Economou F, Gavriilidis K, Kallinterakis V & Yordanov N (2015)
Do Fund Managers Herd in Frontier Markets – and Why?,
International Review of Financial Analysis, 40, pp. 76-87.

DOI: 10.1016/j.irfa.2015.03.017

Do Fund Managers Herd in Frontier Markets – and Why?

Fotini Economou[a], Konstantinos Gavriilidis[b,*],
Vasileios Kallinterakis[c,] and Nikolay Yordanov[d]

[a] Centre of Planning and Economic Research, Hellenic Open University & Open University of Cyprus, 11 Amerikis str. 106 72 Athens, Greece
[b] University of Stirling Management School, Stirling FK9 4LA, UK
[c] University of Liverpool Management School, Chatham Building, Chatham Street, Liverpool L69 7ZH, UK
[d] Ernst&Young Audit OOD, Polygraphia Office Center, 47A, Tsarigradsko Shose Blvd., fl. 4, 1124 Sofia, Bulgaria
*Corresponding Author. Email: konstantinos.gavriilidis@stir.ac.uk

Abstract

Frontier markets constitute a category of markets for which very little is known regarding the behaviour of their institutional investors. This study attempts to shed light on this issue by investigating whether fund managers herd in frontier markets and whether their herding is intentional or not using data on quarterly portfolio holdings of funds from two such markets (Bulgaria and Montenegro). Results show that fund managers herd significantly in both markets; controlling for the interaction of their herding with different market states, we find that herding is stronger for both markets during periods of positive market performance and high volume, while in the case of Montenegro it also appears significant during periods of low volatility. Our findings are consistent with fund managers herding intentionally, in anticipation of informational and/or professional payoffs. We also find that Bulgarian (Montenegrin) fund managers herd significantly after (before) the outbreak of the 2008 global financial crisis and we attribute this to a volume-effect, since Montenegro (Bulgaria) saw the heaviest trading activity before (after) the crisis' outbreak.

Keywords: herding; mutual funds; frontier markets; intent

JEL Classification: G02; G10; G15; G23

1. Introduction

Institutional herding has been at the focus of much research conducted in behavioural finance during the past couple of decades with extensive evidence from a series of markets confirming that fund managers herd significantly in their trades internationally. The propensity of fund managers towards imitating each other has been rationalized through several theoretical designs over time. Less skilled fund managers in the acquisition/processing of information, for example, may choose to copy the trades of their better-informed peers in order to extract informational payoffs (Devenow and Welch, 1996). Less able/reputed fund managers may also imitate the trades of their better-able peers with the purpose of improving on their image and protecting their career prospects (Scharfstein and Stein, 1990). Relative homogeneity among fund managers (in terms of their educational background and professional framework) can also lead them to produce correlated trades (De Bondt and Teh, 1997), while a similar argument has been advanced for characteristic trading, given the tendency of fund managers to follow various styles (e.g. momentum/contrarian, value/growth etc) in their investments (Bennett et al., 2003).

Empirical evidence from a wide cross-section of long-established capital markets, both developed as well as emerging, has identified the sources of herding with both intentional (e.g. fund managers aiming at extracting informational payoffs or improving their professional image) as well as unintentional (e.g. characteristic trading) reasons. It is, however, interesting to note the absence of research on whether – and why – fund managers herd in the specific segment of markets known as *frontier markets*. The term “frontier markets” has been used to describe those emerging markets whose financial systems in general and stock exchanges in particular exhibit a lesser degree of development compared to traditional, longstanding emerging markets (De Groot et al., 2012). Such environments are normally typified by inexperienced market participants, low overall trading activity and incomplete institutional frameworks with weaknesses in the presence and enforceability of disclosure rules. Adding to the above the fact that the infancy stage of their financial development precludes the possibility of their institutional investment section being developed suggests that fund managers in frontier markets lack the investment experience of their counterparts in developed markets while at the same time having to operate in environments of high risk and questionable informational quality. The presence of such conditions increases the likelihood that institutional herding in frontier markets will not only be significant but also intentional and it is this issue that we seek to address in our study.

To examine whether fund managers herd in frontier markets and whether they do so intentionally or not, we use two unique data sets of institutional holdings involving quarterly portfolio statements of funds from Bulgaria and Montenegro for the January 2005 – December 2012 period. Our results denote that institutional herding in both markets is significant, while after partitioning our data on the basis of various market states (market returns; market volatility; market volume) we find that it is intentional, driven by informational and career considerations. We also find that Bulgarian (Montenegrin) fund managers herd significantly after (before) the outbreak of the 2008 global crisis and we attribute this to a volume-effect, since Montenegro (Bulgaria) saw the heaviest trading activity before (after) the crisis' outbreak.

Our research produces important contributions to the extant literature on herd behaviour. First, our study contributes to our understanding of institutional herding by providing evidence on the propensity of fund managers to herd in frontier markets for the first time in the literature. Key to this contribution is the fact that, unlike their developed and emerging counterparts, frontier markets are very small in terms of the size of both their fund-industry and their capitalization/volume; this allows us the opportunity to test for institutional herding under very concentrated market conditions, entailing features (e.g. a small number of fund managers facilitates peer-observation) capable of inducing imitation among institutional investors. Secondly, our findings confirm that, although fund managers in frontier markets can herd equally intentionally as their peers in more developed markets (Holmes et al., 2013; Gavriilidis et al., 2013), their herding is significantly influenced by their markets' volume. Considering the relative illiquidity of frontier markets, this indicates that the decision of their fund managers to herd is heavily reliant on the prevailing trading activity, since high volume renders their herding feasible by reducing trading frictions, thus allowing "good" fund managers to trade on their information and "bad" fund managers to copy them.

In view of the growing interest on behalf of the global investment community in frontier markets[1], the findings presented in our study are of particular interest to investors, as they can be used as input to inform their strategies in these markets, more so in view of recent evidence (Goetzmann et al., 2005; Speidell and Krohne, 2007; Berger et al., 2011) regarding the diversification benefits conferred by investing in frontier markets. From the perspective of frontier markets' regulators our results should be of concern, since the presence of intentional institutional herding can lead funds to choose sub-optimal portfolio allocations; what is more, given the leverage funds command in these markets and the latter's overall low trading activity, their herding can also be potentially destabilizing, thus accentuating the need for regulatory measures aiming at reducing the herding tendencies of funds in these markets.

The rest of the paper is organized as follows: section 2 presents the key motivations (intentional and unintentional) underlying the decision of fund managers to herd. Section 3 introduces the data sets and the empirical framework employed; section 4 outlines and discusses the empirical results and section 5 concludes.

2. Institutional Herding and its Motivations

Herding as a practice constitutes a “passive” (in the sense that funds engaging in herding end up copying their peers) management strategy, leading to portfolio-allocations that may be neither optimal, nor in line with investors’ risk-preferences, compared for example to an active management strategy. The prevalence of herd behaviour among fund managers is considered undesirable from a regulatory viewpoint too, since institutional investors’ dominance in equity trading internationally implies that any herding on their behalf can destabilize prices and render markets riskier (Goodhart et al., 1999). A key issue arising is why market participants as sophisticated as fund managers would choose to resort to peer-mimicking in their trades instead of relying on their private signals. A series of studies (Bikhchandani and Sharma, 2001; Holmes et al., 2013; Gavriilidis et al., 2013) argued that the choice to herd can be either motivated by intent or be the product of an environmental state commonly affecting all investors that prompts similar reactions on their behalf (“spurious” herding).

To begin with, herding is **intentional** when the choice to herd is motivated by the anticipation of a positive externality (a benefit) and usually presupposes a relative view of one’s position vis-à-vis others. A fund manager, for example, may consider his information to be of low quality or his information-processing abilities to be inadequate compared to his peers'; in other words he may perceive himself to be in an asymmetric situation relative to other fund managers. It would, therefore be rational for him to copy his peers' trades, in order to free-ride on their informational superiority and extract *informational payoffs* (Devenow and Welch, 1996). If fund managers end up discarding their private signals in favour of their peers' actions, this will slow down the signal-flow to the market (information blockage), render the public pool of information poorer and lead to the evolution of informational cascades (Banerjee, 1992; Bikhchandani et al., 1992). A second possibility is that the benefits anticipated by fund managers when choosing to mimic their peers intentionally are linked to *professional payoffs*. The issue here relates to the relative performance assessment investment professionals are subject to periodically (e.g. every quarter). A "bad" manager (one e.g. of low ability) has every incentive to copy his "good" peers in order to conceal his true quality and improve his professional image (i.e. appear "good" too). If this happens, the assessment process within asset management companies faces a jamming, since it grows impossible to determine whether a manager performs well as a result of his high ability or his peer-mimicking (Scharfstein and Stein, 1990). Ability aside, reputation can also be a factor here, with less reputed finance professionals being more susceptible towards following the actions of the well-reputed ones (Trueman, 1994; Clement and Tse, 2005).

