model (PS), and the Treynor and Mazuy (1966) market-timing model (Timing). This table reports average returns and alphas in monthly percentages. ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively.

Table 5
Style portfolios.

Panel A: Contrarian-buy Index.

Style	Contrarian Buy	Average	CAPM	FF3	FF5	FS	PS	Timing
Growth	Low	0.54*	−0.12*	−0.1*	−0.07	−0.06	−0.07	−0.08
		(1.9)	(−1.76)	(−1.75)	(−1.18)	(−1.06)	(−1.29)	(−1.23)
	High	0.62**	−0.05	−0.01	0.05	0.07	0.03	0.05
		(2.14)	(−0.62)	(−0.14)	(0.91)	(1.24)	(0.57)	(0.69)
	High-Low	0.08	0.07	0.09	0.12**	0.13**	0.1*	0.13*
		(1.39)	(1.31)	(1.59)	(2.07)	(2.27)	(1.83)	(1.89)
Blend	Low	0.54**	−0.07	−0.11***	−0.16***	−0.16***	−0.17***	−0.12**
		(2.09)	(−1.45)	(−2.77)	(−3.92)	(−3.87)	(−4.28)	(−2.49)
	High	0.63**	0.03	−0.01	−0.06*	−0.05	−0.08**	−0.05
		(2.47)	(0.67)	(−0.3)	(−1.67)	(−1.42)	(−2.09)	(−1.06)
	High-Low	0.09**	0.1**	0.1**	0.09**	0.1**	0.09**	0.07
		(2.07)	(2.24)	(2.21)	(2.03)	(2.23)	(1.97)	(1.28)
Value	Low	0.53**	−0.01	−0.12*	−0.24***	−0.24***	−0.26***	−0.19***
		(2.16)	(−0.09)	(−1.86)	(−3.93)	(−3.88)	(−4.17)	(−2.64)
	High	0.64***	0.1	0	−0.11**	−0.1*	−0.12**	−0.11*
		(2.63)	(1.08)	(−0.06)	(−2.02)	(−1.84)	(−2.26)	(−1.72)
	High-Low	0.11**	0.11**	0.12***	0.13***	0.14***	0.13***	0.08
		(2.44)	(2.49)	(2.61)	(2.85)	(2.99)	(2.85)	(1.48)

Panel B: Contrarian-sell Index.

Style	Contrarian Sell	Average	CAPM	FF3	FF5	FS	PS	Timing
Growth	Low	0.64**	−0.02	0.01	0.05	0.05	0.03	0.01
		(2.21)	(−0.25)	(0.13)	(0.72)	(0.78)	(0.48)	(0.14)
	High	0.52*	−0.14**	−0.11**	−0.06	−0.04	−0.07	−0.04
		(1.84)	(−2.31)	(−2.08)	(−1.08)	(−0.76)	(−1.32)	(−0.64)
	High-Low	−0.12	−0.12*	−0.11*	−0.1	−0.09	−0.1	−0.05
		(−1.64)	(−1.69)	(−1.76)	(−1.52)	(−1.33)	(−1.45)	(−0.62)
Blend	Low	0.65**	0.05	0	−0.05	−0.04	−0.06*	−0.03
		(2.54)	(1.01)	(0.08)	(−1.17)	(−0.89)	(−1.72)	(−0.68)
	High	0.51**	−0.08	−0.13***	−0.18***	−0.18***	−0.18***	−0.13**
		(2.01)	(−1.63)	(−2.78)	(−3.84)	(−3.78)	(−3.97)	(−2.47)
	High-Low	−0.14***	−0.13**	−0.13**	−0.13**	−0.14**	−0.12**	−0.1
		(−2.66)	(−2.49)	(−2.44)	(−2.34)	(−2.49)	(−2.13)	(−1.56)
Value	Low	0.62***	0.08	−0.02	−0.15***	−0.14***	−0.17***	−0.13**
		(2.57)	(0.92)	(−0.38)	(−2.87)	(−2.74)	(−3.18)	(−2.17)
	High	0.55**	0.01	−0.1	−0.19***	−0.19***	−0.2***	−0.18**
		(2.21)	(0.06)	(−1.49)	(−2.8)	(−2.68)	(−2.97)	(−2.21)
	High-Low	−0.07	−0.08	−0.08	−0.04	−0.04	−0.04	−0.04
		(−1.51)	(−1.63)	(−1.63)	(−0.8)	(−0.79)	(−0.73)	(−0.73)

Panel A presents the performance of portfolios sorted on both mutual fund style and contrarian-buy index (*CB*). We first sort the sample into three portfolios according to investment styles from Morningstar classification, which are growth, blend, and value. We further divide each of these three styles portfolios into two groups based on the lagged Contrarian-buy Index. *CB* is the average tendency of mutual funds to buy against the market sell, which is constructed by multiplying the fund holdings change of each quarter times the return of each stock during the same quarter. We sum up the *CB* of each stock fund bought to get the *CB* of the fund during that quarter. Panel B presents the performance of portfolios sorted on both mutual fund style and contrarian-sell index (*CS*). We first sort the sample into three portfolios according to the investment styles from Morningstar classification, which are growth, blend, and value. We further divide each of these three style portfolios into two groups based on the lagged Contrarian-sell Index. *CS* is the average tendency of mutual funds to sell against the market buy, which is constructed by multiplying the fund's holdings change of each quarter times the return of each stock during the same quarter. We sum up the *CS* of each stock fund sold to get the *CS* of the fund during that quarter. The monthly return series spans from January 1993 to March 2023. We consider risk-adjusted returns based on the capital asset pricing model (CAPM), the Fama and French (1993) three-factor model (FF3), Fama and French (2015) five-factor model (FF5), the Ferson and Schadt (1996) conditional model (FS), the Pástor and Stambaugh (2003) five-factor model (PS), and the Treynor and Mazuy (1966) market-timing model (Timing). We report average returns and alphas in monthly percentages. ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively.

points annually, which is both economically and statistically significant.[7]

In the second column of Table 6, we use the Contrarian-sell Index (*CS*) as a predictive variable. Consistent with our portfolio analysis, *CS* has a negative and significant slope coefficient of −1.05 (*t-statistic* of −8.11). Column 3 of Table 6 shows that the significance in the association of *CB* and *CS* with fund performance is not altered when both measures are included as predictors of fund performance in the

[7] One standard deviation of the Contrarian-buy Index is approximately 5 %.

Table 6
Predictive panel regressions.

