Do closed-end fund investors herd?

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Abstract

We provide the first investigation of herding among closed-end fund investors, drawing on the US closed-end fund market for the 1992-2016 period. Results suggest closed-end fund investors herd significantly, with their herding being mainly driven by non-fundamentals. Closed-end fund herding rises in economic/market uncertainty, with its significance being mainly concentrated in the post-2007 period. Herding among closed-end funds is strongly motivated by discounts, is more pronounced than that among their net asset values and tends to grow inversely with fund-size. The fact that closed-end fund herding is noise-driven and linked to their discounts raises the possibility that it is related to the noise trader risk attributed to closed-end funds by investor sentiment theory.

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1. Introduction

Although herd behaviour has been extensively investigated over the past three decades for a multitude of asset classes (mainly equities, but also bonds, derivatives and currencies) internationally, its presence in closed-end fund shares has been largely unexplored. This is surprising, considering the fact that closed-end funds are susceptible to noise trading as a result of retail investors forming the bulk of their clientele (Flynn, 2012; Huang, 2015). Retail investors have been traditionally viewed as the prime candidates for the role of noise traders, a view that has been motivated by evidence demonstrating that they (being less sophisticated than their institutional counterparts) exhibit strong correlation in their trades due to the systematic influence of behavioural biases (Barber et al., 2009a; 2009b; Barber and Odean, 2013). This suggests that herding, being a form of noise trading, is likely to be encountered among retail traders, something that has been empirically confirmed in several studies to date (Dorn et al., 2008; Kumar, 2009; Kumar and Lee, 2006). In view of the above evidence from equity markets, one would expect herding to be significant in closed-end funds, given closed-end funds’ majority retail clientele and the fact that they are traded like ordinary stocks. This paper provides the first in-depth examination of this issue, by assessing the presence and determinants of closed-end fund herding.¹

From a theoretical perspective, herding arises when investors sideline their private signals (or observed fundamentals) and track their peers’ trades (Hirshleifer and Teoh, 2003). Suggested motivations for herding include the anticipation of positive externalities, such as informational payoffs (when investors choose to infer information from the trades of their better-informed peers; Banerjee, 1992; Bikhchandani et al., 1992) and professional payoffs

¹ We study herding in the closed-end fund market based on closed-end fund shares returns (see section 2), not closed-end fund portfolios, so, in effect, the herding captured here is the “market-wide” herding. To simplify our presentation, we will be using the term “closed-end fund herding” in the paper (more so, since market-wide herding refers to herding among stocks in a market and closed-end funds themselves are traded like stocks).
(when low-quality investment professionals mimic their high-quality peers to pose as being of equally high quality; Scharfstein and Stein, 1990; Jiang and Verardo, 2018). Fads (Choi and Sias, 2009) and style investing (Celiker et al., 2015) can also promote herding by prompting correlation in the trades of investors tracking popular sectors or a particular investment strategy, while such a correlation can also be observed among investment professionals as a result of the requirements of their common regulatory framework (Blake et al., 2017). Furthermore, high correlation among trades, in particular those of retail investors, can also arise as a result of behavioural biases systematically affecting their trading decisions (Barber et al., 2009a; 2009b; Barber and Odean, 2013).

Empirically, the presence of herding has been confirmed internationally for several asset classes, with the bulk of evidence stemming from equities. Herding has been detected at the market-wide (Chang et al., 2000; Hwang and Salmon, 2004; Goodfellow et al., 2009; Chiang and Zheng, 2010; Economou et al., 2011; Economou et al., 2015; Galariotis et al., 2016b; Guney et al., 2017) and industry (Zhou and Lai, 2009; Demirer et al., 2010; Gebka and Wohar, 2013) levels in developed, emerging and frontier equity markets, often manifesting itself asymmetrically, contingent on market conditions.² At the micro level, institutional investors have been found to herd – to varying degrees - when trading equities internationally (Choi and Skiba, 2015). Compared to earlier studies (Lakonishok et al., 1992; Grinblatt et al., 1995; Wermers, 1999) that reported limited evidence of herding among US funds, recent studies (Sias, 2004; Choi and Sias, 2009; Celiker et al., 2015) show that US fund managers exhibit stronger herding tendencies. Significant herding has also been documented among institutional investors in the UK (Wylie, 2005), Germany (Kremer and Nautz, 2013), Portugal (Holmes et al., 2013), South Korea (Choe et al., 1999) and Spain (Gavriilidis et al., 2013), while several

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² Herding asymmetries have been detected with respect to market performance (up/down markets), volatility (high/low volatility) and volume (high/low volume), without, however, appearing uniform across markets.
studies have also confirmed the presence of herding among retail investors (Dorn et al., 2008; Kumar, 2009; Kumar and Lee, 2006). Equities aside, evidence suggests that herding is also present in bonds (Galariotis et al., 2016a), currencies (Carpenter and Wang, 2007), futures (Demirer et al., 2015), options (Bernales et al., 2016) and REITs (Philippas et al., 2013).

However, to date, herding has not been investigated for closed-end funds. Conceptually, a closed-end fund is a publicly listed, corporate entity whose objective is to invest its assets in other corporations’ securities for income or profit. Unlike open-end mutual funds, where investors can create/redeem their share in the fund at net asset value, closed-end funds’ capitalization is fixed, reflected through their publicly traded shares outstanding. As a result, an investor can participate in a closed-end fund via the secondary market (by buying and selling its shares), not by creating/redeeming shares in its portfolio. Closed-end funds have historically been observed to trade at a discount, namely at market values below their net asset value (NAV, hereafter), for the most part of their life, a stylized empirical fact known as the “closed-end fund puzzle”; their discounts exhibit persistence and mean-reversion, while they are also strongly correlated among them (Flynn, 2010; Cherkes, 2012). A large array of explanations has been put forward to account for this puzzle, including agency costs (Malkiel, 1995), tax liabilities (Kim, 1994), market segmentation (Bonser-Neal et al., 1990), liquidity (Cherkes et

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3 Generally, closed-end funds usually trade at a premium (of around 10%, on average) during the first few months following their public listing (largely due to underwriting costs reducing their NAVs) before beginning to trade at a discount for most of the rest of their lives. In case closed-end funds are terminated, merged with another fund or converted into open-ended form, their prices rise and their discounts tend to shrink (Flynn, 2012).

4 The closed-end fund puzzle refers to how the deviations of closed-end funds’ market value from their NAV run counter to various notions of neoclassical finance. To begin with, since a closed-end fund’s sole purpose is to invest in other corporations’ securities, its fundamental value would be expected to be equal to the value of its portfolio; with closed-end funds trading mostly at a discount, this means one can buy them for less than what their portfolios are worth, while also violating Modigliani and Miller’s principle of additivity (namely that a firm’s value should be equal to the sum of the values of its assets; Dimson and Minio-Kozerski, 1999). Second, this further constitutes a violation of the law of one price, according to which, assets offering a claim to the same risk-return distribution (the closed-end fund and its portfolio) should bear the same value. Third, these discounts raise arbitrage-issues (one can go long in the fund and short its underlying portfolio). For more on the closed-end fund puzzle literature, see the reviews by Cherkes (2012) and Fletcher (2013).
al., 2009) and investor sentiment (Lee et al., 1991), with empirical evidence for each appearing mixed.