However, it is possible that institutional herding is **unintentional**, due to the presence of factors in the funds' industry common to all managers leading them to exhibit convergence in their trades. It is possible, for example, that fund managers behave similarly due to the innate *relative homogeneity* (De Bondt and Teh, 1997; Wermers, 1999) in their ranks. The idea here is that investment professionals bear certain common traits in terms of their educational background, their investment experience, the signals received (they have to analyze the same/similar indicators) and their interpretation, as well as the regulatory framework[2] they are subject to. It is also possible that herding is unintentional due to the common – among fund managers – practice of *style investing* (e.g. Bennett et al., 2003). If several funds pursue contrarian strategies, for example, one would expect correlation in their trades (they would herd into recent losers and out of recent winners) as a result of the same style followed, without this being due to intent.

In view of the above motives underlying institutional herding, the possibility of fund managers imitating each other in their trades has been extensively researched during the past two decades with evidence from a large array of long-established developed and emerging markets - including the US (Li and Yung, 2004; Sias, 2004; Choi and Sias, 2009; Liao et al., 2011), Germany (Walter and Weber, 2006; Kremer and Nautz, 2013), South Korea (Choe et al., 1999; Kim and Wei, 2002a; 2002b) and Taiwan (Hung et al., 2010; Lu et al., 2012) - suggesting that investment professionals exhibit significant mimicry in their trading behaviour. However, no evidence has as yet been reported regarding institutional herding for the specific subset of markets known as frontier markets, despite the increased attention they have been receiving recently from professional investors (De Groot et al., 2012). To begin with, frontier economies are free-market in their orientation, undergoing their initial steps in terms of economic development (Umland, 2008), as opposed to other long-established emerging markets. The high growth rates frontier markets tend to exhibit coupled with their young and fast-growing populations suggest a sustainable growth potential for these economies for the future (Behar and Hest, 2010). Given the infancy stage of their financial systems, their regulatory frameworks are expected to be incomplete, with challenges possibly arising in the implementation of their rules

(2010 Meketa Investment Group white paper on frontier markets, p. 6). In such environments, corporate disclosure is likely to be less credible and transparency is expected to be low, leading investors to place less faith in public information and - given their relatively limited investment experience – grow more susceptible to non-fundamental trading patterns (such as herding). Stock exchanges in frontier markets tend to enjoy overall low trading activity, while the low per capita income in most of these markets further contributes to their illiquidity as it fails to allow for wide participation on behalf of their local investors (Kallinterakis et al., 2010). Despite their market-orientation, the presence of restrictions over the entry and trading conduct of foreign investors (Behar and Hest, 2010) is a likely occurrence in frontier markets, further curtailing investors' participation there. Equity listings in frontier markets often involve rather high numbers of stocks, most of which are expected to suffer from thin trading[3], in view of the aforementioned low volumes characterizing these markets.

Funds operating in such environments can consider herding a viable strategy for several reasons. The very fact that public information is of uncertain quality constitutes a good first motive for a manager to observe (and copy) the trades of his peers for the purpose of extracting informational payoffs. This is a strong possibility in frontier markets, since fund managers there would be expected to be less experienced compared to their counterparts in developed markets and would thus be more inclined towards imitating their peers as opposed to relying on their own private signals. What is more, the fact that fund industries in frontier markets are relatively underdeveloped compared to their more advanced peers implies that the number of funds in these markets is bound to be small, thus facilitating observation in the first place and rendering it more likely that fund managers know each other. Under such conditions, "bad" managers are aware of who is "good" in their industry which makes it easier to know whom to follow; this is an important issue here, since any underperformance in a small professional community is likely to confer a more personalized stigma over its bearer (Do et al., 2008).

Consequently, the discussion has so far indicated that the specific conditions in frontier markets encourage intentional herding among institutional investors in anticipation of both informational as well as professional payoffs; however, no evidence on the issue of herding significance and intent has been produced to date for these markets. Our study contributes to the extant literature by investigating institutional herding in two frontier markets (Bulgaria and Montenegro) and produces results indicating that fund managers not only herd significantly in these markets, but also that their herding is due to intent. The next section presents the data used in this paper, followed by the empirical design employed to assess the significance and intent of herding.

3. Data - Methodology

3. 1 Data

Our study is based on two unique data sets involving quarter-end reports of domestic equity fund-holdings from two markets, Bulgaria and Montenegro, for the January 2005 – December 2012 period. Data on Bulgarian fund-holdings were obtained from Bulgaria's Financial Supervision Commission and include a total of 25 funds; data on Montenegrin fund-holdings were obtained both from the Montenegro Stock Exchange and individual funds and include a total of 6 funds. The data in both countries' reports contains information on the name of each stock held, its ISIN code, the number of shares of each stock held by the fund at the end of each quarter and the value (in Bulgarian Leva for Bulgarian funds; in Euros for Montenegrin funds) of the fund's position in each stock at the end of each quarter. We excluded from our sample those funds whose reports were filed at the semi-annual frequency as well as funds whose reports were not available for each consecutive quarter for our sample period.

Table 1 presents some descriptive statistics regarding our two data sets. According to panel A, the 25 Bulgarian funds of our sample invested at any point during our sample period in 143 stocks of their home-market; the equivalent figure for the 6 Montenegrin funds of our sample is 82. Although funds in each market appear to invest in a rather wide selection of stocks, the overall picture does not indicate considerable trading activity. In the case of Bulgaria, the average number of stocks *held* by at least one fund per quarter is 86.2 (panel B), whereas the average number of stocks *actively traded* by at least one fund per quarter is 59.7 (panel C). Similarly for Montenegro, the average number of stocks *held* by at least one fund per quarter is 58.9 (panel B) and the average number of stocks *actively traded* by at least one fund per quarter is 25.8 (panel C). In other words, it seems that, on average, about a third of the stocks held by Bulgarian funds and just over half of the stocks held by Montenegrin funds each quarter are not traded at all. What is more, institutional participation per stock per quarter is notably thin. In the case of Bulgaria, the average number of *holding* funds per stock per quarter equals 3.8 (panel D), whereas the average number of *active* funds per stock per quarter is 3.0 (panel E). As far as Montenegro is concerned, the average number of *holding* funds per stock per quarter equals 2.3 (panel D), whereas the average number of *active* funds per stock per quarter is 1.5 (panel E). Therefore, the overall picture from our sample markets is one where trading activity is undertaken each quarter on average for a fraction of the stocks held and by a very small number (two to three) of funds per stock. The small size of both markets' fund industries increases the probability that fund managers there know each other, while the very fact that each fund manager has, on average, one or two of his peers to monitor for each stock he invests in, facilitates peer-observation, thus rendering these markets very appealing in terms of both studying herding and establishing intent behind it.

Panels F and G present a series of descriptive statistics (mean; median; standard deviation; quartiles' distribution) for the full sample period (panel F) and each year (panel G) of the market returns/volatility/volume for Bulgaria and Montenegro, based on the BG40 and NEX20 indices respectively. On balance, the average return for Montenegro is positive for the full sample period (around 4.6 percent; see panel F), mainly driven by the strong performance of the NEX20 index during the 2005-2007 period (cumulative return equal to almost 75 percent) as the figures in panel G indicate. Conversely, the average return of the BG40 for the full sample period is -0.19 percent (see panel F), something largely attributed to the fact that the BG40's performance during the bullish period of 2005-2007 (cumulative return equal to almost 37 percent) was less strongly positive compared to Montenegro's. As regards volatility, its mean value appears always larger for Montenegro, something further confirmed when examining its median value, both for the full sample period and year-on-year. Looking at the volume figures, we notice that trading activity exhibits an overall rising trend in Bulgaria, as its average annual value rises steadily between 2005-2007, decreases significantly during 2008-2009 and increases again afterwards; conversely, average volume in Montenegro peaks in 2007 and dwindles to low levels afterwards. Overall, the highest average volume values in Montenegro are observed during the 2005-2007 period and 2009, with the highest average volume values in Bulgaria observed during the 2007-2009 period and 2012. Combining the above with the fact that the average volume in Montenegro was larger than Bulgaria's during the 2005-2007 period (with the picture reversing itself afterwards), one can notice that the heaviest trading activity in Bulgaria (Montenegro) was observed after (before) the outbreak of the 2008 global financial crisis.