Variable	Dependent Variable: Fama and French five-factor alpha (t + 1)		
	1	2	3
CB	0.69***		0.535***
	(8.453)		(4.807)
CS		−1.05***	−0.428**
		(−8.11)	(−2.394)
Size	0.006***	0.005**	0.005**
	(2.568)	(2.424)	(2.459)
Age	-0.001	-0.001	-0.001
	(−0.387)	(−0.296)	(−0.333)
Fee	−0.002	−0.001	−0.002
	(−0.27)	(−0.166)	(−0.224)
Turnover	-0.001	-0.001	-0.001
	(−1.084)	(−1.27)	(−1.157)
Flow	0.011***	0.011***	0.011***
	(10.035)	(10.108)	(10.023)
TE	0.025***	0.025***	0.025***
	(3.298)	(3.295)	(3.321)
Alpha	0.118***	0.118***	0.118***
	(8.07)	(8.072)	(8.072)
Intercept	−0.041	−0.043	−0.035
	(−0.801)	(−0.844)	(−0.701)
N	313,687	313,687	313,687
Adj_RSQ	0.0063	0.0063	0.0063

This table presents results of predictive panel regressions estimating the association between contrarian indices and future fund performance. The dependent variable, future fund performance, is measured using the Fama and French five-factor alphas (in monthly percentages). Factor loadings are estimated from rolling-window regressions over the previous three years. *CB* is constructed from the fund holdings increase of each quarter multiplying the return of each stock during the same quarter, while *CS* is constructed from the fund holdings decrease of each quarter multiplying the return of each stock during the same quarter. The panel regressions control for fund size (*Size*), fund age (*Age*), expense ratio (*Fee* in percent), fund turnover (*Turnover*), fund percentage flows in the previous quarter (*Flow*), tracking error (*TE*), and fund alpha (*Alpha* in percent) estimated over the previous three years. The regressions include time fixed effects, and the standard errors are clustered by funds. t-statistics are shown in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively.

regression.[8] The inclusion of other fund characteristics such as fund size, age, net flow, expense, turnover, past alpha, and tracking error, does not reduce the predictive ability of contrarian indices on mutual fund performance.[9]

4. What drives the asymmetry?

4.1. Mandatory disclosure

Institutional investors are mandated to disclose their holdings information to the public following the Securities Exchange Act of 1934 and the Investment Company Act of 1940. The Securities and Exchange Commission (SEC) required mutual funds to increase their disclosure frequency from a semi-annual basis to a quarterly basis in May 2004. We evaluate the robustness of the predictive power of *CB* and *CS* by using the oservations after May 2004 only as the change may have affected the relation between funds' contrarian trades and performance. Table 7 shows that the post-2004 subsample results are similar to those reported in Table 6 for the entire sample period.

Table 7
Predictive Panel Regressions: Sub-periods by mandatory disclosure May 2004.

Variable	Dependent Variable: Fama and French five-factor alpha (t + 1)		
	_1	_2	_3
CB	0.816***		0.73***
	(9.422)		(5.792)
CS		−1.0***	−0.204
		(−8.331)	(−1.14)
Size	0.005**	0.004*	0.004*
	(1.992)	(1.889)	(1.944)
Age	0.001	0.001	0.001
	(0.514)	(0.584)	(0.538)
Fee	−0.01	−0.009	−0.01
	(−1.087)	(−0.997)	(−1.068)
Turnover	-0.001***	-0.001***	-0.001***
	(−4.016)	(−4.19)	(−4.062)
Flow	0.01***	0.01***	0.01***
	(9.939)	(9.967)	(9.929)
TE	0.014	0.014*	0.014*
	(1.644)	(1.673)	(1.665)
Alpha	0.057***	0.058***	0.057***
	(3.83)	(3.91)	(3.837)
Intercept	0.015	0.006	0.017
	(0.293)	(0.121)	(0.328)
N	273,378	273,378	273,378
Adj_RSQ	0.0069	0.0069	0.0069

This table presents results of predictive panel regressions estimating the association between contrarian indices and future fund performance for the period after May 2004. The dependent variable, future fund performance, is measured using Fama and French five-factor model (in monthly percentages). Factor loadings are estimated from rolling-window regressions over the previous three years. *CB* is constructed by multiplying the fund's holdings increase of each quarter times the return of each stock during the same quarter, while *CS* is constructed from the fund holdings decrease of each quarter multiplied by the return of each stock during the same quarter. The panel regressions control for fund size (*Size*), fund age (*Age*), expense ratio (*Fee* in percent), fund turnover (*Turnover*), fund percentage flows in the previous quarter (*Flow*), tracking error (*TE*), and fund alpha (*Alpha* in percent) estimated over the previous three years. The regressions include time-fixed effects, and the standard errors are clustered by funds. t-statistics are shown in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively.

4.2. Seasonal effects

Kamstra, Kramer, Levi, and Wermers (2017) find strong evidence of seasonality in investors' risk aversion. They investigate aggregate investor flows and argue that investors prefer safe mutual funds in the autumn and risky funds in the spring. To test whether the predictability of mutual fund trading activity is related to a particular season, we add three interaction terms between quarters and contrarian indices to access the seasonal effect. Specifically, we multiply *CB* and *CS* with quarter two, three, and four dummy variables.

Table 8 presents estimation results accounting for seasonal effects. The coefficients of interactions of *CB* and *CS* with the quarterly dummy variables indicate the presence of seasonal effects in the predictive relations. For example, Column 1 shows that contrarian buy has a positive predictive effect on fund performnace in quarters one, three, and four but negative in quarter two. We observe the opposite predictive relations in Column 2 for contrarian sell except for quarter 4. The seasonal patterns we observe for *CB* are generally consistent with the 'Sell in May and Go Away' empirical evidence documented in the literature (Bouman & Jacobsen, 2002; Kamstra et al., 2017; Wagner, Lee, & Margaritis, 2022; Zhang & Jacobsen, 2021).

4.3. Macroeconomic cycle

Bollen and Busse (2001) first reported that mutual fund managers

[8] Our results are robust to alternative fund performance measures, such as Value-at-Risk, Information Ratio, Treynor Ratio, and Sharp Ratio. We present these results in Tables A4 and A5 in the appendix. We thank an anonymous referee for the suggestion.

[9] We also incorporated additional variables such as GDP growth, market volatility, and term spread into our analysis. The results remain robust after considering these extra controls. We present these results in Table A6 in the appendix. We thank again an anonymous reviewer for the suggestion.

exhibit significant timing ability, especially when using daily data. Using macroeconomic indicators, Kacperczyk et al. (2014) find that mutual funds have stock picking ability in boom periods and market timing in recessions. A more recent study by Bodnaruk, Chokaev, and Simonov (2018) provides further evidence that mutual funds are more sensitive to downside risk, thus, possessing more downside-risk-timing ability. Those findings suggest that the macroeconomic cycle plays an important role in an investor's investment decisions. One possible explanation for the buy and sell asymmetry in investors' contrarian behaviour is that mutual fund managers possess market timing skills in recessions.

Table 8
Seasonal effects.