Our study investigates herding in the context of the US closed-end fund industry for the 1992-2016 period by testing a series of hypotheses. In view of closed-end fund shares being mainly in the hands of retail investors\(^5\) and the propensity of the latter toward noise trading, we hypothesise that herding will be observed in this asset class. As a result, our first hypothesis is as follows:

**Hypothesis 1**: The closed-end fund market is characterized by significant herding.

If hypothesis 1 is supported, and given prior evidence for other asset classes, then the question is raised as to whether herding manifests itself asymmetrically contingent on market conditions. Noise trading tends to boost the volume of trade (Black, 1986) and volatility (Brown, 1999), while also being more likely to grow during market upswings (Grinblatt and Keloharju, 2001; Lamont and Thaler, 2003); with closed-end funds being susceptible to noise trading, this leads to the following hypotheses:

**Hypothesis 2a**: Herding in the closed-end fund market will be stronger on days when market performance is positive.

**Hypothesis 2b**: Herding in the closed-end fund market will be stronger on days when market volatility is high.

**Hypothesis 2c**: Herding in the closed-end fund market will be stronger on days when market volume is high.

\(^5\) Earlier studies (Weiss 1989; Lee et al., 1991; Sias, 1997) reported that institutional ownership corresponded, on average, to less than 10% of closed-end funds’ capitalization pre-1990s in the US (the market of our study’s focus). Huang (2015) shows that, by and large, this has changed little since, with the equivalent average figure hovering around 13% for the 1987-2005 period. These figures suggest that retail investors are the dominant clientele in closed-end funds, with Flynn (2012) ascribing this to their IPOs being marketed to small investors.
In view of closed-end funds’ susceptibility to noise trading, it is reasonable to assume that sentiment (and non-fundamental factors, in general) will play a key role in their trading dynamics, in line with the predictions of investor sentiment theory (Flynn, 2012) and the extant evidence on the role of sentiment in retail investors’ trades (Kumar and Lee, 2006). It follows, therefore, that closed-end fund herding, if present, would also be expected to be noise-driven, i.e. motivated by non-fundamentals and affected by sentiment. Furthermore, the fact that closed-end funds are not subject to creations/redemptions of shares in their portfolios by their investors (unlike open-end funds) renders them less susceptible to investors’ flows, thus reducing the need for their managers to respond to these flows during up/down markets through purchases/sales of stocks. This, in turn, removes a major herding driver for fund managers when rebalancing their portfolios and (given that NAVs are reflective of the values of the portfolios under management) suggests that herding among closed-end funds should be more pronounced than herding among their net asset values. To test for the above, we propose the following three hypotheses:

**Hypothesis 3a**: Closed-end fund herding is strongly non-fundamentals driven.

**Hypothesis 3b**: Closed-end fund herding is affected by sentiment.

**Hypothesis 3c**: Herding among closed-end funds is stronger than herding among their NAVs.

If herding is significant and noise-driven in the closed-end fund market, the large volume of evidence (Cherkes, 2012) on the latter’s discounts would necessitate investigating whether this herding is motivated by premiums or discounts and their magnitude and variations over time. Key to this is investor sentiment theory, which postulates that closed-end funds trade at a discount as compensation for their enhanced noise trader risk (Lee et al., 1991). Assuming herding is noise-driven, we would expect it to be stronger for discounts compared to premiums.
and rise in magnitude as these discounts grow deeper (i.e. as closed-end fund prices deviate further downward from their NAVs). We, therefore, propose the following hypotheses:

**Hypothesis 4a**: Herding is stronger when closed-end funds trade, on average, at a discount.

**Hypothesis 4b**: Herding is stronger when closed-end fund discounts grow deeper.

Our results confirm the presence of herding in the closed-end fund market. However, that herding is not characterized by significant asymmetries. Herding is evident on both up- and down-market days and on days when volatility/volume are high; nevertheless, the difference in herding between high and low volatility/volume days is not significant. Results also show that non-fundamentals driven herding is significantly stronger than fundamentals-driven herding in the closed-end fund market, with herding in the latter being stronger than herding among the NAVs. Although evidence of asymmetry in herding is found with respect to the VIX (herding is significant on high VIX days only, i.e. days of higher expected volatility – and therefore deteriorating sentiment), the differences are again insignificant. Herding is found to exist only when closed-end funds trade on average at a discount, and grows in magnitude as the cross-sectional discounts grow larger.

In a series of robustness tests, we find that herding significance is concentrated in the period following the outbreak of the global financial crisis (i.e. from 2007 onward), with earlier years returning no evidence of herding. We also find that herding interacts significantly with Baker et al. (2016)’s Economic Policy Uncertainty index (which measures macroeconomic uncertainty, compared to the stock return uncertainty measured by VIX), being evident during periods of high economic policy uncertainty. Additionally, we show that, while NAV does affect closed-end funds’ trading dynamics, it does not foment herding among them. Further, we report evidence on herding being significant irrespective of fund-size, with its magnitude, however, bearing an inverse relation to closed-end fund capitalization.
Our study contributes significantly to the behavioural finance literature, by producing evidence on the herding dynamics of a previously unexplored asset class, while at the same time offering novel insights to the debate on the closed-end fund puzzle. With herding being noise-driven and appearing stronger as discounts grow deeper, our findings suggest that herding is likely related to the noise trader risk associated with closed-end funds by investor sentiment theory. This is further supported by our results showing herding to be stronger during periods typified by high uncertainty (reflected through high-VIX, high volatility and high macroeconomic uncertainty), given that uncertainty can give rise to pessimistic sentiment (with which deeper discounts are associated).

The rest of our paper is organized as follows: section 2 presents the data utilized in our research, alongside a series of descriptive statistics and outlines the empirical design employed. Section 3 presents and discusses the results and section 4 provides concluding remarks and a discussion of our study’s implications.

2. Data and Methodology

We obtain data on daily closing prices, net asset values, market capitalization and volumes of trade for all US closed-end funds active at any point during the 02/01/1992-30/12/2016 period from Bloomberg and Thomson-Reuters Datastream. In total, our sample includes 698 closed-end funds, including active, dead and suspended ones, thus mitigating any survivorship bias.

Our empirical design follows the Chang et al. (2000) herding model, which aims at measuring herding at the aggregate (market) level using price-data. The notion underlying the model stems from Christie and Huang (1995), who argued that herding can be reflected through the relationship between the cross-sectional return dispersion and the absolute performance of the market. As Black (1972) showed, this relationship is expected to be positive, courtesy of
the differential sensitivities of publicly traded securities to market movements. As the market’s absolute return grows, therefore, and in the absence of herding, its cross-sectional return dispersion would also be expected to rise, in a linear fashion. However, if herding is present during extreme absolute market return periods, the cross-sectional return dispersion would be expected to decline relative to the no-herding scenario (as herding would lead securities to converge more closely to the market consensus, reflected through the average market return). This, in turn, suggests that the above mentioned positive and linear relationship between the cross-sectional return dispersion and absolute market returns may not hold in this case. Chang et al. (2000) proposed the following specification for empirical testing:

\[ CSAD_{m,t} = \beta_0 + \beta_1 |R_{m,t}| + \beta_2 R_{m,t}^2 + \epsilon_t. \]  

(1)

Here \( R_{m,t} \) refers to the average return of all actively traded stocks on day \( t \), while \( CSAD_{m,t} \) is calculated as follows:

\[ CSAD_{m,t} = \frac{\sum_{i=1}^{n} |R_{i,t} - R_{m,t}|}{n}. \]  

(2)

In Equation (2), \( n \) is the number of actively traded stocks on day \( t \) and \( R_{i,t} \) is the first logarithmic difference of closing prices for stock \( i \) on day \( t \), expressed as \( R_{i,t} = \ln P_t - \ln P_{t-1} \) (where \( P_t \) and \( P_{t-1} \) are the closing prices of stock \( i \) on days \( t \) and \( t-1 \), respectively). In our study’s context, \( R_{m,t} \) corresponds to the average return of all actively traded closed-end funds on day \( t \), with \( R_{i,t} \) being closed-end fund \( i \)’s log-differenced return for day \( t \). In the absence of herding, the relationship between the cross-sectional return dispersion and absolute market returns would be expected to be positive and linear; as a result, \( \beta_1 \) would be expected to be significantly positive and \( \beta_2 \) insignificant (since non-linearities would not be expected to characterize the relationship between \( CSAD_{m,t} \) and \( |R_{m,t}| \) in a rational asset pricing setting). In the presence of herding during days with substantial market movements (high values of \( |R_{m,t}| \)), the relationship between \( CSAD_{m,t} \) and \( |R_{m,t}| \) would be non-linear: \( \beta_2 \) would be significant and
negative (because herding would lead to a lower cross-sectional dispersion of returns compared to case of rational pricing, as mentioned previously).