3. 2 Methodology

The seminal measure used in the literature to identify herding among fund managers was the one proposed by Lakonishok et al. (1992), according to which, herding is calculated based on the fraction of funds buying stock *i* in a given period *t* as follows:

$$H_{i,t} = [|B_{i,t}/(B_{i,t} + S_{i,t}) - p_t|] - AF_{i,t} \tag{1}$$

In the above equation, $B_{i,t}$ ($S_{i,t}$) represents the fraction of funds increasing (decreasing) their positions in stock *i* (effectively, the proportion of buyers and sellers, respectively) during period *t*. p_t is calculated as the number of "buyers" relative to the total number of active funds in the market across all stocks within period *t*, the term "active" here referring only to those funds which have changed their position in stock *i* within the period. Essentially, p_t is calculated by averaging $B_{i,t}/(B_{i,t} + S_{i,t})$ across all stocks within a period, reflecting the average institutional demand for stocks within that period, or equivalently the expected proportion of buyers for that period (Wermers, 1999). If funds trade independently from each other (i.e. there is no herding), $B_{i,t}/(B_{i,t} + S_{i,t}) = p_t$ for any stock *i* during period *t*. To account for the random variations of $B_{i,t}/(B_{i,t} + S_{i,t})$ around p_t, Lakonishok et al. (1992) employ an adjustment factor ($AF_{i,t}$) which is equal to the expected value of $|B_{i,t}/(B_{i,t} + S_{i,t}) - p_t|$ under the assumption that $B_{i,t}$ follows a binomial distribution with probability of "success" $p = p_t$. The presence of herding in this case is asserted via the deviations of $|B_{i,t}/(B_{i,t} + S_{i,t}) - p_t|$ from its expected value (reflected through the $AF_{i,t}$). The Lakonishok et al. (1992) measure has been widely utilized in several herding studies, yet has been found to suffer from drawbacks rendering it less appropriate for the context of our study. First of all, it implicitly assumes that short-selling is possible; however, the rudimentary institutional design and relatively low trading volume typifying frontier markets would suggest that short-selling is an activity either not allowed or not feasible in these markets. If short-selling is not allowed/feasible, then the buy-side in the Lakonishok et al. (1992) measure will appear stronger (the number of funds selling a stock at the end of each period will never be more than the number of funds holding the stock at the beginning of the period), leading to distortions in the binomial distribution of $B_{i,t}$ and, ultimately, upward biases in $B_{i,t}$ – and herding (for a concise discussion of this, see Wylie, 2005). Secondly, their measure assumes that the ex-ante probability of a fund manager buying a stock depends exclusively on the degree of herding (Wylie, 2005); in reality, the low trading volume of frontier markets may pose far greater a concern to the buy-decisions of their fund managers, since illiquidity can introduce frictions in the trading process by delaying the execution of a buy-order, irrespective of whether the order was motivated by herding or not. Thirdly, the measure captures the tendency of fund managers to trade in a given direction over and above what would be expected from them if their trades were random and independent, without accounting for the fact that this correlation in institutional demand may be due to herding as much as habit-investing (the case of funds following their own trades from previous periods).

However, disentangling between funds following each other versus funds following their past trades merits an intertemporal examination of institutional demand, something not possible in the Lakonishok et al. (1992) measure, since it identifies herding within – rather than across – periods.

The above prompted us to empirically identify herding in this study by employing the design proposed by Sias (2004) – rather than the Lakonishok et al. (1992) one - which aims at extracting herding through the temporal dependence of institutional demand and which, in line with the scope of this study, has been used in research (Holmes et al., 2013; Gavriilidis et al., 2013) for the purpose of examining whether institutional herding is intentional or not. In this model's context, institutional demand is defined as the raw fraction of funds buying security *k* in period *t* and is denoted by $\mathrm{Raw}\Delta_{k,t}$, as follows:

$$Raw\Delta_{k,t} = \frac{Number\ of\ funds\ buying\ security\ k\ during\ period\ t}{Total\ number\ of\ funds\ active\ in\ security\ k\ during\ period\ t} \qquad (2)$$

If a fund increases its position in security *k* in period *t* compared to period *t-1*, it is identified as a "buyer"; conversely, if it decreases its position in security *k* in period *t* compared to period *t-1*, it is identified as a "seller". The next step is to standardize $Raw\Delta_{k,t}$ by subtracting in each period from each security's $Raw\Delta_{k,t}$ its cross-sectional (across all active stocks in that period) average and divide it by its cross-sectional standard deviation:

$$\Delta_{k,t} = \frac{\mathrm{Raw}\Delta_{k,t} - \overline{\mathrm{Raw}\Delta_{t}}}{\sigma(\mathrm{Raw}\Delta_{k,t})} \qquad (3)$$

Sias (2004) assumes that $\Delta_{k,t}$ follows an autoregressive process of order one in order to gauge the temporal dependence in the structure of institutional demand; more specifically:

$$\Delta_{k,t} = \beta_t \Delta_{k,t-1} + \varepsilon_{k,t} \qquad (4)$$

Equation (4) has both its sides standardized and since it bears only one explanatory variable ($\Delta_{k,t-1}$), its slope (β_t) constitutes the cross-sectional correlation between institutional demand in periods *t* and *t-1*, respectively. Sias (2004) showed that the slope-coefficient can be broken into two components, the former being due to funds following their own past trades and the latter being due to funds following the trades of their peers (herding):

$$\begin{aligned} &\beta_t = \rho(\Delta_{k,t}, \Delta_{k,t-1}) = \\ &\left[\frac{1}{(K-1)\sigma(Raw\Delta_{k,t})\sigma(Raw\Delta_{k,t-1})}\right] x \sum_{k=1}^{K}\left[\sum_{n=1}^{Nk,t} \frac{(D_{n,k,t} - \overline{Raw\Delta_t})(D_{n,k,t-1} - \overline{Raw\Delta_{t-1}})}{N_{k,t}N_{k,t-1}}\right] \\ &+\left[\frac{1}{(K-1)\sigma(Raw\Delta_{k,t})\sigma(Raw\Delta_{k,t-1})}\right] x \sum_{k=1}^{K}\left[\sum_{n=1}^{Nk,t} \sum_{m=1, m\neq n}^{Nk,t-1} \frac{(D_{n,k,t} - \overline{Raw\Delta_t})(D_{m,k,t-1} - \overline{Raw\Delta_{t-1}})}{N_{k,t}N_{k,t-1}}\right] \end{aligned} \qquad (5)$$

$N_{k,t}$ is the total number of funds which are active in stock *k* in period *t*, $D_{n,k,t}$ is a dummy variable whose value equals one (zero) if fund *n* is a buyer (seller) of stock *k* in period *t*, $Raw\Delta_{k,t}$ is the raw fraction of funds buying stock *k* in period *t*, $\sigma(Raw\Delta_{k,t})$ is the cross sectional standard deviation of $Raw\Delta_{k,t}$ across all active securities in period *t* and $\overline{Raw\Delta_t}$ is the cross-sectional average of $Raw\Delta_{k,t}$ in period *t*. The first additive component of equation (5) represents that part of β_t due to funds following their own past trades; a positive value of this component would suggest that funds in period *t* trade in the direction of their trades in the previous period, while a negative value would suggest that funds in period *t* trade in a direction opposite to that of their trades in period *t-1*. The second additive component of equation (5) reflects that part of β_t due to funds following other funds (herding); a positive (negative) value for this component indicates that funds in period t follow (trade against) other funds' trades of period *t-1*.

Having established with equations (4) and (5) whether institutional herding is significant or not in our sample markets, the next step is to assess whether it is motivated by intent or not. To that end, we condition it upon a variety of factors reflective of market conditions (market returns; market volatility; market volume) whose relationship to herding intent is described below.

- **Market returns**: if the market exhibits negative performance, the likelihood of fund managers making a loss increases, thus leading them to face issues in their performance evaluation. As a result, during periods of market slumps, "bad" managers bear an enhanced incentive to mimic their "good" peers in order to "share the blame". More specifically, in a down-market, where most (if not, all) managers have performed badly, it is preferable for a "bad" manager's trades to appear similar to those of his "good" peers, as he can then claim he did no worse than them and attribute his performance to adverse market conditions. However, "bad" managers would also prefer to mimic their "good" peers during bullish markets, since underperforming during good times would only help confirm their poor ability. Consequently, if herding is intentional (i.e. driven by informational and professional reasons), a relationship between herding and the market's return (which would translate into differences in herding between periods of positive and periods of negative market returns) would be expected to arise, although the direction of this relationship is ambiguous. Conversely, if herding is spurious (due, e.g. to relative homogeneity or characteristic trading), we would not expect to witness any such differences arising in herding significance. If herding is driven by relative homogeneity and changes in the market's return quarter-to-quarter (given the quarterly frequency of our data) have an impact over herding, this would imply that the population composition of fund managers exhibits significant variability between successive quarters, something highly unlikely. If herding is driven by characteristic trading, then as Holmes et al. (2013) argued, it is likely that the market performance can affect the profitability of investment styles, yet not the propensity of people to engage in those (i.e. their level).

To proxy for market returns in our sample markets, we use the quarter-end closing prices of the BG40 (for Bulgaria) and NEX20 (for Montenegro) indices, calculate their quarterly log-differenced returns and, for each index, rank those returns in ascending order. Using the β_t series from equation (4) and its two components ("funds following their own trades"; "funds following the trades of other funds") from equation (5) for each market, we partition β_t and its two components into two parts contingent upon whether the market return of the quarter is positive or negative, respectively.

- **Market volatility**: if volatility in a market is high, the public pool of information becomes more difficult to process and "bad" managers (with below-average processing skills) may, thus be prompted to copy their "good" peers in order to reduce the perceived complexity of the informational environment (and improve their professional image). If volatility in a market is low, this can also encourage "bad" managers to mimic their "good" peers, since it makes it easier for "bad" managers to identify the behaviour of their "good" counterparts (Holmes et al., 2013). Consequently, if herding is due to intent, we would anticipate a relationship to exist between herding and market volatility (we would expect herding to exhibit differences between periods of high and periods of low volatility), though again here it is not possible to assert the sign of this relationship. Conversely, if herding is spurious (due, e.g. to relative homogeneity or characteristic trading), we would not expect to witness any such differences arising in herding significance; this is because neither relative homogeneity among fund managers, nor the level of style investing would be expected to vary with market volatility.