Variable	Dependent variable: Fama and French five-factor alpha (t + 1)		
	1	2	3
CB	0.766***		0.365*
	(5.013)		(1.931)
CB_Q2	−0.919***		−0.29
	(−4.551)		(−1.111)
CB_Q3	0.927***		0.778***
	(4.416)		(3.112)
CB_Q4	−0.411*		0.125
	(−1.912)		(0.466)
CS		−1.795***	−1.378***
		(−6.955)	(−4.078)
CS_Q2		2.727***	2.442***
		(8.838)	(5.367)
CS_Q3		−1.343***	−0.54
		(−3.733)	(−1.177)
CS_Q4		1.913***	2.035***
		(5.739)	(4.512)
Q2	−0.076***	−0.045***	−0.046***
	(−9.212)	(−4.718)	(−4.75)
Q3	−0.096***	−0.096***	−0.094***
	(−9.279)	(−7.938)	(−7.764)
Q4	−0.062***	−0.041***	−0.038***
	(−7.312)	(−4.152)	(−3.715)
Size	0.006***	0.005**	0.005**
	(2.56)	(2.313)	(2.365)
Age	-0.001	-0.001	-0.001
	(−0.509)	(−0.386)	(−0.398)
Fee	−0.004	−0.004	−0.004
	(−0.408)	(−0.433)	(−0.467)
Turnover	-0.001	-0.001	-0.001
	(−1.09)	(−1.236)	(−1.121)
Flow	0.011***	0.011***	0.011***
	(10.036)	(10.157)	(10.073)
TE	0.026***	0.027***	0.028***
	(3.499)	(3.645)	(3.655)
Alpha	0.117***	0.115***	0.115***
	(7.961)	(7.852)	(7.857)
Intercept	0.047	0.039	0.046
	(0.898)	(0.739)	(0.865)
N	313,687	313,687	313,687
Adj_RSQ	0.0074	0.0074	0.0074

This table controls for seasonality in the association between the contrarian indices and future fund performance. The dependent variable, future fund performance, is measured using Fama and French five-factor model (in monthly percentages). Factor loadings are estimated from rolling-window regressions over the previous three years. *CB* is constructed from the fund holdings increase of each quarter multiplying the return of each stock during the same quarter, while *CS* is constructed from the fund's holdings decrease of each quarter multiplied by the return of each stock during the same quarter. We control seasonal effects by having interaction terms between contrarian indices and dummy variables of quarter 2 (*Q2*), quarter 3 (*Q3*), and quarter 4 (*Q4*). The panel regressions control for fund size (*Size*), fund age (*Age*), expense ratio (*Fee* in percent), fund turnover (*Turnover*), fund percentage flows in the previous quarter (*Flow*), tracking error (*TE*), and fund alpha (*Alpha* in percent) estimated over the previous three years. The regressions include time-fixed effects, and the standard errors are clustered by the fund. t-statistics are shown in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively.

We measure recessions using the National Bureau of Economic Research (NBER) definition of the business cycle indicator from the NBER website. A recession starts at the peak of a business cycle and ends at the trough. The sample spans 354 months of which 28 (7.9%) are classified as NBER recession months. We construct a dummy variable, *Recession*, which equals one for a recession month, and zero otherwise. We examine the interaction terms between our contrarian measures and the recession dummy to gauge the effect of the business cycle on *CB* and *CS*.

Table 9 presents the results considering the effects of investment decisions across the business cycle. The results provide evidence that recessions have a negative impact on contrarian-buy mutual funds and a positive effect on contrarian-sell mutual funds. Column 1 shows that the outperformance of mutual funds with contrarian-buy behaviour decrease by 180% (= −1.22/0.967) in recession months. In contrast, column 2 shows that the underperformance of mutual funds with contrarian-sell behaviour decreases by 173% (= 2.556/−1.471). In summary, the results show that the contrian buy and sell effects on future fund performance are both reversed in recession months.

Table 9
Booms and recessions.

Variable	Dependent variable: Fama and French five-factor alpha (t + 1)		
	1	2	3
CB	0.967***		0.755***
	(10.2)		(6.18)
CS		−1.471***	−0.647***
		(−9.926)	(−3.359)
CB_Recession	−1.22***		−0.496
	(−5.552)		(−1.456)
CS_Recession		2.556***	2.089***
		(6.99)	(3.529)
Recession	0.251***	0.279***	0.282***
	(10.587)	(11.143)	(11.06)
Size	0.003	0.003	0.003
	(1.389)	(1.228)	(1.271)
Age	-0.001	-0.001	-0.001
	(−0.559)	(−0.517)	(−0.541)
Fee	0	0.001	0
	(−0.053)	(0.07)	(0.009)
Turnover	-0.001	-0.001	-0.001
	(−0.811)	(−0.959)	(−0.85)
Flow	0.011***	0.011***	0.011***
	(10.351)	(10.454)	(10.328)
TE	0.011	0.011	0.011
	(1.376)	(1.412)	(1.485)
Alpha	0.125***	0.124***	0.124***
	(8.115)	(8.107)	(8.13)
Intercept	−0.171***	−0.175***	−0.17***
	(−3.285)	(−3.38)	(−3.273)
N	269,683	269,683	269,683
Adj_RSQ	0.0073	0.0073	0.0073

This table presents results of regressions of contrarian indices on future fund performance under different market conditions. The dependent variable, future fund performance, is measured using the Fama and French five-factor model (in monthly percentages). Factor loadings are estimated from rolling-window regressions over the previous three years. *CB* is constructed from the fund holdings increase of each quarter multiplying the return of each stock during the same quarter, while *CS* is constructed from the fund holdings decrease of each quarter multiplied by the return of each stock during the same quarter. We control market conditions by having interaction terms between contrarian indices and dummy variables of *Recession* (equals one if there is a recession and zero otherwise). The panel regressions control for fund size (*Size*), fund age (*Age*), expense ratio (*Fee* in percent), fund turnover (*Turnover*), fund percentage flows in the previous quarter (*Flow*), tracking error (*TE*), and fund alpha (*Alpha* in percent) estimated over the previous three years. The regressions include time-fixed effects, and the standard errors are clustered by the fund. t-statistics are shown in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively.

4.4. Market sentiment

Baker and Wurgler (2006) provide evidence that firms with higher investor sentiment would have lower subsequent stock returns. They further argue that market-wide sentiment should have more substantial impacts on stocks. Hudson, Yan, and Zhang (2020) find investor sentiment affects mutual fund herding in the UK. Thus, one possible explanation for the asymmetry between buying and selling in contrarian behaviour is its sensitivity to market sentiment. When market sentiment is high and stocks are generally overpriced, contrarian-sell would have better performance. Contrarian-buy funds would have better performance when sentiment is low. Another possible explanation is that the momentum strategy works well in high-sentiment periods but adds no value during low-sentiment periods (Antoniou et al., 2013).