Equation (1) is used to test for hypothesis 1, i.e. whether closed-end fund herding is significant or not; to test for hypotheses 2a-2c (i.e. to assess whether herding presents itself asymmetrically between up/down market days, high/low volatility days and high/low volume days) we employ a series of empirical extensions of the Chang et al. (2000) model. To begin with, we assess herding on up/down market days by employing the following empirical specification:

\[
CSAD_{m,t} = \beta_0 + \beta_1 D^{up}|R_{m,t}| + \beta_2 (1 - D^{up})|R_{m,t}| + \beta_3 D^{up}R^2_{m,t} + \beta_4 (1 - D^{up})R^2_{m,t} + \epsilon_t. \quad (3)
\]

The dummy variable \(D^{up}\) is equal to one (zero) on days with positive (negative) values of \(R_{m,t}\); a significantly negative value of \(\beta_3\) (\(\beta_4\)) would suggest the presence of herding on days of positive (negative) average performance for the closed-end fund market.

We test whether herding varies between high and low volatility days based on Equation (4), as follows:

\[
CSAD_{m,t} = \beta_0 + \beta_1 D^{high-VT}|R_{m,t}| + \beta_2 (1 - D^{high-VT})|R_{m,t}| + \beta_3 D^{high-VT}R^2_{m,t} + \\
\beta_4 (1 - D^{high-VT})R^2_{m,t} + \epsilon_t. \quad (4)
\]

Here, \(D^{high-VT}= 1\) on high volatility days and 0 on low volatility ones. We proxy volatility via the squared value of \(R_{m,t}\) and, in line with earlier studies (e.g. Guney et al., 2017), we deem a day to be of high (low) volatility if its volatility is higher (lower) than its 30-day moving average value.

To test for herding between high and low volume days, we utilize the following specification:

\[
CSAD_{m,t} = \beta_0 + \beta_1 D^{high-VL}|R_{m,t}| + \beta_2 (1 - D^{high-VL})|R_{m,t}| + \beta_3 D^{high-VL}R^2_{m,t} + \\
\beta_4 (1 - D^{high-VL})R^2_{m,t} + \epsilon_t. \quad (5)
\]
In Equation (5), $D_{hi-g}^{VL}$ is a dummy variable equal to one (zero) for high (low) volume days; similar to earlier studies (e.g. Economou et al., 2011), a day is taken be a high (low) volume one if its volume is above (below) its 30-day moving average.

To assess whether closed-end fund herding is noise-driven (hypotheses 3a-3c) we first test whether herding is fundamentals-motivated (hypothesis 3a); to that end, we first remove the fundamentals-component from CSAD, by regressing the latter on Fama and French (2015)’s five factors, as follows:

$$CSAD_{m,t} = \gamma_0 + \gamma_1 (r_{m,t} - r_{f,t}) + \gamma_2 HML_t + \gamma_3 SMB_t + \gamma_4 RMW_t + \gamma_5 CMA_t + u_t. \quad (6)$$

In Equation (6), $r_{m,t} - r_{f,t}$ captures the excess market return, HML is the High Minus Low return factor (“value” factor), SMB is the Small Minus Big return factor (“size” factor), RMW is the Robust Minus Weak return factor (“profitability” factor) and CMA is the Conservative Minus Aggressive factor (“investment” factor). With the above factors being controlled for, the error term ($u_t$) here captures the variation of CSAD due to non-fundamental factors, in line with Galariotis et al. (2015), such that:

$$CSAD_{NONFUND,t} = u_t. \quad (7)$$

The part of CSAD due to fundamental information is, thus, calculated as:

$$CSAD_{FUND,t} = CSAD_{m,t} - CSAD_{NONFUND,t}. \quad (8)$$

Having partitioned CSAD into the above two components, we can now assess whether closed-end funds herd due to fundamental or non-fundamental factors by re-estimating Equation (1) utilizing each of the two CSAD-parts separately as follows:

$$CSAD_{FUND,t} = \beta_0 + \beta_1 |R_{m,t}| + \beta_2 R_{m,t}^2 + e_t. \quad (9)$$

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6 Source for these factors: [http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html](http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html).

7 Galariotis et al. (2015) removed the fundamentals’ component from CSAD by regressing CSAD on the Fama and French (1993) three factors and Carhart (1997)’s momentum factor jointly. We chose not to include the momentum factor in Equation (6); although we agree with Galariotis et al. (2015)’s viewpoint that momentum can bear a relationship to macro fundamentals, it can also reflect behaviourally biased trading (e.g. Odean, 1998) and, as a result, controlling for it can potentially lead non-fundamental CSAD components to be factored out.
\[ CSAD_{NONFUND,t} = \beta_0 + \beta_1 |R_{m,t}| + \beta_2 R_{m,t}^2 + e_t. \]  

Significantly negative values for \( \beta_2 \) in Equations (9) and (10) would suggest the presence of herding motivated by fundamentals and non-fundamentals, respectively.

To gauge whether herding is subject to sentiment-effects (hypothesis 3b), we estimate the following equation:

\[ CSAD_{m,t} = \beta_0 + \beta_1 D^{high-VIX} |R_{m,t}| + \beta_2 (1 - D^{high-VIX}) |R_{m,t}| + \beta_3 D^{high-VIX} R_{m,t}^2 + \beta_4 (1 - D^{high-VIX}) R_{m,t}^2 + e_t. \]  

Sentiment here is proxied via the CBOE VIX index, which is a gauge of the expected market volatility of the next 30 calendar days in the US market and is calculated as an implied volatility index with the S&P 500 options as its underlying benchmark. The dummy \( D^{high-VIX} \) in Equation (11) equals one (zero) if the VIX is above (below) its 30-day moving average, i.e. reflective of pessimism (optimism) regarding future volatility.

To assess whether herding in closed-end funds differs from the herding of their NAVs (hypothesis 3c), we re-estimate Equation (1) using NAV-returns as input and compare the results to those from Equation (1) using closed-end fund returns.