We calculate market volatility for each of the two markets for each quarter using the daily closing prices of the BG40 (for Bulgaria) and NEX20 (for Montenegro) indices based on the approach proposed by Schwert (1989); following that, we rank the quarterly volatility figures in ascending order, split them into a high-volatility half and a low-volatility half and then partition β_t and its two components accordingly.

- Market volume: trading volume is considered to be an effective information flow proxy (Jiang and Kryzanowski, 1998), since high trading activity in a market encourages the participation of informed traders (it allows them to trade more easily on their information by reducing frictions in the trading process; Romano, 2007). If so, then the visibility of "good" fund managers (key candidates for informed traders) in the market should increase during periods with high volume, thus rendering it easier for "bad" managers to mimic them. However, it is possible that periods with low trading activity are also conducive to institutional herding. Fund managers can experience problems in seeing their orders being executed during low-volume periods, thus being faced with increased liquidity risk and performance-related issues. The latter here arise when a fund manager wishes to rid his portfolio off certain stocks (e.g. recent losers) and cannot sell them due to the low volume in the market hindering transactions. Under such conditions, investing into (or out of) the same stocks as their peers is a rational option; because stocks that other funds will be flocking towards will enjoy higher liquidity, this guarantees that any order placed for these stocks will be executed with higher probability. If herding is intentional, we would therefore expect a relationship between herding and market volume to unfold (herding would exhibit differences between periods of high and periods of low volume), yet as indicated above, its direction would be hard to assert. Conversely, if herding is unintentional, such a relationship would not be expected to arise, because variations in market volume between quarters would not be expected to affect either the relative homogeneity among fund managers, or the level of their characteristic trading. To control for the impact of market volume over herding, we use the daily volume (in shares) observations of the BG40 (for Bulgaria) and NEX20 (for Montenegro) indices, aggregate them for each index in each quarter, rank the quarterly volume figures of each market in ascending order, split them into a high-volume half and a low-volume half and then partition β_t and its two components accordingly.

All data on the daily/quarter-end closing prices and daily volumes of the BG40 and NEX20 indices were obtained from the websites of the Bulgarian and Montenegrin stock exchanges, respectively. Controlling for the impact of market returns, market volatility and market volume over institutional herding concludes our empirical investigation of intent among fund managers in Bulgaria and Montenegro. However, since our sample window includes the outbreak of the 2008 global credit crisis, we consider it appropriate to assess its impact over institutional herding in our sample markets, more so given research evidence stipulating that financial crises are turning points in herding-evolution (Hwang and Salmon, 2004). To that end, we split our sample period into a pre-crisis (January 2005 – December 2007) and a crisis (March 2008 – December 2012) sub-period and then partition β_t and its two components in line with this split.

4. Results – Discussion

We begin by presenting the results from equations (4) and (5), i.e. the estimates of β_t and its two components, "funds following their own trades" and "funds following the trades of other funds" for the Bulgarian and Montenegrin markets. We present results for stocks for which there was one or more funds trading (panel A in tables 2-6) and for which there were two or more funds trading (panel B in tables 2-6). The two thresholds employed here are in line with what we discussed earlier regarding the low (two to three) average number of active funds per stock in the two markets and are used here to gauge the robustness of our results. For the purpose of our discussion, any reference of statistical significance will pertain to estimates significant either at the 5 or 1 percent significance levels.

Table 2 shows that the quarterly cross-correlation (β_t) of institutional demand for both markets is positive, highly significant and much greater in size compared to Sias' (2004) estimate; whereas Sias in the US context reports an estimate of 0.119 for β_t, we report higher values for Bulgaria (0.237 for ≥ 1 fund and 0.252 for ≥ 2 funds) and, in particular, for Montenegro (0.743 for ≥ 1 fund and 0.767 for ≥ 2 funds) which suggest the presence of strong temporal dependence in funds' trades in our sample markets[4]. Thus, whereas the quarter-on-quarter cross-correlation of institutional demand is around 12 percent in the US in Sias' sample, the corresponding figures we report for Bulgaria (24-25 percent) and Montenegro (74-77 percent) are considerably higher, suggesting that funds' trades are, on average, far more correlated over time in frontier markets than in developed ones. The temporal dependence of Bulgarian funds' equity-demand is herding-driven, as the "funds following other funds' trades" part is significantly positive (0.289 for ≥ 1 fund and 0.295 for ≥ 2 funds); conversely, their habit investing seems to bear no effect over it, with the “funds following their own trades” part appearing insignificantly negative (-0.052 for ≥ 1 fund and -0.043 for ≥ 2 funds). The temporal dependence of Montenegrin funds’ demand appears to be motivated equally strongly both by herding (the “funds following other funds’ trades” part equals 0.362 for ≥ 1 fund and 0.403 for ≥ 2 funds and is statistically significant in both cases) and habit investing (the “funds following their own trades” part equals 0.381 for ≥ 1 fund and 0.364 for ≥ 2 funds, and is statistically significant in both cases).

Having established that institutional herding is significant in our two frontier markets, the next step is to examine whether it is driven by intent or not by assessing its interactions with different market states in line with what we mentioned in the previous section. We first partition β_t and its two components into two parts, contingent upon whether the market’s quarterly performance has been positive or negative (i.e. whether the market in quarter t has gone up or down relative to quarter t-1) and report the results in table 3. As the table indicates, β_t appears positive in Bulgaria and Montenegro in all tests, with its values in absolute terms being larger during negative as opposed to positive market quarters in all cases. However, its significance in Bulgaria appears during quarters with positive market performance, while disappearing during negative market quarters; conversely, its significance in Montenegro manifests itself irrespective of the market’s performance. Overall, the coefficients reported in table 3 are largely in line with those reported in table 2, suggesting that the quarter-on-quarter cross-correlation of institutional demand in our sample frontier markets is substantially higher (18 percent and above) compared to the US one reported in Sias (2004), even when conditioning upon market performance. The insignificance of the “funds following their own trades” part documented in table 2 for Bulgaria is confirmed here, with its estimates appearing insignificant during both up and down quarters. On the other hand, that part appears significant for Montenegro irrespective of the market's performance. The part "funds following other funds' trades" appears significant for Bulgaria and Montenegro only during periods of positive market returns[5], denoting an impact of market returns over institutional herding and suggesting that the latter is not spurious but rather driven by intent. A possible explanation here is that this is due to "bad" managers tracking the trades of their better-informed peers during market rallies in order to avoid making poor investments - and the concomitant personalized stigma conferred by underperforming during up markets. What is more, given the evidence (Grinblatt and Keloharju, 2001; Lamont and Thaler, 2003) suggesting that bullish markets tend to attract more noise investors, it is possible that the institutional herding documented here during up markets is the result of a concerted effort on behalf of fund managers to exploit noise traders during periods of optimistic sentiment.

We now examine whether institutional herding in our sample markets interacts with market volatility; to that end, we rank the quarterly values of market volatility in ascending order, split them into two halves ("high volatility"; "low volatility") and partition β_t and its two components accordingly. Results from table 4 indicate that β_t is significantly positive for both markets in all cases, without its difference between periods of high and periods of low volatility exhibiting any statistical significance. Compared to Sias (2004) estimates, the β_t –values reported here (16 percent and above) are in excess of those reported for funds in the US. Again here, the "funds following their own trades" part appears insignificant (significant) for Bulgaria (Montenegro) for both volatility halves, thus confirming our earlier findings in tables 2 and 3 on this part for the two markets. Herding appears insignificant in Bulgaria during periods of both high and low volatility as the estimates of the "funds following others' funds trades" indicate; conversely, the estimate of that part appears significant during periods of low volatility for Montenegro[6], suggesting the presence of intent in fund managers' herding there, possibly due to the fact that tranquil market conditions render it easier for less informed managers to monitor the trades of their better informed peers.

We now turn to assess whether market volume impacts upon institutional herding; similarly to controlling for the impact of volatility previously, we rank the quarterly values of market volume in ascending order, split them into two halves ("high volume"; "low volume") and partition β_t and its two components accordingly. Results in table 5 show that β_t is positive and significant for both markets in all cases; its difference between periods of high and periods of low volume exhibits no statistical significance. The values of β_t hover above 24 percent in our tests, again confirming that institutional demand in these two markets bears a stronger persistence quarter-on-quarter compared to the US. The "funds following their own trades" part remains insignificant in Bulgaria regardless of the volume levels; conversely, this part is significant for Montenegro for both high and low volume periods. The "funds following other funds' trades" part is significant for both markets during high volume periods[7], thus suggesting that fund managers' herding is motivated by intent. The source of this intent could be attributed to informational reasons, since high volume reduces frictions in trading (e.g. thin trading) and encourages the participation of informed investors ("good" fund managers constitute prime candidates for this role), thus increasing their visibility in the market – and allowing less informed fund managers to track their trades more easily.