We measure market sentiment using the monthly investor sentiment index (BW sentiment index) constructed by Baker and Wurgler (2006). The BW sentiment index is based on the first principal components of five sentiment proxies. Baker and Wurgler also provide an alternative version of the sentiment index by orthogonalising each of the proxies with macroeconomic indicators before constructing the principal components.

We create two dummy variables for each index, with each month classified as either a high-sentiment month or a low-sentiment month. A high-sentiment month is a month with an above-median sentiment in the sample period. *Sentiment1* (*Sentiment2*) is a dummy variable which equals one in a high-sentiment month based on the BW sentiment index (the alternative BW sentiment index) and zero otherwise. We then interact sentiment variables with *CB* and *CS* as our primary variables of interest. Table 10 presents the results of regressing fund performance on the (lagged) contrarian and sentiment variables and their interactions. The contrarian effect diminishes when market sentiment is high. Columns 1 and 2 show that when market sentiment is high, the *CB* coefficient decreases sizeably from 0.799 to 0.482, whereas the *CS* coefficient increases from −1.187 to −0.355. The results indicate that the buy and sell asymmetry of contrarian behaviour is mainly arising in the low market sentiment period.

5. Determinants of contrarian indices

This section investigates the relationship between fund contrarian indices (*CB* and *CS*) and several fund characteristics that are often associated with fund performance or herding behaviour. Specifically, we use *CB* and *CS* as dependent variables and include fund age, alpha, expense ratio, net flows, size, tracking error, turnover, team management, manager ownership, and average manager tenure as explanatory variables. We also control for market volatility and GDP growth. All the variables are standardized to have zero mean and standard deviation of one. Columns 1 and 2 of Table 11 present the regression results for *CB*

Table 10
Market sentiment.

Variable	Dependent variable: Fama and French five-factor alpha (t + 1)					
	1	2	3	4	5	6
CB	0.799***		0.533***	1.185***		0.954***
	(8.583)		(3.822)	(11.788)		(6.368)
CS		−1.187***	−0.581***		−1.605***	−0.529**
		(−8.976)	(−2.89)		(−11.423)	(−2.46)
CB_Sentiment1	−0.317*		0.019			
	(−1.944)		(0.096)			
CS_Sentiment1		0.832**	0.925**			
		(2.139)	(2.084)			
CB_Sentiment2				−1.231***		−0.906***
				(−7.599)		(−4.306)
CS_Sentiment2					1.957***	0.908**
					(6.136)	(2.285)
High_Sentiment1	0.017	0.024**	0.023**			
	(1.606)	(2.132)	(2.069)			
High_Sentiment2				0.117***	0.134***	0.125***
				(10.223)	(11.226)	(10.591)
Size	0.006**	0.005**	0.005**	0.005**	0.005**	0.005**
	(2.501)	(2.374)	(2.412)	(2.309)	(2.192)	(2.227)
Age	−0.001	−0.001	−0.001	−0.001	−0.001	−0.001
	(−0.353)	(−0.263)	(−0.299)	(−0.241)	(−0.166)	(−0.197)
Fee	−0.003	−0.002	−0.002	−0.003	−0.002	−0.003
	(−0.287)	(−0.183)	(−0.238)	(−0.324)	(−0.195)	(−0.277)
Turnover	−0.001	−0.001	−0.001	−0.001	−0.001	−0.001
	(−1.088)	(−1.246)	(−1.13)	(−1.105)	(−1.265)	(−1.144)
Flow	0.011***	0.011***	0.011***	0.011***	0.011***	0.011***
	(10.055)	(10.139)	(10.057)	(10.103)	(10.151)	(10.106)
TE	0.025***	0.025***	0.025***	0.026***	0.026***	0.026***
	(3.327)	(3.351)	(3.383)	(3.446)	(3.506)	(3.504)
Alpha	0.118***	0.118***	0.118***	0.117***	0.118***	0.117***
	(8.058)	(8.082)	(8.095)	(8.026)	(8.099)	(8.049)
Intercept	−0.034	−0.039	−0.032	−0.015	−0.028	−0.013
	(−0.682)	(−0.781)	(−0.639)	(−0.295)	(−0.555)	(−0.251)
N	313,687	313,687	313,687	313,687	313,687	313,687
Adj_RSQ	0.0073	0.0073	0.0073	0.0073	0.0073	0.0073

This table considers the association between contrarian indices and future fund performance under different market sentiments. The dependent variable, future fund performance, is measured using Fama and French five-factor model (in monthly percentages). Factor loadings are estimated from rolling-window regressions over the previous three years. *CB* is constructed from the fund's holdings increase of each quarter multiplied by the return of each stock during the same quarter, while *CS* is constructed from the fund holdings decrease of each quarter multiplying the return of each stock during the same quarter. We control market conditions by having interaction terms between contrarian indices and dummy variables of high sentiment (*Sentiment* equals one if the market sentiment is above the median of the sample and zero otherwise). The panel regressions control for fund size (*Size*), fund age (*Age*), expense ratio (*Fee* in percent), fund turnover (*Turnover*), fund percentage flows in the previous quarter (*Flow*), tracking error (*TE*), and fund alpha (*Alpha* in percent) estimated over the previous three years. The regressions include time fixed effects, and the standard errors are clustered by the fund. t-statistics are shown in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively.

Table 11
Determinants of contrarian buy and contrarian sell.