To gauge whether closed-end funds’ widely documented discounts affect their herding (hypotheses 4a and 4b), we perform a battery of tests based on the weighted deviation of our sample funds’ prices from their NAVs, which is calculated as follows:

\[ VWD_t = \sum_{i=1}^{nt} W_i DEV_{i,t}. \]  

Equation (12) offers the value-weighted discount index of Lee et al. (1991), which is calculated based on the NAV-weighted deviation of each closed-end fund’s price from its NAV on day \( t \); with \( NAV_{i,t} \) corresponding to closed-end fund \( i \)’s NAV on day \( t \), each closed-end fund’s weight is calculated as:

\[ W_i = \frac{NAV_{i,t}}{\sum_{i=1}^{nt} NAV_{i,t}}. \]
The deviation of each closed-end fund’s price from its NAV on day $t$ (in return-terms) is given as follows:

$$DEV_{it} = \frac{NAV_{it} - P_{it}}{NAV_{it}}.$$  \hspace{1cm} (14)

Having calculated $VWD_t$, we first examine whether it is the presence of market-wide premiums or discounts that leads to herding among closed-end funds (hypothesis 4a) by re-estimating Equation (1) separately for days of a cross-sectional discount ($VWD_t > 0$) and for days of a cross-sectional premium ($VWD_t < 0$). To test for hypothesis 4b, we rank the $VWD_t$-values in ascending order, separate them into “moderate” (falling between the 25th and 75th quantile of the $VWD_t$-distribution, i.e. Q25-Q75) and “extreme” (falling outside Q25-Q75) and estimate herding for each of those subsets; we also estimate herding separately for days corresponding to the extreme left- (falling below Q25) and extreme right- (falling above Q75) tail of the $VWD_t$-values’ distribution.

Table 1 presents some descriptive statistics for our sample data. As expected, almost three-quarters (74.3%) of our sample’s fund-days correspond to closed-end funds trading at a discount. The dominance of discounts among closed-end funds is further illustrated by the fact that the $VWD_t$ is positive (indicative of a discount) in 91% of our sample window’s days, suggesting that closed-end funds’ average price deviation from their NAV is negative. This deviation stands, on average, at -4.30% for the whole sample period (i.e. across all fund-days), with the average discount (premium) documented being equal to approximately -8.72% (8.49%). The CSAD has an average value of 0.84%, accompanied by a variance equal to 0.0014%; the average return ($R_{m,t}$) of our sample’s closed-end funds is -0.0075%, while its variance equals 0.0044%.\(^8\) Both CSAD and $R_{m,t}$ appear significantly positively skewed and

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\(^8\) The low average value of -0.0075% could be due to the fact that our sample window encompasses a full 25 years, during which the US market witnessed periods of prolonged upswings as well as major crashes (including the Dot Com crash and the global financial crisis post 2007).
leptokurtic, with the departures from normality in their time series further confirmed by the significant values of the Shapiro-Wilk and Shapiro-Francia test-statistics.

3. Results – Discussion

3.1. Do closed-end funds herd and is their herding asymmetric?

We begin the discussion of our findings with the presentation of the results from Equation (1), in order to first assess whether closed-end funds herd in the US market. As the estimates from Panel A in Table 2 denote, herding is present, with the coefficient $\beta_2$ being a significant -1.3473, a value notably higher (in absolute terms) compared to those reported for both the US and international equity markets in prior studies using the Chang et al. (2000) measure (see e.g. Chiang and Zheng, 2010). However, as seen in Panel B of Table 2, there are no significant asymmetries when the performance of the closed-end funds’ industry is taken into account; coefficients $\beta_3$ and $\beta_4$ are both significantly negative, with there being no significant difference in herding between up and down markets, despite $\beta_4$ being larger in absolute terms than $\beta_3$.\(^9\) In contrast, evidence of asymmetric herding is detected when controlling for high/low volatility (Panel C in Table 2) and volume (Panel D in Table 2), where herding is present only on days when volatility and volume are high (i.e. in excess of their 30-day moving average). There is no evidence of herding on low volatility/volume days ($\beta_4$ is insignificant). Although the above point towards the presence of herding asymmetries with respect to volatility and volume (similar to other international markets\(^10\)), the differences

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\(^9\) To examine whether extreme positive/negative market returns motivate herding, we re-estimated Equation (3), first by setting $D_{up} = 1$ for $R_{mt,t}$-values falling in the top quartile of the $R_{mt,t}$-distribution and then by setting $D^{up} = 1$ for $R_{mt,t}$-values falling in the bottom quartile of the $R_{mt,t}$-distribution. Both estimations returned us with significantly negative values of $\beta_3$ and $\beta_4$, with the difference between the two appearing insignificant in both cases. Results are not presented here for brevity purposes and are available from the authors on request.

\(^10\) Herding has been detected on high volatility/volume days in Tan et al. (2008) for Chinese A-shares and Chiang and Zheng (2010) for international stock markets.
between $\beta_3$ and $\beta_4$ are not significant in Panels C and D\textsuperscript{11}, indicating that these asymmetries are weak, at best.\textsuperscript{12} Overall, the above results confirm hypothesis 1 (closed-end fund herding is significant), yet not hypotheses 2a-2c (given the insignificance of the herding asymmetries reported here).

3.2. Is closed-end fund herding noise-driven?

The $\beta_2$-estimate in Panel A of Table 2 is substantially more negative than its equivalent values in other studies investigating international stock markets. This renders it likely that the strong herding reported here is noise-driven, more so considering the dominant position of retail investors in closed-end funds’ market capitalization. Results from the estimations of Equations (9) and (10) (Table 3, Panels A and B, respectively) support this argument, since $\beta_2$ is found to be of greater magnitude (-1.2849 versus -0.0625) and significance (p-value of 0.0000 versus 0.0710) for the non-fundamentals’ test compared to the fundamentals’ one. This indicates that closed-end fund herding is strongly non-fundamentals driven.\textsuperscript{13}

Further to that, the estimates reported in Panel C of the same table for Equation (11) show that closed-end funds herd only on high-VIX days (when the VIX exceeds its 30-day moving average). This suggests a positive relationship between their herding and the VIX, in line with extant evidence from equity (Chiang et al., 2013) and REITs (Philippas et al., 2013) markets, where rising VIX-values (indicative of deteriorating sentiment regarding future

\textsuperscript{11} To examine whether extreme high/low volatility (volume) motivates herding, we re-estimated Equation (4) (Equation (5)), first by setting $D_{VT}^{high}\_VT (D_{VT}^{high}\_VL) = 1$ for volatility- (volume-) values falling in the top quartile of the volatility- (volume-) distribution and then by setting $D_{VT}^{high}\_VT (D_{VT}^{high}\_VL) = 1$ for volatility- (volume-) values falling in the bottom quartile of the volatility- (volume-) distribution. Results suggest the presence of herding only within the top quartile of volatility/volume (for the first test) and outside the bottom quartile of volatility/volume (for the second test). These results are in line with those presented in Panels C and D of Table 2, with the difference between $\beta_3$ and $\beta_4$ being insignificant in all tests. Results are not presented here for brevity purposes and are available from the authors on request.

\textsuperscript{12} Assuming a longer (250-day) moving average to benchmark volatility/volume against yielded similar results; results are not reported here for brevity reasons and are available from the authors on request.

\textsuperscript{13} We also tested for the difference between fundamentals- and non-fundamentals-driven herding (i.e. between the $\beta_2$-values from Equations (9) and (10)). In unreported results, we found the difference to be significant. Results are available from the authors on request.
volatility) have been found to promote herding. However, given the insignificant difference between $\beta_3$ and $\beta_4$, this relationship appears to be a weak one.