We conclude our empirical investigation by assessing the impact of the ongoing global credit crisis over institutional herding. Table 6 presents the estimates of β_t and its two components for the pre-crisis (January 2005 – December 2007) and crisis (March 2008 – December 2012) sub-periods. As the table shows, β_t is significantly positive for our markets both before and after the crisis' outbreak, without its difference between the two sub-periods being significant. The "funds following their own trades" part is significant for both sub-periods for Montenegro, with the difference being significant at the 5 percent level; the significance of that part for Bulgaria appears only following the crisis' outbreak, without however its difference between the two sub-periods exhibiting any statistical significance. As regards the "funds following other funds' trades" part, it appears significant before the crisis' outbreak for Montenegro and after the crisis' outbreak for Bulgaria; the difference of the "funds following other funds' trades" estimates before and after the crisis' outbreak is insignificant for both markets. The fact that institutional herding is significant in Montenegro (Bulgaria) before (after) the outbreak of the crisis is an interesting finding and a possible explanation for it can be traced in what we discussed earlier (see table 1, panel G) regarding trading activity being the heaviest in Montenegro (Bulgaria) prior to (following) the crisis' outbreak. In line with our previous discussion of the results from table 5, this demonstrates again here that high volume promotes herding among fund managers in these two markets. The role of volume in herding is important for frontier markets, as they are characterized by relatively low overall trading activity compared to their more developed counterparts. If volume is high, it is more likely that "good" fund managers in a frontier market will be able to trade on their information and "bad" fund managers will be able to follow them (both because their "good" peers will be more visible and because high volume reduces trading frictions), thus suggesting that herding in relatively illiquid environments is facilitated during periods of increased trading activity.

5. Conclusion

This paper examines herding among fund managers in two frontier markets (Bulgaria; Montenegro) and whether it is intentional or spurious in nature. Despite the wealth of evidence on institutional herding from several long-established (developed and emerging) markets, research on this issue has never been undertaken in frontier markets to date. This is rather surprising, considering the fact that frontier markets bear several features (high concentration; low trading volumes; relatively inexperienced professional investors; incomplete institutional design; low transparency) capable of motivating herding among their fund managers. Drawing on two unique databases of quarterly fund-holdings from Bulgaria and Montenegro respectively, we find that fund managers herd significantly in both markets, with their herding being of higher magnitude compared to that reported in earlier studies on developed markets.

To assess whether fund managers in Bulgaria and Montenegro herd intentionally or not, we examine the interactions of their herding with variables reflective of the state of the market, namely market returns, market volatility and market volume by testing for herding during quarters of positive/negative market performance, high/low volatility and high/low trading volume. Our results suggest that fund managers herd in both markets during quarters of positive market performance and high volume, while in the case of Montenegro their herding also appears significant during low volatility quarters. Our findings are consistent with fund managers herding intentionally, in anticipation of informational and/or professional payoffs. More specifically, herding during up-markets can be attributed to “bad” managers tracking the trades of their “good” peers in order to avoid underperforming during positive market periods (given the career implications this will entail); it can also be due to fund managers collectively trying to exploit noise investors during euphoric times, when the presence of noise traders would be expected to be more pronounced. Herding during high volume periods can be the result of high volume reducing frictions in trading and encouraging “good” fund managers to trade on their information, thus facilitating their monitoring on behalf of their less informed peers. Controlling for the impact of the 2008 financial crisis, we find that Bulgarian (Montenegrin) fund managers herd significantly after (before) its outbreak and we showed that this is related to these markets’ trading activity, since volume in Bulgaria (Montenegro) was heavier after (before) the crisis’ outbreak. Overall, trading volume appears to exert considerable influence over institutional herding in both markets and this needs to be viewed within the specific context of frontier markets, whose trading activity is relatively low. In such environments, an increase in liquidity allows “good” fund managers the opportunity to trade on their information, thus increasing their visibility and rendering it easier for less skilled/informed fund managers to observe and track their trades, more so given that liquidity reduces trading frictions.

Our results are particularly appealing to professional investors whose interest in frontier markets has grown over the recent years as a result of evidence indicating that investing in frontier equities bears beneficial effects over international portfolio diversification. Given that less information is generally available regarding frontier markets, an investor trading in a frontier market would be naturally interested in its domestic funds' herding during different market states, as he could potentially use it as input for his strategy.

What is more, our results carry important implications for the regulatory authorities in frontier capital markets, since intentional herding among fund managers suggests lack of skills (be it in the acquisition or processing of information) and this can raise two issues. On the one hand, herding leads fund managers to choose portfolio allocations that may be sub-optimal, thus not acting in the interests of their clientele; on the other hand, the leverage commanded by funds and the relatively low turnover of frontier markets can lead their herding to cause price-pressure and potential destabilization. It is important that regulators in these markets realize the above risks and take measures aiming at encouraging diversity in the investment conduct of funds. A possibility (Gavriilidis et al., 2013) would be for regulators to issue periodical statements with the level of correlation in funds' holdings/trades alongside each fund's expense-fees in order for the public to be aware of the extent to which funds herd, before deciding to place their money with any of them.

Notes

1. Berger et al. (2011) and De Groot et al. (2012) present detailed information on the launch of a series of mutual funds and exchange-traded funds benchmarked against frontier markets, providing easier access to frontier markets' investments.
2. An example of the impact of financial regulation over the propensity of fund managers to trade similar stocks is illustrated by a series of studies on pension funds in Chile (Olivares, 2008) and Poland (Voronkova and Bohl, 2005); in both markets, pension fund managers are subject to a) limitations in the opportunity set of stocks they can invest into and b) the obligation to satisfy a pre-defined minimum-performance requirement based on relative performance evaluation. As both studies show, pension fund managers herd significantly in both markets, with the portfolios of pension funds in each market being very similar, as they are tilted heavily towards the constituents of each market's top-capitalization index.
3. According to the 2010 Meketa Investment Group white paper on frontier markets "A frontier market manager may need up to two weeks to build a position in a security, and, conversely, may need even more time to exit – even under normal market conditions" (p. 5).
4. Sias (2004) reports estimates for β_t and its component parts for stocks traded by numbers of funds exceeding certain thresholds (for stocks traded by at least 5, 10 and 20 funds). We do not employ such thresholds here given the very small (see table 1) number of active funds per stock. The 0.119-value mentioned here pertains to Sias' full-sample test (i.e. from stocks traded by at least one fund).
5. The difference in the β_t estimates and its constituent parts ("funds following their own trades"; "funds following other funds' trades") between periods of positive and periods of negative market returns is insignificant for both markets.

6. The difference in the β_t estimates and its constituent parts ("funds following their own trades"; "funds following other funds' trades") between periods of high and periods of low market volatility is insignificant for both markets.
7. The difference in the β_t estimates and its constituent parts ("funds following their own trades"; "funds following other funds' trades") between periods of high and periods of low market volume is insignificant for Bulgaria. The difference in the β_t estimates and its "funds following their own trades" part's estimates between periods of high and periods of low market volume is insignificant for Montenegro as well; however, the difference of the "funds following other funds' trades" estimates between high and low volume periods is significant at the 5 percent level for Montenegro.

References

Banerjee, A. V. (1992), 'A Simple Model of Herd Behavior', The Quarterly Journal of Economics, 107: 797-817.

Behar, G. and S. Hest (2010), 'Topics in Frontier Markets: Aligning Portfolios with the Global Economy' Northern Trust Research Report.

Bennett, J. R., R. Sias and L. Starks (2003), 'Greener Pastures and the Impact of Dynamic Institutional Preferences', Review of Financial Studies, 16: 1203-1238.

Berger, D., K. Pukthuanthong and J. J. Yang (2011), 'International diversification with frontier markets'. Journal of Financial Economics, 101, 227-242.

Bikhchandani, S., D. Hirshleifer and I. Welch (1992), 'A Theory of Fads, Fashion, Custom, and Cultural Change as Informational Cascades', Journal of Political Economy, 100: 992-1026.

Bikhchandani, S. and S. Sharma (2001), 'Herd Behaviour in Financial Markets', IMF Staff Papers, 47: 279-310.

Choe, H., B.-C. Kho and R.M. Stulz (1999), 'Do Foreign Investors Destabilize Stock Markets? The Korean Experience in 1997', Journal of Financial Economics, 54: 227-264.

Choi, N. and R.W. Sias (2009), 'Institutional Industry Herding', Journal of Financial Economics, 94: 469-491.

Clement, M.B. and S. Y. Tse (2005), 'Financial Analyst Characteristics and Herding Behaviour in Forecasting', The Journal of Finance, 60: 307-341.

De Bondt, W.F.M. and L.L. Teh (1997), 'Herding Behavior and Stock Returns: an Exploratory Investigation', Swiss Journal of Economics and Statistics, 133: 293-324.

De Groot, W., J. Pang and L. Swinkels (2012), 'The Cross-section of Stock Returns in Frontier Emerging Markets', Journal of Empirical Finance, 19: 796-818.

Devenow, A. and I. Welch (1996), 'Rational Herding in Financial Economics', European Economic Review, 40: 603-615.

Do, V., M.G. Tan and J. Westerholm (2008), 'Correlated Trading in Concentrated Market', Journal of International Finance and Economics, 8: 148-163.

Gavriilidis, K., V. Kallinterakis and M.P. Leite Ferreira (2013), 'Institutional Industry Herding: Intentional or Spurious?', Journal of International Financial Markets, Institutions and Money, 26: 192-214.