Variable	*CB*	*CS*	*CB*	*CS*
Age	−0.055	−0.117	−0.067	−0.108
	(−0.826)	(−0.937)	(−0.968)	(−0.866)
*Age*Team*			0.009	0.015
			(0.726)	(1.104)
*Age*Manager Ownership*			0.007	−0.028***
			(0.977)	(−3.032)
Alpha	0.009	−0.01	0.033**	−0.007
	(1.177)	(−1.203)	(2.298)	(−0.441)
*Alpha*Team*			−0.006	−0.014
			(−0.539)	(−1.122)
*Alpha*Manager Ownership*			−0.023**	0.013
			(−2.063)	(1.447)
Fee	−0.009	0.019***	−0.047**	0.031*
	(−1.146)	(2.583)	(−2.497)	(1.844)
*Fee*Team*			0.013	0.009
			(1.245)	(0.909)
*Fee*Manager Ownership*			0.036*	−0.027*
			(1.882)	(−1.951)
Flow	0.029***	−0.023***	0.015	−0.016*
	(4.947)	(−5.811)	(1.044)	(−1.666)
*Flow*Team*			−0.008	0.002
			(−0.792)	(0.379)
*Flow*Manager Ownership*			0.027***	−0.013***
			(3.86)	(−2.687)
Size	0.028***	−0.052***	0.005	−0.044***
	(3.068)	(−5.86)	(0.238)	(−2.734)
*Size*Team*			0.013	0.03**
			(1.11)	(2.395)
*Size*Manager Ownership*			0.014	−0.038***
			(0.68)	(−2.995)
TE	−0.021***	0.031**	−0.039	0.063***
	(−2.7)	(2.193)	(−1.607)	(2.943)
*TE*Team*			0.004	0.006
			(0.193)	(0.531)
*TE*Manager Ownership*			0.021	−0.05***
			(1.01)	(−4.163)
Turnover	−0.189	−0.435	−0.168	−0.429
	(−0.833)	(−1.141)	(−0.747)	(−1.125)
*Turnover*Team*			−0.017	−0.01
			(−0.692)	(−0.744)
*Turnover*Manager Ownership*			−0.003	0.003
			(−0.294)	(0.551)
Team	−0.012	0.03***	−0.018	0.047**
	(−1.435)	(3.05)	(−1.221)	(2.388)
Manager Ownership	−0.043**	0.051***	−0.042**	0.035**
	(−2.503)	(3.587)	(−2.147)	(2.418)
Manager Tenure	0.002	−0.009**	0	−0.008**
	(0.581)	(−2.387)	(−0.009)	(−2.053)
Market Volatility	0.044	−0.02	0.019	−0.016
	(1.228)	(−0.843)	(0.674)	(−0.642)
GDP Growth	0.1	0.144	0.121	0.202
	(0.322)	(0.269)	(0.394)	(0.426)
Intercept	−0.051	−0.502	−0.07	−0.51
	(−0.213)	(−1.236)	(−0.281)	(−1.259)

This table presents the estimated coefficients from regressions of the contrarian-buy index (*CB*) and contrarian-sell index (*CS*) on fund characteristics. *CB* is the average tendency of mutual funds to buy against the market sell, which is constructed from the fund's holdings change of each quarter, multiplied by the return of each stock during the same quarter. We sum up the *CB* of each stock fund bought to get the *CB* of the fund during that quarter. The monthly return series spans from January 1993 to March 2023. *CS* is the average tendency of mutual funds to sell against the market buy, which is constructed from the fund's holdings change of each quarter, multiplied by the return of each stock during the same quarter. We sum up the *CS* of each stock fund sold to get the *CS* of the fund during that quarter. *Age* is the natural log of fund age in years; *Alpha* is the fund's three-factor alpha estimated over the previous three years; *Fee* is the fund expense ratio; *Flow* is the fund flow in the previous quarter; *Size* is the natural log of the previous quarter-end TNAs; Tracking Error (*TE*) is the standard deviation of the fund's three-factor residual estimated over the previous three years; *Turnover* is the fund's turnover ratio. *Team* is a dummy variable indicating whether the fund is managed by more than one manager. *Manager Ownership* is a dummy variable showing whether the fund manager has ownership in the managed fund. *Manager Tenure* is the number of years that the current manager has been the portfolio manager of the fund. The regression is standardized to have a mean of zero and a standard deviation of one. The statistical inference is based on the Fama & MacBeth (1973) procedure with Newey & West, 1987 adjustments. ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively.

and *CS*. Columns 3 and 4 present results with extra interaction terms between different characteristics. Our findings are summarised as follows:

Age: Chevalier and Ellison (1999) provide evidence that younger mutual funds are less likely to deviate from their peers. We do not find significant age related effects other than the interaction effect with manager ownership in column 4 of Table 11 indicating that younger funds with manager ownership in the fund exhibit lower tendency for contrarian sell.

Alpha: Prior studies provide evidence of persistence in U.S. mutual funds performance (Brown & Goetzmann, 1995; Carhart, 1997; Grinblatt & Titman, 1994; Hendricks, Patel, & Zeckhauser, 1993) implying that a fund's past alpha may be positively related to manager skill. We find that funds past alphas are positively associated with *CB* and negatively associated with *CS* although the effect is not statistically significant. The only exception is shown in column 3 where we find a positive and significant effect of alpha on contrarian buy although in part this effect is offset by the interaction of alpha with manager ownership in the fund.

Fees: Mutual fund fees can be viewed as the price investors are willing to pay for a manager's skill. There is mixed evidence for the relation between cost and skill. Chen et al. (2004) find that fees have no relationship with U.S. mutual fund performance. Otten and Bams (2002) provide evidence that fees are negatively related to European fund performance. We find that higher *CS* is positively associated with higher expense ratios, while *CB* negatively relates to the expense but only in column 3 with the effect in part offset by the positive interaction with manager ownership.

Flow: Gruber (1996) and Zheng (1999) show that mutual funds experiencing inflow outperform those experiencing outflow. They argue that investors are smart enough to pick skilled fund managers. However, Sapp and Tiwari (2004) argue that the smart money effect is explained by momentum. Thus, mutual fund flow might have a negative relation with the contrarian behaviour of mutual funds. We find that fund flow is positively associated with *CB* with the effect primarily driven by the interaction with manager ownership in the fund as shown in column 3. On the other hand, fund flow is negatively associated with *CS* with the negative effect amplified by manager ownership in the fund.

Size: Previous studies show that fund size may affect fund performance in different aspects. For example, Cremers and Petajisto (2009) find that large funds are less active, and Kacperczyk et al. (2005) find that large funds are less industry-concentrated. Our results provide evidence that large funds have a higher level of contrarian buy behaviour and a lower level of contrarian sell behaviour.

Tracking error: Since contrarian funds trade in the opposite direction of the market, such strategy may induce a sizeable tracking error relative to a benchmark. The results provide evidence that funds with a higher level of contrarian buy tend to have lower tracking errors. Funds with a higher level of contrarian sell tend to have higher tracking errors although the effect is lower if the manager has ownership in the fund.

Turnover: Contrarian funds tend to trade less, indicated by the coefficients of fund turnover. Both *CB* and *CS* are negatively related to turnover although the effect is not statistically significant.

Team Management: Patel and Sarkissian (2017) find that team management benefits fund performance by 50 basis points. It is thus interesting to see whether team versus single management has an impact on contrarian behaviour. The finding shows that funds managed by teams have a higher tendency of contrarian sell behaviour. However, there is no evidence that the choice between one or more managers has an effect on contrarian buy.

Manager Ownership: Ma and Tang (2019) find that managerial ownership reduces risk-taking behaviour, especially among managers with potential agency conflicts. We find evidence that managerial ownership decreases contrarian buy behaviour while increases contrarian sell behaviour.

Average Manager Tenure: Previous studies show that manager tenure is positively related with fund performance (Golec, 1996). If long tenure is a measure of better human capital and better experience, it is likely to be associated with better performance. Our results show that longer tenure reduces manager's contrarian sell behaviour but does not have a significant impact on contrarian buy behaviour.