To test hypothesis 3c we estimate Equation (1) utilizing NAV-returns as input and again document evidence of herding. This appears less strong compared to the herding reported originally utilizing closed-end funds’ returns (the $\beta_2$ in Panel D of Table 3 is smaller, in absolute terms, than its corresponding value in Panel A of Table 2), thus suggesting that closed-end fund (majority retail) investors herd more strongly than these funds’ managers (NAVs are reflective of the values of the managed portfolios).14

Taken together, the above denote that herding among US closed-end funds is mainly non-fundamentals driven and stronger compared to herding among their NAVs, with evidence also suggesting that it bears a weak positive relationship with the VIX. These findings suggest that closed-end fund herding is not only significant, but also noise-driven, thus leading us to accept hypotheses 3a and 3c (yet not 3b, in view of the insignificant difference in herding between high and low VIX days). Our results showcase that noise trading is pronounced in this asset class, consistent with the predictions of investor sentiment theory (Lee et al., 1991). However, the latter also postulates that the systematic risk induced by this noise trading is compensated for via closed-end funds’ discounts. As a result, if the herding documented here is related to noise trader risk, we would expect it to be more pronounced when noise trader risk is at its highest, i.e. when discounts grow in size. In the next sub-section we will therefore assess whether herding is determined by these discounts, in terms of their magnitude and variation.

14 The difference between the $\beta_2$-estimate in the herding test with closed-end funds’ returns and that with NAV-returns is statistically significant, with the relevant F-test statistic being equal to 80.16 (p-value = 0.0000).
3.3. Do closed-end funds’ price-deviations from their NAVs affect their herding?

Table 4 presents the results from herding estimations for various patterns of Lee et al. (1991)’s value-weighted discount index \( (VWD_t) \). This variable indicates for each day the (weighted) average discount/premium, measured across all funds traded on that day. It can be seen from Panels A and B that herding is present on days with cross-sectional discounts \( (VWD_t > 0) \), yet absent on days with cross-sectional premiums \( (VWD_t < 0) \). The fact that \( \beta_2 \) in Panel A of Table 4 is larger, albeit marginally, in absolute terms than its equivalent in Panel A of Table 2 (-1.4742 versus -1.3473) suggests that herding grows even stronger when closed-end funds trade, on average, at a discount. When comparing herding between “moderate” (Panel C) and “extreme” (Panel D) \( VWD_t \) values it can be seen that it is present only for days corresponding to the latter. Splitting “extreme” \( VWD_t \) values into those of the left- (Panel E) and those of the right- (Panel F) tail of the \( VWD_t \) values' distribution further reveals that herding is evident only for the extreme right-tail of the distribution (i.e. motivated by extreme discounts alone).\(^{15}\) The above findings suggest that discounts are related to herding among closed-end funds, with this herding rising as the discounts grow deeper (thus leading us to accept hypotheses 4a-4b). Combined with the results in section 3.2 where we showed that closed-end fund herding is noise-driven, these results support the possibility that herding is related to closed-end funds’ noise trader risk (which is compensated via their discounts as per investor sentiment theory).

3.4. Robustness tests

3.4.1. Closed-end fund herding within and outside crises

\(^{15}\) It is interesting to note here that \( \beta_2 \) assumes even larger (in absolute terms) values in panels D and F, thus indicating that herding grows as discounts deepen.
Research to date has produced inconsistent evidence regarding the effect of financial crises on herding, with some studies (Chiang and Zheng, 2010; Galariotis et al., 2015) showing that herding rises following a crisis’ outbreak and others (Choe et al., 1999; Hwang and Salmon, 2004) that it begins to decline. To assess the presence of closed-end fund herding within and outside crises-periods, we focus on our sample period’s two major crises (Dot Com crash; global financial crisis) and estimate herding for the following sub periods: pre Dot Com crash (02/01/1992-23/03/2000); Dot Com crash (24/03/2000-09/10/2002); between crisis period (10/10/2002 – 09/10/2007); and post global financial crisis’ outbreak (10/10/2007-30/12/2016). Regarding the post outbreak years, we treat the whole period from 10/10/2007 until the end of our sample window (30/12/2016) as one period due to the fact that this period witnessed a major global crisis (2007-2009) followed by the Euro Zone sovereign debt crisis that broke out shortly thereafter and has since continued to affect global markets. However, to isolate each of these two crises’ effects, we also estimate herding separately for each, i.e. during the global financial crisis (10/10/2007 – 06/03/2009)16 and after the global financial crisis (09/03/2009 – 30/12/2016).

Results are presented in Table 5 and denote that herding among closed-end funds has been evident ($\beta_2$ is significantly negative) following the global financial crisis’ outbreak only (Panel D), with no evidence of herding surfacing for the pre 2007 years. Herding retains its significance when splitting the post 2007 sub period into a global financial crisis (Panel E) and a post global financial crisis (essentially encompassing the Euro Zone sovereign debt crisis; Panel F) one, appearing stronger during the former. A possible explanation for the significant herding post 2007 may well rest with the fact that the global crisis affected US retail investors more directly than other financial episodes (such as the Dot Com crash), given its adverse impact on the real estate sector that led to a host of issues, including mortgage repayment

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16 For more on the choice of this sub period’s start-/end-dates, see Guney et al. (2017).
difficulties, repossessions and a slump in the values of real estate assets (Galariotis et al., 2015). Considering the majority retail clientele of closed-end funds, these conditions would be expected to affect this asset class substantially, prompting herding e.g. due to retail investors unloading their positions in closed-end funds for liquidity reasons (such as to facilitate the servicing of their mortgages).

3.4.2. Closed-end fund herding and Economic Policy Uncertainty

The evidence presented in section 3.2 above demonstrated that herding among closed-end funds is likely noise-driven, being strongly non-fundamentals motivated, more pronounced than their NAV-herding and appearing only on high-VIX days (i.e. on days of deteriorating sentiment). Furthermore, we noted that the difference between herding on high- and low-VIX days is insignificant, thus denoting that the documented sentiment-effect is a weak one. Since the VIX-index reflects an aspect of investors’ sentiment associated with future stock price uncertainty (essentially their future 30-day volatility expectations), we assess whether herding interacts significantly with a sentiment-index capturing an alternative form of uncertainty and to that end, we draw on Baker et al. (2016)’s Economic Policy Uncertainty (EPU) index and modify Equation (11) as follows:

\[
CSAD_{m,t} = \beta_0 + \beta_1 D^{high-EPU} |R_{m,t}| + \beta_2 (1 - D^{high-EPU}) |R_{m,t}| + \beta_3 D^{high-EPU} R_{m,t}^2 + \beta_4 (1 - D^{high-EPU}) R_{m,t}^2 + e_t. \tag{14}
\]

The dummy \(D^{high-EPU}\) equals one (zero) for months when the index is above (below) its median value, indicative of higher (lower) perceived uncertainty regarding economic policy. Results are reported in Table 6, Panel A and suggest the presence of herding for high uncertainty months only (\(\beta_3\) alone is significantly negative), with the difference between \(\beta_3\)

and $\beta_4$ being statistically significant. The results from the high-low VIX and high-low EPU estimations appear to support each other, denoting that closed-end funds herd more during periods of higher uncertainty (on days with pessimistic views regarding future short-term volatility – when controlling for the VIX - and on months with higher uncertainty regarding economic policy – when controlling for the EPU-index). Combined with our earlier results on herding being evident on high volatility days only (Table 2, Panel C), it appears that closed-end fund herding rises with uncertainty, possibly due to risk-aversion, with investors resorting to mimicking their peers’ trades in order to mitigate this uncertainty. This is largely motivated by the fact that uncertain periods render analytical processing of fundamentals more prone to errors, thus prompting investors to perceive the trades of others as useful enough to monitor (and, potentially, follow) as a source of information. What is more, our earlier findings (section 3.3) on discounts motivating herding are relevant here, since uncertain periods are likely to accommodate pessimistic sentiment (which tends to amplify closed-end funds’ discounts).