Goetzmann, W., L. Li and K.G. Rouwenhorst (2005), 'Long-term Global Market Correlations', Journal of Business, 78: 1-38.

Goodhart, C., P. Hartmann, D. Llewellyn, L. Rojas-Suarez and S. Weisbrod (1999), 'Financial Regulation: Why, How and Where Now?' Routledge, London.

Grinblatt, M. and M. Keloharju (2001), 'What Makes Investors Trade?' Journal of Finance, 56: 589-616.

Holmes, P. R., V. Kallinterakis and M.P. Leite Ferreira (2013), 'Herding in a Concentrated Market: a Question of Intent', European Financial Management, 19 (3): 497-520.

Hung W., C.-C. Lu and C.F. Lee (2010), 'Mutual Fund Herding and its Impact on Stock Returns: Evidence from the Taiwan Stock Market', Pacific-Basin Finance Journal, 18: 477-493.

Hwang, S. and M. Salmon (2004). 'Market Stress and Herding', Journal of Empirical Finance, 11: 585-616.

Jiang, L. and L. Kryzanowski (1998), 'Trading Activity, Quoted Liquidity, and Stock Volatility', Multinational Finance Journal, 1 (3): 199-227.

Kallinterakis, V, N. Munir and M. Radovic-Markovic (2010), "Herding, Illiquidity and Extreme Market States: Evidence from Banja Luka", Journal of Emerging Market Finance, 9 (3): 305-325.

Kim, W. and S.-J. Wei (2002a), 'Offshore Investment Funds: Monsters in Emerging Markets?', Journal of Development Economics, 68: 205-224.

Kim, W. and S.-J. Wei, (2002b), 'Foreign Portfolio Investors Before and During a Crisis', Journal of International Economics, 56: 77-96.

Kremer, S. and D. Nautz (2013), 'Causes and Consequences of Short-Term Institutional Herding', Journal of Banking & Finance, 37 (5): 1676–1686.

Lakonishok, J., A. Shleifer and R. Vishny (1992), 'The Impact of Institutional Trading on Stock Prices', Journal of Financial Economics, 32: 23-43.

Lamont, O.A. and R.H. Thaler (2003), 'Can the Market Add and Subtract? Mispricing in Tech Stock Carve-Outs', Journal of Political Economy, 111: 227-268.

Li, D.D. and K. Yung (2004), 'Institutional Herding in the ADR Market', Review of Quantitative Finance and Accounting, 23: 5-17.

Liao, T.-L., C.-J. Huang and C.-W. Wu (2011), 'Do Fund Managers Herd to Counter Investor Sentiment?', Journal of Business Research, 64: 207-212.

Lu, Y.-C., H. Fan and C.-C. Nieh (2012), 'The Price Impact of Foreign Institutional Herding on Large-Size Stocks in the Taiwan Stock Market', Review of Quantitative Finance and Accounting, 39: 189-208.

Meketa Investment Group (2010), 'Frontier Markets', White Paper.

Olivares, J.A. (2008), 'Rear-view-mirror Driving in Defined Contribution Systems: the Strange Formula of the Chilean Pension Funds', Applied Economics, 40: 2009 – 2019.

Romano, M. G. (2007), 'Learning, Cascades and Transaction-costs', Review of Finance, 11: 527-560.

Scharfstein, D. S. and J.C. Stein (1990), 'Herd Behaviour and Investment', The American Economic Review, 80: 465-479.

Schwert, G.W. (1989), 'Why Does Stock Market Volatility Change Over Time', The Journal of Finance, 44: 1115-1553.

Sias, R. W. (2004), 'Institutional Herding', Review of Financial Studies, 17: 165-206.

Speidell, L.S. and A. Krohne (2007), 'The Case for Frontier Markets', The Journal of Investing, 16: 12-22.

Trueman, B. (1994), 'Analyst Forecasts and Herding Behaviour', Review of Financial Studies, 7: 97-124.

Umland, K. (2008), 'Frontier Markets: New Investment Opportunities and Risks', Working Paper, Institute of Fiduciary Education.

Voronkova, S. and M.T. Bohl (2005), 'Institutional Traders' Behaviour in an Emerging Stock Market: Empirical Evidence on Polish Pension Fund Investors', Journal of Business Finance & Accounting, 32: 1537-1560.

Walter, A. and M. Weber (2006), 'Herding in the German Mutual Fund Industry', European Financial Management, 12: 375-406.

Wermers, R. (1999), 'Mutual Fund Herding and the Impact on Stock Prices', The Journal of Finance, 54: 581-622.

Wylie, S. (2005). 'Fund manager herding: A test of the accuracy of empirical results using UK data', The Journal of Business, 78: 381-403.

Table 1: Descriptive Statistics

Panel A: Sample data

Number of stocks		Number of funds		Number of quarter-holding positions		Number of stock-quarters	
Bulgaria	143	Bulgaria	25	Bulgaria	9912	Bulgaria	1880
Montenegro	82	Montenegro	6	Montenegro	5255	Montenegro	1615

Panel B: Average number of stocks per quarter held by at least one fund

	Jan 2005-Dec 2012	2005	2006	2007	2008	2009	2010	2011	2012
Bulgaria	86.2	49.5	73.3	88.5	95.8	94.0	94.7	95.3	98.2
Montenegro	58.9	50.5	57.3	58.5	60.8	60.8	60.9	61.0	61,1

Panel C: Average number of stocks per quarter actively traded by at least one fund

	Jan 2005-Dec 2012	2005	2006	2007	2008	2009	2010	2011	2012
Bulgaria	59.7	24.0	47.8	68.8	72.0	64.7	64.8	66.2	69.3
Montenegro	25.8	23.0	26.3	38.0	30.0	21.0	21.0	22.3	24,9

Panel D: Average number of holding funds per stock per quarter

	Jan 2005-Dec 2012	2005	2006	2007	2008	2009	2010	2011	2012
Bulgaria	3.8	1.7	2.1	3.5	4.7	4.6	4.6	4.7	4.7
Montenegro	2.3	2.1	2.0	2.1	2.3	2.3	2.4	2.4	2.5

Panel E: Average number of actively trading funds per stock per quarter

	Jan 2005-Dec 2012	2005	2006	2007	2008	2009	2010	2011	2012
Bulgaria	3.0	1.6	2.0	3.0	3.9	3.2	3.2	3.3	3.4
Montenegro	1.5	1.7	1.8	1.7	1.4	1.3	1.4	1.4	1.5

Panel F: Full sample period statistics on market returns/volatility/volume

	Mean	Median	Standard Deviation	Quartiles of Distribution P_25	P_50	P_75	P_100
BG40 returns	-0.0019	-0.0036	0.2219	-0.0978	-0.0036	0.1301	0.5576
BG40 volume	78255035.24	50517852.20	75302475.16	42554157	50517852	92328230	331548377
BG40 volatility	0.0960	0.0739	0.0543	0.0610	0.0739	0.1280	0.3008
NEX20 returns	0.0459	0.0220	0.2697	-0.1240	0.0220	0.2273	0.7866
NEX20 volume	62743058.44	32623533.52	68735684.98	4994210	7526724	11340384	14272456
NEX20 volatility	0.1263	0.1156	0.0598	0.0789	0.1156	0.1612	0.2967

Panel G: Year-by-year statistics on market returns/volatility/volume

	Mean	Median	Standard Deviation	Quartiles of Distribution P_25	P_50	P_75	P_100
2005							
BG40 Returns	0.0355	-0.0131	0.2007	-0.1364	-0.0131	0.2555	0.2560
BG40 Volume	20088356.25	14565305.00	15628556.42	10082345	14565305	30094368	42867555
BG40 Volatility	0.0907	0.0868	0.0356	0.0631	0.0868	0.1183	0.1354
NEX 20 Returns	0.3236	0.3211	0.1402	0.2022	0.3211	0.4449	0.4499
NEX 20 volume	49344186.82	48651043.50	19130241.03	34376901	48651044	64311472	72073881
NEX 20 volatility	0.1563	0.1351	0.0495	0.1276	0.1351	0.1850	0.2299
2006							
BG40 Returns	0.0636	0.0840	0.0747	0.0197	0.0840	0.1075	0.1301
BG40 Volume	51168166.00	43458010.00	29619234.21	33271005	43458010	69065328	93455393
BG40 Volatility	0.0494	0.0475	0.0101	0.0424	0.0475	0.0564	0.0631
NEX 20 Returns	0.2443	0.2576	0.1555	0.1469	0.2576	0.3416	0.4204
NEX 20 volume	94254544.01	75439795.35	74034723.74	37839724	75439795	150669364	193447179
NEX 20 volatility	0.0872	0.0859	0.0208	0.0724	0.0859	0.1021	0.1135

Panel G: Year-by-year statistics on market returns/volatility/volume (continued)