In summary, the results in Table 11 indicate that mutual funds with larger fund size, higher fund flow, lower tracking error, and manager ownership are more likely to buy against the crowd but sell with the crowd. Most of the interaction terms are statistically insignificant except for the interaction terms involving manager's ownership in the fund. Market volatility and GDP growth controls do not have a significant effect on contrarian behaviour.

6. Conclusion

Previous studies show that investors who have superior skills tend to exhibit anti-herding behaviour. In this study, we find that a crucial feature of the effects of anti-herding is the asymmetry between buy and sell. We begin by creating fund-level measures of the tendency to buy or sell against the crowd. Using the stock return of the same trading quarter as a proxy of the crowd, we test whether the contrarian-buy and contrarian-sell measures have different predictive power on the cross-sectional mutual fund future performance.

Using mutual fund data from 1993 to 2022, we find that mutual funds' performance differs substantially in their trading directions with the market. The contrarian-buy behaviour is related positively to the following period's mutual fund returns, while the contrarian-sell exhibits a negative prediction. Our findings are robust to various risk-adjusted performance measures.

We next provide evidence that the difference in buy and sell of contrarian behaviour is more significant for the period after the mandatory disclosure change of May 2004, when fund holding information has become more accurate. We also find that seasonal effects exist in contrarian behaviour. Contrarian-buy makes a negative prediction of fund performance in the summer period, while contrarian-sell makes a positive prediction, both consistent with a 'Sell in May and go away' strategy.

To understand what drives the asymmetry, we study how the business cycle and market sentiment influence asymmetry. We find that the asymmetry of contrarian-buy and contrarian-sell reversed during recessions and disappear during period with high market sentiment.

To gain a further understanding of the difference between buying and selling contrarian behaviour, we also study how mutual fund characteristics relate to our contrarian measures. We find that mutual funds with larger size, lower tracking error, higher flow, and no manager ownership are more likely to buy against the crowd but sell with the crowd.

Our analysis is inspired by the literature on contrarian behaviour as a sign of skills, and the literature on the asymmetric institutional trades on buy- and sell-order. Our findings contribute to the study of how investors shape their sequential decision-making processes. They call for further investigations, both theoretical and empirical, to gain a better understanding of the reasons for different managerial abilities associated with buys and sells. The mutual fund industry is an ideal setting to study contrarian investor behaviour, and our study is a step in this direction.

Appendix A

Table A1
Decile portfolios: contrarian index and fund performance.

Panel A: Contrarian-Buy Index.

Num_CB rank	1	2	3	4	5	6	7	8	9	10	D10-D1
Num_CB	0.29	0.39	0.44	0.47	0.5	0.53	0.55	0.59	0.63	0.74	0.45
Average	0.61	0.75	0.74	0.83	0.83	0.79	0.81	0.89	0.79	0.85	0.24
	(2.23)	(2.78)	(2.72)	(3.12)	(3.15)	(3)	(3.09)	(3.36)	(2.95)	(3.07)	(1.47)
CAPM α	−0.23	−0.08	−0.1	0	0	−0.04	−0.02	0.06	−0.04	0	0.24**
	(−3.45)	(−1.13)	(−1.65)	(−0.02)	(0.02)	(−0.88)	(−0.35)	(1.13)	(−0.69)	(0.05)	(2.13)
FF3 α	−0.24	−0.09	−0.13	−0.02	−0.03	−0.06	−0.04	0.04	−0.07	0	0.24**
	(−3.55)	(−1.29)	(−2.09)	(−0.43)	(−0.63)	(−1.49)	(−1.1)	(0.84)	(−1.34)	(−0.03)	(2.21)
FF5 α	−0.23	−0.08	−0.15	−0.03	−0.05	−0.1	−0.06	0.04	−0.09	0.02	0.25**
	(−3.3)	(−1.12)	(−2.4)	(−0.63)	(−1.16)	(−2.45)	(−1.53)	(0.84)	(−1.58)	(0.33)	(2.27)
FS α	−0.23	−0.09	−0.15	−0.02	−0.05	−0.1	−0.06	0.06	−0.06	0.05	0.28**
	(−3.27)	(−1.23)	(−2.36)	(−0.38)	(−1.09)	(−2.37)	(−1.27)	(1.26)	(−1.05)	(0.67)	(2.5)
PS α	−0.23	−0.08	−0.15	−0.04	−0.06	−0.11	−0.08	0.03	−0.11	0	0.23**
	(−3.27)	(−1.13)	(−2.39)	(−0.87)	(−1.32)	(−2.64)	(−1.99)	(0.55)	(−2.01)	(−0.01)	(2.13)
Timing α	−0.2	−0.04	−0.12	−0.08	−0.09	−0.08	−0.04	0.06	−0.1	0.01	0.2
	(−2.47)	(−0.43)	(−1.68)	(−1.28)	(−1.64)	(−1.71)	(−0.72)	(0.96)	(−1.52)	(0.08)	(1.63)

Panel B: Contrarian-sell Index.

Num_CS rank	1	2	3	4	5	6	7	8	9	10	D10-D1
Num_CS	0.21	0.33	0.37	0.41	0.44	0.47	0.49	0.53	0.58	0.71	0.5
Average	0.83	0.82	0.81	0.83	0.85	0.79	0.85	0.74	0.66	0.7	−0.13
	(2.96)	(3.03)	(3.02)	(3.13)	(3.23)	(2.99)	(3.17)	(2.82)	(2.45)	(2.57)	(−1.63)
CAPM α	−0.01	−0.02	−0.03	0	0.02	−0.04	0.01	−0.08	−0.18	−0.14	−0.13
	(−0.17)	(−0.25)	(−0.51)	(−0.03)	(0.47)	(−0.72)	(0.22)	(−1.22)	(−3.24)	(−2.14)	(−1.07)
FF3 α	−0.03	−0.04	−0.04	−0.03	0	−0.06	−0.01	−0.1	−0.19	−0.15	−0.12
	(−0.42)	(−0.66)	(−0.9)	(−0.74)	(−0.04)	(−1.26)	(−0.11)	(−1.69)	(−3.36)	(−2.28)	(−1.12)
FF5 α	−0.04	−0.05	−0.04	−0.06	−0.03	−0.09	−0.03	−0.15	−0.17	−0.13	−0.09
	(−0.46)	(−0.76)	(−0.85)	(−1.28)	(−0.56)	(−1.75)	(−0.56)	(−2.36)	(−3.03)	(−1.89)	(−0.82)
FS α	−0.01	−0.03	−0.02	−0.05	−0.02	−0.06	−0.04	−0.15	−0.16	−0.12	−0.1
	(−0.15)	(−0.54)	(−0.44)	(−1.16)	(−0.39)	(−1.3)	(−0.75)	(−2.36)	(−2.82)	(−1.7)	(−0.89)
PS α	−0.06	−0.07	−0.06	−0.07	−0.03	−0.09	−0.04	−0.15	−0.17	−0.14	−0.08
	(−0.82)	(−1.09)	(−1.23)	(−1.66)	(−0.74)	(−1.86)	(−0.76)	(−2.28)	(−3.03)	(−2.09)	(−0.72)
Timing α	−0.04	−0.04	−0.01	−0.04	−0.05	−0.11	−0.05	−0.13	−0.13	−0.09	−0.05
	(−0.49)	(−0.59)	(−0.27)	(−0.8)	(−0.88)	(−1.89)	(−0.79)	(−1.78)	(−1.88)	(−1.16)	(−0.44)