3.4.3. Do NAVs promote herding in the closed-end fund market?

We now turn to the role of NAV in closed-end fund herding; earlier we reported results (Table 3, Panel D) indicating that herding among closed-end funds was stronger compared to that among their NAVs. An issue worth exploring in this context is whether the NAVs themselves give rise (or, at least, contribute) to herding among closed-end funds; to that end, we estimate the following equation:

$$CSAD_{m,t} = \beta_0 + \beta_1 |R_{m,t}| + \beta_2 R^2_{m,t} + \beta_3 R^2_{NAV,t} + e_t.$$

(15)

If NAV-returns promote herding, $\beta_3$ will be significantly negative, in line with similar empirical calibrations of the Chang et al. (2000) measure (see e.g. Guney et al., 2017). Results are presented in Table 6, Panel B and show that herding among closed-end funds remains robust after accounting for NAVs’ squared returns ($\beta_2$ remains significantly negative), with $\beta_3$ being
significant (indicating that NAV-returns affect the trading dynamics of closed-end funds), yet positive (denoting that NAV-returns produce no herding among closed-end funds).\textsuperscript{18}

3.4.4. Does size affect closed-end fund herding?

Evidence (Lakonishok et al., 1992; Wermers, 1999; Sias, 2004) suggests that small stocks accommodate stronger herding than large ones, a fact attributed to the higher information and liquidity risks surrounding stocks of low market capitalization.\textsuperscript{19} To examine whether closed-end funds exhibit size effects in their herding, we rank our sample closed-end funds according to their market capitalization, partition them into three equal-size terciles (small; mid; large) and estimate Equation (1) for each. Results are reported in Table 6, Panels C to E and showcase that herding is present for all capitalization terciles, with its magnitude increasing ($\beta_2$ grows more negative) as capitalization declines.\textsuperscript{20} This suggests that, much like with stocks, investors herd the most when trading closed-end funds of small size, possibly as a response to smaller closed-end funds’ higher information/liquidity and noise trader risk-levels (institutional ownership declines with size in closed-end funds, implying above-average retail traders’ participation for smaller funds; Huang, 2015).

4. Conclusion

This study provides the first detailed investigation of herding in the closed-end fund market, drawing on the universe of US closed-end funds for the 1992-2016 period. Closed-end funds are found to herd significantly, with their herding being mainly non-fundamentals driven.

\textsuperscript{18} Similar results were generated when accounting for lagged NAV-returns in Equation (15); results are available from the authors on request.

\textsuperscript{19} Small capitalization stocks tend to enjoy limited analyst coverage, thus being subject to higher informational uncertainty (information risk). This reduces their visibility in the market (investors’ attention for them is limited), leading them to demonstrate low volume levels; the issue arising for a holder of small stocks is that, in case of them underperforming, their low liquidity will render selling them more difficult (liquidity risk).

\textsuperscript{20} The difference of $\beta_2$-values between the largest and smallest capitalization terciles is statistically significant; results are not presented here for brevity reasons and are available from the authors on request.
stronger compared to herding among their NAVs and motivated by uncertainty. What is more, their herding is present when they trade at a discount, on average, with herding rising in magnitude as the discounts grow deeper. Closed-end fund herding is present irrespective of fund-size, yet grows in magnitude as funds’ capitalization declines. Upon partitioning our sample window, we detect significant herding for the post 2007 period (corresponding to the global financial crisis and the concomitant Euro Zone one) only. Overall, these findings denote that closed-end fund herding is noise-driven and linked to their widely documented discounts, thus raising the possibility that this herding is not irrelevant to their widely cited noise trader risk (for which their discounts have been argued to compensate by investor sentiment theory).

The evidence presented in this study bears interesting implications for researchers from two perspectives. On the one hand, if herding among closed-end funds is related to their noise trader risk, then it would be interesting to assess whether it could be used as a risk-factor when testing asset pricing models in this asset class. On the other hand, the fact that herding is relevant to the closed-end funds’ discounts and hence, puzzle, raises the possibility that other modes of behavioural investments linked to herding (e.g. feedback trading, which has been found to co-exist with herding in investors’ trades internationally; Choi and Skiba, 2015) are also related to that puzzle.
References


The table presents our sample’s properties (Panel A) and descriptive statistics (Panel B) of key variables characterizing it; these variables include CSAD\textsubscript{m,t} (the cross-sectional absolute deviation of closed-end funds’ returns), R\textsubscript{m,t} (the average return of closed-end funds), the price-deviation from net asset value (\((P-NAV)/NAV\)), the discounts (negative price-deviations from net asset value), the premiums (positive price-deviations from net asset value) and the VWD\textsubscript{t} index of Lee et al. (1991), which is the weighted price-deviation from NAV across all closed-end funds. We report statistics on the mean, variance, skewness and kurtosis; we also report statistics from the Shapiro-Wilk (S-W) and Shapiro-Francia (S-F) tests for the normality of closed-end funds’ returns. Our data covers the sample period from 02/01/1992 to 30/12/2016. * indicates significance at the 1% level.
Table 2: Testing for unconditional and conditional (on market performance, volatility and volume) herding

<table>
<thead>
<tr>
<th>Panel</th>
<th>( \beta_0 )</th>
<th>( \beta_1 )</th>
<th>( \beta_2 )</th>
<th>( \beta_3 )</th>
<th>( \beta_4 )</th>
<th>( R^2 )</th>
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<td>A: Unconditional herding</td>
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**Panel B: Herding conditional on market performance**

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**F-stat**

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<td>( H_0: \beta_3 = \beta_4 )</td>
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**F-stat**

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**F-stat**

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<td>(0.4014)</td>
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</tbody>
</table>

Table 2 presents the estimates from the following equations:

- **Panel A**: CSAD\(_{m,t}\) = \( \beta_0 + \beta_1|R_{m,t}| + \beta_2 R^2_{m,t} + e_t \) (A)
- **Panel B**: CSAD\(_{m,t}\) = \( \beta_0 + \beta_1 D^\text{up}|R_{m,t}| + \beta_2 (1 - D^\text{up})|R_{m,t}| + \beta_3 D^\text{up}R^2_{m,t} + \beta_4 (1 - D^\text{up})R^2_{m,t} + e_t \) (Panel B)
- **Panel C**: CSAD\(_{m,t}\) = \( \beta_0 + \beta_1 D^{\text{high-Vol}}|R_{m,t}| + \beta_2 (1 - D^{\text{high-Vol}})|R_{m,t}| + \beta_3 D^{\text{high-Vol}}R^2_{m,t} + \beta_4 (1 - D^{\text{high-Vol}})R^2_{m,t} + e_t \) (Panel C)
- **Panel D**: CSAD\(_{m,t}\) = \( \beta_0 + \beta_1 D^{\text{high-Volume}}|R_{m,t}| + \beta_2 (1 - D^{\text{high-Volume}})|R_{m,t}| + \beta_3 D^{\text{high-Volume}}R^2_{m,t} + \beta_4 (1 - D^{\text{high-Volume}})R^2_{m,t} + e_t \) (Panel D)

The equations are estimated for the 02/01/1992 – 30/12/2016 sample period. Parentheses include the estimates’ p-values based on heteroscedasticity-autocorrelation corrected standard errors. The F-test is used to test for the significance of the difference between the pair of coefficients \( \beta_3, \beta_4 \). CSAD\(_{m,t}\) is the daily cross-sectional absolute deviation of our closed-end funds’ returns and \( R_{m,t} \) is their daily average return. \( D^\text{up} = 1 \) if \( R_{m,t} > 0 \), 0 otherwise in Panel B. \( D^{\text{high-Vol}} = 1 \) if volatility on day \( t \) is higher than its 30-day moving average, 0 otherwise in Panel C. \( D^{\text{high-Volume}} = 1 \) if volume on day \( t \) is higher than its 30-day moving average, 0 otherwise in Panel D.
Table 3: Testing whether herding is noise-related