	Mean	Median	Standard Deviation	Quartiles of Distribution P_25	P_50	P_75	P_100
2007							
BG40 Returns	0.2755	0.2192	0.1962	0.1522	0.2192	0.3988	0.5576
BG40 Volume	120163647	58275233.00	132939841	47448022	58275233	192879272	319087303
BG40 Volatility	0.1258	0.1328	0.0382	0.0970	0.1328	0.1547	0.1624
NEX 20 Returns	0.1793	0.0161	0.4087	-0.0452	0.0161	0.4038	0.7866
NEX 20 volume	182371866	174771405	68570104.27	124957580	174771405	239786153	260510145
NEX 20 volatility	0.1632	0.1673	0.0273	0.1416	0.1673	0.1847	0.1893
2008							
BG40 Returns	-0.2506	-0.2738	0.1864	-0.4082	-0.2738	-0.0930	-0.0436
BG40 Volume	111259569	42792203.50	147033839	34466538	42792204	188052599	331548377
BG40 Volatility	0.1915	0.1677	0.0763	0.1402	0.1677	0.2429	0.3008
NEX 20 Returns	-0.2455	-0.2503	0.0997	-0.3304	-0.2503	-0.1606	-0.1407
NEX 20 volume	39314393.46	38725795.90	14703558.97	27780531	38725796	50848256	56800580
NEX 20 volatility	0.1977	0.1934	0.0814	0.1352	0.1934	0.2602	0.2967
2009							
BG40 Returns	-0.1036	-0.0346	0.3933	-0.4100	-0.0346	0.2028	0.2657
BG40 Volume	97115763.88	78868664.46	52135342.59	61843060	78868664	132388467	172116959
BG40 Volatility	0.1153	0.1187	0.0297	0.0940	0.1187	0.1367	0.1473
NEX 20 Returns	0.0484	0.0785	0.3956	-0.2673	0.0785	0.3641	0.4635
NEX 20 volume	100358221	102881773	66751010.75	44556718	102881773	156159724	168522307
NEX 20 volatility	0.1631	0.1744	0.0471	0.1288	0.1744	0.1973	0.2050
2010							
BG40 Returns	-0.0332	-0.0465	0.0853	-0.1014	-0.0465	0.0349	0.0734
BG40 Volume	48457635.74	47263890.33	6406524.22	43211227	47263890	53704045	56251610
BG40 Volatility	0.0597	0.0600	0.0036	0.0568	0.0600	0.0626	0.0635
NEX 20 Returns	-0.0721	-0.0544	0.1425	-0.1887	-0.0544	0.0445	0.0631
NEX 20 volume	13390549.79	13315904.29	3893056.66	10477188	13315904	16303912	18073747
NEX 20 volatility	0.0664	0.0648	0.0140	0.0551	0.0648	0.0777	0.0832
2011							
BG40 Returns	0.0003	-0.0250	0.1079	-0.0771	-0.0250	0.0776	0.1489
BG40 Volume	79489297.93	88452276.13	22462795.72	65608739	88452276	93369857	94674692
BG40 Volatility	0.0690	0.0725	0.0168	0.0566	0.0725	0.0813	0.0847
NEX 20 Returns	-0.0538	-0.0712	0.0720	-0.1099	-0.0712	0.0024	0.0406
NEX 20 volume	14743409.03	15310150.78	3132271.93	12424842	15310151	17061977	17784186
NEX 20 volatility	0.1063	0.1045	0.0316	0.0816	0.1045	0.1310	0.1443
2012							
BG40 Returns	0.0066	0.0071	0.0753	-0.0478	0.0071	0.0611	0.0965
BG40 Volume	98297846.85	87402405.52	58635962.53	60728636	87402406	135867058	179142676
BG40 Volatility	0.0668	0.0673	0.0054	0.0626	0.0673	0.0711	0.0726
NEX 20 Returns	-0.0566	-0.0343	0.1033	-0.1394	-0.0343	0.0262	0.0294
NEX 20 volume	8167297.00	7526724.05	4579633.68	4994210	7526724	11340384	14272456
NEX 20 volatility	0.0702	0.0716	0.0109	0.0614	0.0716	0.0789	0.0805

Sample data include quarterly holdings of funds from Bulgaria and Montenegro for the January 2005 - December 2012 period. For each quarter we calculate the number of stocks held/traded by at least one fund; for each quarter we also calculate the number of funds holding/active in each stock for stocks traded by at least one fund. Panels B-E provide the time series' averages of these figures for each year as well as their total average throughout the sample period. Panel F presents descriptive statistics (mean; median; standard deviation; distribution quartiles) on the market variables (market returns; market volatility; market volume) used in this study to identify herding intent for the full sample period (January 2005 – December 2012) while panel G presents descriptive statistics on these variables for each year separately. The returns/volatility/volume for Bulgaria correspond to those of the market's main index (BG40), while those of Montenegro to those of the NEX20 index. The returns for the full sample period and each year separately have been calculated as first logarithmic differences; the volatility for the full sample period and each year separately has been calculated based on Schwert (1989). Volume figures for both markets refer to number of shares in thousands. All data have been obtained from the respective stock exchanges (Bulgarian Stock Exchange and Montenegro Stock Exchange).

Table 2: Tests for herding – Buyer if increased position

Market	Average coefficient (β)	Partitioned slope coefficient: Funds following their own trades	Partitioned slope coefficient: Funds following others' trades	Average R^2
Panel A: No of active funds per stock ≥ 1				
Bulgaria	0.237 (0.0012)	-0.052 (0.5720)	0.289 (0.0081)	0.0647
Montenegro	0.743 (0.0003)	0.381 (0.0001)	0.362 (0.0026)	0.4810
Panel B: No of active funds per stock ≥ 2				
Bulgaria	0.252 (0.0026)	-0.043 (0.6835)	0.295 (0.0102)	0.0689
Montenegro	0.767 (0.0017)	0.364 (0.0026)	0.403 (0.0019)	0.5002

This table reports the results from equation (4), namely $\Delta_{k,t} = \beta_t \Delta_{k,t-1} + \varepsilon_{k,t}$. For each security and quarter between January 2005 and December 2012 we calculate the fraction of funds that increase their position in the security in the Bulgarian and Montenegrin markets. A fund is defined as increasing its position if it holds a greater fraction of the firm's shares at the end of the quarter than it held at the beginning. All data are standardized (i.e. rescaled to zero mean, unit variance) each quarter. We then estimate quarterly cross-sectional regressions of institutional demand on lagged institutional demand. Because there is a single independent variable in each regression and the data are standardized, these regression coefficients are also the cross-sectional correlations between institutional demand and lagged institutional demand. The first column reports the time-series' average of these 31 correlation coefficients and associated p-values (in parentheses). The second and third columns report the portion of the correlation that results from funds following their own lagged trades and the portion that results from funds following the previous trades of other funds (herding).

Table 3: Tests for herding conditional upon market returns

Market	Average coefficient (β)		Funds following their own trades		Funds following others' trades		Average R^2	
	Positive market returns	Negative market returns	Positive market returns	Negative market returns	Positive market returns	Negative market returns	Positive market returns	Negative market returns
Panel A: No of active funds per stock ≥ 1								
Bulgaria	0.1818 (0.0025)	0.2270 (0.0901)	-0.1526 (0.3609)	0.0658 (0.2467)	0.3344 (0.0489)	0.1612 (0.0731)	0.0464	0.0941
Montenegro	0.6905 (0.0012)	0.8565 (0.0009)	0.2902 (0.0166)	0.4893 (0.0121)	0.4003 (0.0043)	0.3672 (0.1725)	0.5012	0.5088
Test for equality of the mean (Bulgaria)	-0.0886		-1.2391		0.9906			
Test for equality of the mean (Montenegro)	-0.9573		-1.2852		0.1968			
Panel B: No of active funds per stock ≥ 2								
Bulgaria	0.1921 (0.0031)	0.2426 (0.0857)	-0.1498 (0.4512)	0.0569 (0.2311)	0.3419 (0.0424)	0.1857 (0.0598)	0.0472	0.0985
Montenegro	0.7331 (0.0022)	0.8726 (0.0001)	0.3003 (0.0301)	0.5025 (0.0101)	0.4328 (0.0039)	0.3701 (0.1536)	0.5233	0.5144
Test for equality of the mean (Bulgaria)	-0.0911		-1.2206		0.9721			
Test for equality of the mean (Montenegro)	-1.1121		-1.2633		0.2257			

For each security and quarter between January 2005 and December 2012 we calculate the fraction of funds increasing their position in the security in the Bulgarian and Montenegrin markets. A fund increases its position if it holds a greater fraction of the firm's shares at the end of the quarter that it held at the beginning. All data are standardized (i.e. rescaled to zero mean, unit variance) each quarter. We then estimate quarterly cross-sectional regressions of institutional demand on lagged institutional demand. Because there is a single independent variable in each regression and the data are standardized, these regression coefficients are also the cross-sectional correlations between institutional demand and lagged institutional demand. We then average our results across two distinctive groups, contingent upon whether the quarterly market return is positive or negative. The BG40 and NEX20 indices are used here to calculate market returns for Bulgaria and Montenegro, respectively. Panels A and B report the estimates from these regressions when taking into account securities traded by at least one and two funds, respectively. The first column reports the time-series' average of these correlation coefficients and associated p-values (in parentheses) for each of the two groups. The second and third columns report the portion of the correlation that results from funds following their own lagged trades and the portion that results from funds following the previous trades of other funds (herding), respectively. For each of the three estimated parts (β; funds following their own trades; funds following others' trades) we perform tests of the difference of their means between positive and negative market quarters whose t-statistics are included in each panel; with respect to these tests, * indicates significance at the 5 percent level and ** indicates significance at the 1 percent level.