Panel A presents the performance of decile portfolios sorted on the fund's number of contrarian-buy index (*Num_CB*). We count the number of stocks being contrarian buys by a fund during each quarter. The decile portfolios are formed at the end of each quarter from 1993Q1 to 2022Q4 and held for one quarter. The monthly return series spans the period from January 1993 to March 2023. Decile 10 is the portfolio of funds with the highest average *Num_CB*. Panel B presents decile portfolio performance sorted on the fund's number of contrarian-sell index (*Num_CS*). We count the number of stocks being contrarian sold by a fund during each quarter. Decile 10 is the portfolio of funds with the highest average *Num_CS*. We consider risk-adjusted returns based on the capital asset pricing model (CAPM), the Fama and French (1993) three-factor model (FF3), Fama and French (2015) five-factor model (FF5), the Ferson and Schadt (1996) conditional model (FS), the Pástor and Stambaugh (2003) five-factor model (PS), and the Treynor and Mazuy (1966) market-timing model (Timing). This table reports average returns and alphas in monthly percentages. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively, for the return differentials between deciles 10 and 1 (D10-D1).

Table A2
Predictive panel regressions.

Variable	Dependent Variable: Fama and French five-factor alpha (t + 1)		
	1	2	3
Num_CB	0.151***		0.113***
	(6.238)		(4.282)
Num_CS		−0.122***	−0.083***
		(−5.165)	(−3.259)
Size	0.006***	0.006***	0.006***
	(2.698)	(2.881)	(2.785)
Age	−0.001	−0.001	−0.001
	(−0.463)	(−0.595)	(−0.589)
Fee	−0.002	−0.003	−0.004
	(−0.273)	(−0.352)	(−0.391)
Turnover	−0.001	−0.001	−0.001
	(−0.979)	(−1.211)	(−1.115)
Flow	0.011***	0.011***	0.011***
	(10.127)	(10.112)	(10.025)
TE	0.025***	0.024***	0.025***
	(3.304)	(3.225)	(3.366)
Alpha	0.118***	0.123***	0.122***
	(8.071)	(8.46)	(8.376)

(*continued on next page*)

Table A2 (*continued*)

Variable	Dependent Variable: Fama and French five-factor alpha (t + 1)		
	1	2	3
Intercept	−0.125**	−0.008	−0.069
	(−2.44)	(−0.159)	(−1.273)
N	313,339	312,337	312,151
Adj_R-sq	0.0061	0.0061	0.0061

This table presents coefficient estimates from predictive panel regressions estimating the association between contrarian indices and future fund performance. The dependent variable, future fund performance, is measured using the Fama and French five-factor model alphas (in monthly percentages). Factor loadings are estimated from rolling-window regressions over the previous three years. To get the number of contrarian buys (*Num_CB*) and the number of contrarian sells (*Num_CS*), we count the number of contrarian buys (sells) for each fund in each quarter and scale it by the total number of buys (sells) for each fund in each quarter. The panel regressions control for fund size (*Size*), fund age (*Age*), expense ratio (*Fee* in percent), fund turnover (*Turnover*), fund percentage flows in the previous quarter (*Flow*), tracking error (*TE*), and fund alpha (*Alpha* in percent) estimated over the previous three years. The regressions include time fixed effects, and the standard errors are clustered by funds. t-statistics are shown in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively.

Table A3
Monthly average return comparison.

	CB Portfolio	*CS Portfolio*	*Market*	*SMB*	*HML*	*RMW*	*CMA*
Average Return (%)	0.34	−0.38	0.88	0.12	0.16	0.35	0.27

Table A3 presents the average monthly performance of different trading strategies. The sample period spans from January 1993 to March 2023. *CB Portfolio* is the average portfolio return sorted on the fund's contrarian-buy index (*CB*); *CS Portfolio* is the average portfolio return sorted on the fund's contrarian-sell index (*CS*). *Market* is the return of market index including all NYSE, AMEX, and NASDAQ firms. *SMB* (Small Minus Big) is the average return on the nine small stock portfolios minus the average return on the nine big stock portfolios; *HML* (High Minus Low) is the average return on the two value portfolios minus the average return on the two growth portfolios; *RMW* (Robust Minus Weak) is the average return on the two robust operating profitability portfolios minus the average return on the two weak operating profitability portfolios; *CMA* (Conservative Minus Aggressive) is the average return on the two conservative investment portfolios minus the average return on the two aggressive investment porfolios.

Table A4
Predictive panel regression using VaR.

Variable	Dependent Variable: Value-at-Risk (t + 1)		
	1	2	3
CB	0.453***		0.317***
	(16.435)		(6.826)
CS		−0.745***	−0.377***
		(−16.086)	(−4.69)
Size	−0.001	−0.002	−0.002
	(−0.835)	(−1)	(−0.967)
Age	0.001***	0.001***	0.001***
	(2.825)	(2.987)	(2.934)
Fee	−0.013	−0.012	−0.012
	(−1.435)	(−1.359)	(−1.393)
Turnover	−0.001***	−0.001***	−0.001***
	(−3.136)	(−3.243)	(−3.19)
Flow	0.005***	0.005***	0.005***
	(9.449)	(9.48)	(9.418)
TE	−2.038***	−2.038***	−2.038***
	(−132.654)	(−132.966)	(−132.838)
Alpha	0.899***	0.899***	0.899***
	(58.622)	(58.544)	(58.609)
Intercept	0.033	0.034	0.038
	(0.736)	(0.741)	(0.834)
N	313,687	313,687	313,687
Adj_R-sq	0.9398	0.9398	0.9398

This table presents coefficient estimates from predictive panel regressions estimating the association between contrarian indices and future fund performance. The dependent variable, future fund performance, is measured using the Value-at-Risk. Specifically, VaR is calculated as the 1st percentile of the monthly returns over the past three year at the end of month t + 1. *CB* is constructed from the fund holdings increase of each quarter multiplying the return of each stock during the same quarter, while *CS* is constructed from the fund holdings decrease of each quarter multiplying the return of each stock during the same quarter. The panel regressions control for fund size (Size), fund age (Age), expense ratio (Fee in percent), fund turnover (Turnover), fund percentage flows in the previous quarter (Flow), tracking error (TE), and fund alpha (Alpha in percent) estimated over the previous three years. The regressions include time fixed effects, and the standard errors are clustered by funds. t-statistics are shown in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively.