<table>
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<tr>
<th>Panel</th>
<th>Equation</th>
<th>$\beta_0$</th>
<th>$\beta_1$</th>
<th>$\beta_2$</th>
<th>$\beta_3$</th>
<th>$\beta_4$</th>
<th>$R^2$</th>
</tr>
</thead>
<tbody>
<tr>
<td>A</td>
<td>$CSA_D^{Fund}_t = \beta_0 + \beta_1</td>
<td>R_{m,t}</td>
<td>+ \beta_2 R_{m,t}^2 + e_t$ (Panel A)</td>
<td>0.0084</td>
<td>0.0093</td>
<td>-0.0625</td>
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<tr>
<td></td>
<td></td>
<td>(0.0000)</td>
<td>(0.0010)</td>
<td>(0.0710)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>B</td>
<td>$CSA_D^{Non-Fund}_t = \beta_0 + \beta_1</td>
<td>R_{m,t}</td>
<td>+ \beta_2 R_{m,t}^2 + e_t$ (Panel B)</td>
<td>-0.0019</td>
<td>0.5486</td>
<td>-1.2849</td>
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<td>(0.0000)</td>
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<tr>
<td>C</td>
<td>$CSA_D^{Sent}_t = \beta_0 + \beta_1</td>
<td>D_{high-VIX}^t</td>
<td>R_{m,t}</td>
<td>+ \beta_2 (1 - D_{high-VIX}^t)</td>
<td>R_{m,t}</td>
<td>+ \beta_3 D_{high-VIX}^t R_{m,t}^2 + \beta_4 (1 - D_{high-VIX}^t) R_{m,t}^2 + e_t$ (Panel C)</td>
<td>0.0066</td>
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<td>(0.0000)</td>
<td>(0.0000)</td>
<td>(0.0000)</td>
<td>(0.4090)</td>
<td></td>
</tr>
<tr>
<td>D</td>
<td>$CSA_D^{NAV}_t = \beta_0 + \beta_1</td>
<td>R_{NAV,t}</td>
<td>+ \beta_2 R_{NAV,t}^2 + e_t$ (Panel D)</td>
<td>0.0036</td>
<td>2.4025</td>
<td>-0.0882</td>
<td></td>
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The equations are estimated for the 02/01/1992 – 30/12/2016 sample period. Parentheses include the estimates’ p-values based on heteroscedasticity-autocorrelation corrected standard errors. The F-test is used to test for the significance of the difference between the pair of coefficients $\beta_3, \beta_4$ in Panel C. $CSA_D^{m,t}$ is the daily cross-sectional absolute deviation of our closed-end funds’ returns, $CSA_D^{NAV,t}$ is the daily cross-sectional absolute deviation of our sample closed-end funds’ NAV-returns, $CSA_D^{Fund,t}$ is the part of the variations of $CSA_D^{m,t}$ due to fundamentals, $CSA_D^{NonFund,t}$ is the part of the variations of $CSA_D^{m,t}$ not due to fundamentals, $R_{m,t}$ is our sample closed-end funds’ daily average return and $R_{NAV,t}$ is the daily average return of their NAVs. $D_{high-VIX}^t = 1$ if the CBOE VIX on day $t$ is higher than its 30-day moving average, 0 otherwise in Panel C.
Table 4: Testing for the effect of closed-end funds’ cross-sectional price deviations from their NAV on herding

<table>
<thead>
<tr>
<th>Panel</th>
<th>Herding condition</th>
<th>Estimate</th>
<th>p-value</th>
<th>Estimate</th>
<th>p-value</th>
<th>Estimate</th>
<th>p-value</th>
<th>R²</th>
</tr>
</thead>
<tbody>
<tr>
<td>A</td>
<td>$VWD_{t} &gt; 0$ (i.e. there exists a cross-sectional discount)</td>
<td>0.0062</td>
<td>(0.0000)</td>
<td>0.5745</td>
<td>(0.0000)</td>
<td>-1.4742</td>
<td>(0.0000)</td>
<td>0.5337</td>
</tr>
<tr>
<td>B</td>
<td>$VWD_{t} &lt; 0$ (i.e. there exists a cross-sectional premium)</td>
<td>0.0083</td>
<td>(0.0000)</td>
<td>0.5033</td>
<td>(0.0000)</td>
<td>4.3028</td>
<td>(0.6430)</td>
<td>0.1987</td>
</tr>
<tr>
<td>C</td>
<td>$VWD_{t}$ is moderate (i.e. its value falls between Q25-Q75)</td>
<td>0.0063</td>
<td>(0.0000)</td>
<td>0.4342</td>
<td>(0.0000)</td>
<td>2.3835</td>
<td>(0.1300)</td>
<td>0.3791</td>
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<tr>
<td>D</td>
<td>$VWD_{t}$ is extreme (i.e. its value falls outside Q25-Q75)</td>
<td>0.0068</td>
<td>(0.0000)</td>
<td>0.5934</td>
<td>(0.0000)</td>
<td>-1.7016</td>
<td>(0.0000)</td>
<td>0.5645</td>
</tr>
<tr>
<td>E</td>
<td>Herding in the extreme left-tail of the $VWD_{t}$ values’ distribution (below Q25)</td>
<td>0.0068</td>
<td>(0.0000)</td>
<td>0.3408</td>
<td>(0.0000)</td>
<td>5.4305</td>
<td>(0.2810)</td>
<td>0.1322</td>
</tr>
<tr>
<td>F</td>
<td>Herding in the extreme right-tail of the $VWD_{t}$ values’ distribution (above Q75)</td>
<td>0.0074</td>
<td>(0.0000)</td>
<td>0.5866</td>
<td>(0.0000)</td>
<td>-1.7059</td>
<td>(0.0000)</td>
<td>0.6398</td>
</tr>
</tbody>
</table>

Table 4 presents the estimates from the following equation:

$\text{CSAD}_{m,t} = \beta_0 + \beta_1 |R_{m,t}| + \beta_2 R^2_{m,t} + \epsilon_t$

The equation is estimated for the 02/01/1992 – 30/12/2016 sample period. Parentheses include the estimates’ p-values based on heteroscedasticity-autocorrelation corrected standard errors. $\text{CSAD}_{m,t}$ is the daily cross-sectional absolute deviation of our closed-end funds’ returns and $R_{m,t}$ is their daily average return. The equation is estimated for: days when $VWD_{t} > 0$ (i.e. days when there exists a cross-sectional discount among closed-end funds; Panel A); days when $VWD_{t} < 0$ (i.e. days when there exists a cross-sectional premium among closed-end funds; Panel B); days of moderate $VWD_{t}$ values (i.e. $VWD_{t}$ values falling between Q25-Q75; Panel C); days of extreme $VWD_{t}$ values (i.e. $VWD_{t}$ values falling outside Q25-Q75; Panel D); days corresponding to the extreme left-tail of the $VWD_{t}$ values’ distribution (falling below Q25; panel E); and days corresponding to the extreme right-tail of the $VWD_{t}$ values’ distribution (falling above Q75; Panel F). In line with Lee et al. (1991), $VWD_{t}$ is calculated as: $VWD_{t} = \sum_{i=1}^{n_t} w_i \text{DEV}_{i,t}$, where $w_i = \frac{\text{NAV}_{i,t}}{\sum_{t=1}^{n_t} \text{NAV}_{i,t}}$ and $\text{DEV}_{i,t} = \frac{\text{NAV}_{i,t} - P_{i,t}}{\text{NAV}_{i,t}}$. In these equations, $\text{NAV}_{i,t}$ corresponds to closed-end fund $i$’s NAV on day $t$ and $P_{i,t}$ is closed-end fund $i$’s closing price on day $t$. 