Table 4: Tests for herding conditional upon market volatility

Market	Average coefficient (β)		Funds following their own trades		Funds following others' trades		Average R²	
	High volatility	Low volatility	High volatility	Low volatility	High volatility	Low volatility	High volatility	Low volatility
Panel A: No of active funds per stock ≥ 1								
Bulgaria	0.1647 (0.0039)	0.2591 (0.0469)	-0.1032 (0.4322)	-0.0322 (0.7632)	0.2679 (0.0698)	0.2913 (0.0744)	0.0332	0.0429
Montenegro	0.7747 (0.0009)	0.7609 (0.0011)	0.4914 (0.0013)	0.2903 (0.0431)	0.2833 (0.1438)	0.4706 (0.0039)	0.4965	0.5228
Test for equality of the mean (Bulgaria)	-0.3710		-0.4792		-0.2113			
Test for equality of the mean (Montenegro)	0.1964		0.6958		-0.5898			
Panel B: No of active funds per stock ≥ 2								
Bulgaria	0.1704 (0.0045)	0.2602 (0.0397)	-0.0987 (0.4809)	-0.0375 (0.7883)	0.2691 (0.0604)	0.2977 (0.0752)	0.0340	0.0436
Montenegro	0.7903 (0.0028)	0.7738 (0.0098)	0.5047 (0.0007)	0.2909 (0.0397)	0.2856 (0.1622)	0.4829 (0.0027)	0.4979	0.5240
Test for equality of the mean (Bulgaria)	-0.3588		-0.4418		-0.2165			
Test for equality of the mean (Montenegro)	0.2155		0.6800		-0.5963			

For each security and quarter between January 2005 and December 2012 we calculate the fraction of funds increasing their position in the security. A fund increases its position if it holds a greater fraction of the firm's shares at the end of the quarter that it held at the beginning. All data are standardized (i.e. rescaled to zero mean, unit variance) each quarter. We then estimate quarterly cross-sectional regressions of institutional demand on lagged institutional demand. Because there is a single independent variable in each regression and the data are standardized, these regression coefficients are also the cross-sectional correlations between institutional demand and lagged institutional demand. We then average our results across two distinctive groups, namely "high volatility" and "low volatility" contingent upon whether the market's volatility during the contemporaneous quarter falls in the top or bottom half of the sample period's quarterly volatility estimates ranked in ascending order. Volatility here is calculated every quarter using the standard deviation of daily returns in line with Schwert (1989) on the basis of BG40 and NEX20 index returns for Bulgaria and Montenegro, respectively. Panels A and B report the estimates from these regressions when taking into account securities traded by at least one and two funds, respectively. The first column reports the time-series' average of these correlation coefficients and associated p-values (in parentheses) for each of the two groups. The second and third columns report the portion of the correlation that results from funds following their own lagged trades and the portion that results from funds following the previous trades of other funds (herding). For each of the three estimated parts (β; funds following their own trades; funds following others' trades) we perform tests of the difference of their means between high and low market volatility quarters whose t-statistics are included in each panel; with respect to these tests, * indicates significance at the 5 percent level and ** indicates significance at the 1 percent level.

Table 5: Tests for herding conditional upon market volume

Market	Average coefficient (β)		Funds following their own trades		Funds following others' trades		Average R^2	
	High volume	Low volume	High volume	Low volume	High volume	Low volume	High volume	Low volume
Panel A: No of active funds per stock ≥ 1								
Bulgaria	0.2531 (0.0071)	0.2466 (0.0386)	-0.1211 (0.3122)	0.0813 (0.0614)	0.3742 (0.0382)	0.1653 (0.0892)	0.0541	0.0769
Montenegro	0.8204 (0.0013)	0.6292 (0.0007)	0.2012 (0.0068)	0.4335 (0.0019)	0.6192 (0.0067)	0.1957 (0.1681)	0.4803	0.5352
Test for equality of the mean (Bulgaria)	-0.0581		-1.6049		1.3575			
Test for equality of the mean (Montenegro)	0.9545		-2.0366		2.1667*			
Panel B: No of active funds per stock ≥ 2								
Bulgaria	0.2744 (0.0068)	0.2531 (0.0422)	-0.1059 (0.3059)	0.0809 (0.0688)	0.3803 (0.0308)	0.1722 (0.0796)	0.0547	0.0773
Montenegro	0.8404 (0.0011)	0.6379 (0.0007)	0.2200 (0.0052)	0.4377 (0.0019)	0.6394 (0.0071)	0.2002 (0.1681)	0.4899	0.5364
Test for equality of the mean (Bulgaria)	-0.0601		-1.5211		1.3672			
Test for equality of the mean (Montenegro)	0.9911		-2.0106		2.2252*			

For each security and quarter between January 2005 and December 2012 we calculate the fraction of funds increasing their position in the security. A fund increases its position if it holds a greater fraction of the firm's shares at the end of the quarter that it held at the beginning. All data are standardized (i.e. rescaled to zero mean, unit variance) each quarter. We then estimate quarterly cross-sectional regressions of institutional demand on lagged institutional demand. Because there is a single independent variable in each regression and the data are standardized, these regression coefficients are also the cross-sectional correlations between institutional demand and lagged institutional demand. We then average our results across two distinctive groups, namely "high volume" and "low volume" contingent upon whether the market's volume during the contemporaneous quarter falls in the top or bottom half of the sample period's quarterly volume values ranked in ascending order. Volume here is calculated every quarter by aggregating the daily volume observations of the BG40 and NEX20 indices for Bulgaria and Montenegro, respectively, each quarter. Panels A and B report the estimates from these regressions when taking into account securities traded by at least one and two funds, respectively. The first column reports the time-series' average of these correlation coefficients and associated p-values (in parentheses) for each of the two groups. The second and third columns report the portion of the correlation that results from funds following their own lagged trades and the portion that results from funds following the previous trades of other funds (herding). For each of the three estimated parts (β; funds following their own trades; funds following others' trades) we perform tests of the difference of their means between high and low market volume quarters whose t-statistics are included in each panel; with respect to these tests, * indicates significance at the 5 percent level and ** indicates significance at the 1 percent level.

Table 6: Tests for herding pre versus post crisis-outbreak

Market	Average coefficient (β)		Funds following their own trades		Funds following others' trades		Average R^2	
	Pre-crisis outbreak	Post-crisis outbreak	Pre-crisis outbreak	Post-crisis outbreak	Pre-crisis outbreak	Post-crisis outbreak	Pre-crisis outbreak	Post-crisis outbreak
Panel A: No of active funds per stock ≥ 1								
Bulgaria	0.2282 (0.0409)	0.2917 (0.0009)	-0.0799 (0.5796)	0.0571 (0.0367)	0.3081 (0.0781)	0.2346 (0.0039)	0.0903	0.0725
Montenegro	0.7124 (0.0006)	0.8128 (0.0045)	0.2322 (0.0003)	0.5531 (0.0042)	0.4802 (0.0008)	0.2597 (0.4177)	0.4736	0.5789
Test for equality of the mean (Bulgaria)	-0.3494		-1.1370		0.7527			
Test for equality of the mean (Montenegro)	-0.7058		-2.7357*		1.0251			
Panel B: No of active funds per stock ≥ 2								
Bulgaria	0.2569 (0.0394)	0.3066 (0.0017)	-0.0655 (0.5537)	0.0599 (0.0302)	0.3224 (0.0667)	0.2467 (0.0011)	0.1009	0.0811
Montenegro	0.7308 (0.0002)	0.8431 (0.0039)	0.2385 (0.0001)	0.5742 (0.0047)	0.4923 (0.0005)	0.2689 (0.4384)	0.4835	0.5844
Test for equality of the mean (Bulgaria)	-0.3200		-1.1112		0.7701			
Test for equality of the mean (Montenegro)	-0.7192		-2.8562*		1.0523			

For each security and quarter between January 2005 and December 2012 we calculate the fraction of funds increasing their position in the security. A fund increases its position if it holds a greater fraction of the firm's shares at the end of the quarter that it held at the beginning. All data are standardized (i.e. rescaled to zero mean, unit variance) each quarter. We then estimate quarterly cross-sectional regressions of institutional demand on lagged institutional demand. Because there is a single independent variable in each regression and the data are standardized, these regression coefficients are also the cross-sectional correlations between institutional demand and lagged institutional demand. We then average our results across two distinctive sub-periods, the one before the crisis-outbreak (January 2005 – December 2007) and the one after the crisis-outbreak (March 2008 - December 2012). Panels A and B report the estimates from these regressions when taking into account securities traded by at least one and two funds, respectively. The first column reports the time-series' average of these correlation coefficients and associated p-values (in parentheses) for each of the two sub-periods. The second and third columns report the portion of the correlation that results from funds following their own lagged trades and the portion that results from funds following the previous trades of other funds (herding). For each of the three estimated parts (β; funds following their own trades; funds following others' trades) we perform tests of the difference of their means before and after the crisis' outbreak whose t-statistics are included in each panel; with respect to these tests, * indicates significance at the 5 percent level and ** indicates significance at the 1 percent level.