Table A5
Predictive panel regression using alternative fund performance measures.

	Information Ratio			Sharp Ratio			Treynor Ratio		
Variable	1	2	3	4	5	6	7	8	9
CB	0.237***		0.086***	0.439***		0.302***	0.037**		−0.101***
	(24.042)		(5.238)	(65.042)		(31.147)	(2.475)		(−3.051)
CS		−0.517***	−0.416***		−0.731***	−0.379***		−0.28***	−0.401***
		(−23.779)	(−12.439)		(−64.529)	(−21.952)		(−7.639)	(−5.802)
Size	0.007***	0.007***	0.007***	0.004***	0.004***	0.004***	0.004**	0.004*	0.004*
	(6.646)	(6.468)	(6.47)	(9.537)	(8.538)	(8.84)	(1.994)	(1.876)	(1.872)
Age	0***	0***	0***	0***	0**	0**	0	0	0
	(−3.254)	(−3.172)	(−3.181)	(−2.788)	(−2.318)	(−2.491)	(−0.086)	(−0.061)	(−0.055)
Fee	−0.004	−0.003	−0.004	0.005***	0.005***	0.005***	−0.05***	−0.049***	−0.049***
	(−1.043)	(−0.92)	(−0.941)	(2.948)	(3.313)	(3.164)	(−4.995)	(−4.983)	(−4.973)
Turnover	0**	0*	0*	0	0	0	0	0	0
	(2.004)	(1.769)	(1.819)	(0.032)	(−0.803)	(−0.389)	(0.044)	(0.009)	(−0.008)
Flow	0.005***	0.005***	0.005***	0.002***	0.002***	0.002***	0	0	0
	(20.99)	(21.029)	(20.989)	(18.43)	(18.64)	(18.41)	(0.28)	(0.174)	(0.268)
TE	0.049***	0.049***	0.049***	−0.018***	−0.018***	−0.018***	0.037***	0.037***	0.037***
	(16.704)	(16.829)	(16.832)	(−14.446)	(−14.285)	(−14.296)	(6.082)	(6.094)	(6.091)
Alpha	0.355***	0.355***	0.355***	0.176***	0.176***	0.176***	−0.113***	−0.113***	−0.113***
	(65.879)	(65.805)	(65.868)	(75.301)	(74.093)	(74.994)	(−11.393)	(−11.414)	(−11.417)
Intercept	−0.213***	−0.209***	−0.208***	0.132***	0.132***	0.136***	−1.066***	−1.068***	−1.069***
	(−8.647)	(−8.579)	(−8.515)	(14.587)	(14.206)	(14.912)	(−59.663)	(−59.802)	(−59.574)
N	313,687	313,687	313,687	313,687	313,687	313,687	313,681	313,681	313,681
Adj_R-sq	0.4414	0.4414	0.4414	0.7186	0.7186	0.7186	0.0577	0.0577	0.0577

This table presents coefficient estimates from predictive panel regressions estimating the association between contrarian indices and future fund performance. Column 1 to column 3 show the results using information ratio as the dependent variable, column 4 to column 6 show the results using sharp ratio as the dependent variable, column 7 to column 9 show the results using Treynor ratio as the dependent variable. Specifically, information ratio is calculated as the mutual fund excess return divided by the tracking error. Sharp ratio is calculated as the difference between fund return and the risk-free rate and scaled by its standard deviation. Treynor ratio is calculated as the difference between fund return and the risk-free rate and scaled by its beta. *CB* is constructed from the fund holdings increase of each quarter multiplying the return of each stock during the same quarter, while *CS* is constructed from the fund holdings decrease of each quarter multiplying the return of each stock during the same quarter. The panel regressions control for fund size (*Size*), fund age (*Age*), expense ratio (*Fee* in percent), fund turnover (*Turnover*), fund percentage flows in the previous quarter (*Flow*), tracking error (*TE*), and fund alpha (*Alpha* in percent) estimated over the previous three years. The regressions include time fixed effects, and the standard errors are clustered by funds. t-statistics are shown in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively.

Table A6
Predictive panel regression with additional controls.

Variable	Dependent Variable: Fama and French five-factor alpha (t + 1)		
	1	2	3
CB	0.824***		0.653***
	(9.518)		(5.825)
CS		−1.226***	−0.504***
		(−8.958)	(−2.821)
Size	0.005**	0.004*	0.004**
	(2.095)	(1.916)	(1.962)
Age	0	0	0
	(−0.16)	(−0.037)	(−0.087)
Fee	−0.004	−0.003	−0.003
	(−0.406)	(−0.292)	(−0.356)
Turnover	0	0	0
	(−0.816)	(−1.041)	(−0.905)
Flow	0.011***	0.011***	0.011***
	(10.05)	(10.135)	(10.032)
TE	0.02***	0.019***	0.02***
	(2.633)	(2.627)	(2.679)
Alpha	0.132***	0.132***	0.132***
	(9.024)	(9.026)	(9.02)
Market Volatility	−0.029***	−0.031***	−0.031***
	(−3.618)	(−3.896)	(−3.817)
GDP Growth	−0.005***	−0.004***	−0.005***
	(−8.85)	(−8.393)	(−9.305)
Term Spread	−0.074***	−0.072***	−0.074***
	(−9.62)	(−9.262)	(−9.583)
Intercept	0.004	0.008	0.022
	(0.064)	(0.12)	(0.343)
N	310,726	310,726	310,726
Adj_R-sq	0.0072	0.0072	0.0072

This table presents coefficient estimates from predictive panel regressions estimating the association between contrarian indices and future fund performance. The dependent variable, future fund performance, is measured using the Fama and

French five-factor model alphas (in monthly percentages). Factor loadings are estimated from rolling-window regressions over the previous three years. *CB* is constructed from the fund holdings increase of each quarter multiplying the return of each stock during the same quarter, while *CS* is constructed from the fund holdings decrease of each quarter multiplying the return of each stock during the same quarter. The panel regressions control for fund size (*Size*), fund age *(Age*), expense ratio (*Fee* in percent), fund turnover (*Turnover*), fund percentage flows in the previous quarter (*Flow*), tracking error (*TE*), and fund alpha (*Alpha* in percent) estimated over the previous three years. Market volatility is calculated over the last three years. Term spread is the difference between 10-year and three-month treasury rate. The regressions include time fixed effects, and the standard errors are clustered by funds. t-statistics are shown in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively.

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