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Table 5: Herding across sub periods

<table>
<thead>
<tr>
<th>Panel</th>
<th>Sub Periods</th>
<th>$\beta_0$</th>
<th>$\beta_1$</th>
<th>$\beta_2$</th>
<th>$R^2$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Panel A</td>
<td>Herding prior to the Dot Com crash (02/01/1992-23/03/2000)</td>
<td>0.0087</td>
<td>0.4342</td>
<td>8.9540</td>
<td>0.5183</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.0000)</td>
<td>(0.0000)</td>
<td>(0.0040)</td>
<td></td>
</tr>
<tr>
<td>Panel B</td>
<td>Herding during the Dot Com crash (24/03/2000-09/10/2002)</td>
<td>0.0072</td>
<td>0.6009</td>
<td>2.0857</td>
<td>0.6266</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.0000)</td>
<td>(0.0000)</td>
<td>(0.2950)</td>
<td></td>
</tr>
<tr>
<td>Panel C</td>
<td>Herding after the Dot Com crash (10/10/2002 – 09/10/2007)</td>
<td>0.0055</td>
<td>0.3882</td>
<td>4.0418</td>
<td>0.4769</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.0000)</td>
<td>(0.0000)</td>
<td>(0.0014)</td>
<td></td>
</tr>
<tr>
<td>Panel D</td>
<td>Herding post global financial crisis’ outbreak (10/10/2007-30/12/2016)</td>
<td>0.0048</td>
<td>0.6321</td>
<td>-1.8675</td>
<td>0.6841</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.0000)</td>
<td>(0.0000)</td>
<td>(0.0000)</td>
<td></td>
</tr>
<tr>
<td>Panel E</td>
<td>Herding during the global financial crisis (10/10/2007 – 06/03/2009)</td>
<td>0.0077</td>
<td>0.5907</td>
<td>-1.7611</td>
<td>0.6615</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.0000)</td>
<td>(0.0000)</td>
<td>(0.0000)</td>
<td></td>
</tr>
<tr>
<td>Panel F</td>
<td>Herding after the global financial crisis (09/03/2009 – 30/12/2016)</td>
<td>0.0048</td>
<td>0.5140</td>
<td>-0.8213</td>
<td>0.6253</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.0000)</td>
<td>(0.0000)</td>
<td>(0.0906)</td>
<td></td>
</tr>
</tbody>
</table>

Table 5 presents the estimates from the following equation:

$$CSAD_{m,t} = \beta_0 + \beta_1 |R_{m,t}| + \beta_2 R^2_{m,t} + \epsilon_t$$

Parentheses include the estimates’ p-values based on heteroscedasticity-autocorrelation corrected standard errors. $CSAD_{m,t}$ is the daily cross-sectional absolute deviation of our closed-end funds’ returns and $R_{m,t}$ is their daily average return. The equation is estimated for the following sub periods: pre Dot Com crash (02/01/1992-23/03/2000); Dot Com crash (24/03/2000-09/10/2002); after the Dot Com crash (10/10/2002 – 09/10/2007); post global financial crisis’ outbreak (10/10/2007-30/12/2016); during the global financial crisis (10/10/2007 – 06/03/2009); after the global financial crisis (09/03/2009 – 30/12/2016).
Table 6: Further robustness tests

<table>
<thead>
<tr>
<th>Panel A: Herding conditional on Baker et al. (2016)’s Economic Uncertainty Policy index</th>
<th>( \beta_0 )</th>
<th>( \beta_1 )</th>
<th>( \beta_2 )</th>
<th>( \beta_3 )</th>
<th>( \beta_4 )</th>
<th>( R^2 )</th>
</tr>
</thead>
<tbody>
<tr>
<td>( \text{F-stat} )</td>
<td>6.3300</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>( \text{H}_0: \beta_3 = \beta_4 )</td>
<td>(0.0018)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>0.0065</td>
<td>0.5565</td>
<td>0.5188</td>
<td>-1.3465</td>
<td>1.3809</td>
<td>0.5047</td>
<td></td>
</tr>
<tr>
<td>(0.0000)</td>
<td>(0.0000)</td>
<td>(0.0000)</td>
<td>(0.0000)</td>
<td>(0.7520)</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Panel B: Herding controlling for NAV-returns

<table>
<thead>
<tr>
<th>Panel C: Herding for small capitalization (bottom size tercile) closed-end funds</th>
<th>( \beta_0 )</th>
<th>( \beta_1 )</th>
<th>( \beta_2 )</th>
<th>( \beta_3 )</th>
<th>( \beta_4 )</th>
<th>( R^2 )</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.0066</td>
<td>0.5286</td>
<td></td>
<td>-1.5677</td>
<td>7.9202</td>
<td>0.5082</td>
<td></td>
</tr>
<tr>
<td>(0.0000)</td>
<td>(0.0000)</td>
<td></td>
<td>(0.0000)</td>
<td>(0.0000)</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Panel D: Herding for mid capitalization (middle size tercile) closed-end funds

<table>
<thead>
<tr>
<th>Panel E: Herding for large capitalization (top size tercile) closed-end funds</th>
<th>( \beta_0 )</th>
<th>( \beta_1 )</th>
<th>( \beta_2 )</th>
<th>( \beta_3 )</th>
<th>( \beta_4 )</th>
<th>( R^2 )</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.0058</td>
<td>0.5411</td>
<td></td>
<td>-1.4549</td>
<td></td>
<td>0.4949</td>
<td></td>
</tr>
<tr>
<td>(0.0000)</td>
<td>(0.0000)</td>
<td></td>
<td>(0.0000)</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Table 6 presents the estimates from the following equations:

- \( CSAD_{m,t} = \beta_0 + \beta_1 |R_{m,t}| + \beta_2 (1 - D^{high-EPU}) |R_{m,t}| + \beta_3 D^{high-EPU} R_{m,t}^2 + \beta_4 (1 - D^{high-EPU}) R_{m,t}^2 + e_t \) (Panel A)
- \( CSAD_{m,t} = \beta_0 + \beta_1 |R_{m,t}| + \beta_2 R_{m,t}^2 + \beta_3 R_{NAV,t}^2 + e_t \) (Panel B)
- \( CSAD_{m,t} = \beta_0 + \beta_1 |R_{m,t}| + \beta_2 R_{m,t}^2 + e_t \) (Panels C to E)

The equations are estimated for the 02/01/1992 – 30/12/2016 sample period. Parentheses include the estimates’ p-values based on heteroscedasticity-autocorrelation corrected standard errors. The F-test is used to test for the significance of the difference between the pair of coefficients \( \beta_3, \beta_4 \) in Panel A. \( CSAD_{m,t} \) is the daily cross-sectional absolute deviation of our closed-end funds’ returns and \( R_{m,t} \) is their daily average return. \( D^{high-EPU} = 1 \) if the EPU index in a month is above its median value, 0 otherwise in Panel A. \( R_{NAV,t} \) is the daily average return of our sample closed-end funds’ NAVs.