Institutional herding and mood

Konstantinos Gavriilidis[a], Vasileios Kallinterakis[b,*] and Belma Öztürkkal[c]

[a]Stirling Management School, University of Stirling, FK9 4LA, United Kingdom
[b]University of Liverpool Management School, Chatham Building, Chatham Street, Liverpool L69 7ZH, United Kingdom
[c]Kadir Has University, Department of International Trade and Finance, Kadir Has Caddesi Cibali, Istanbul 34083, Turkey

Abstract

Drawing on a unique data set of daily portfolio holdings for Turkish mutual funds we investigate the relationship between mood and institutional herding on the premises of various established mood proxies (weekend effect; holiday effect; Ramadan; sunshine; new/full moon) for the January 2002 – August 2008 period. Results indicate that fund managers in Turkey herd significantly, with their herding growing in magnitude as the number of active funds per stock rises and appearing stronger on the buy- than the sell-side. Although the relationship of mood with institutional herding occasionally assumes the correct sign as per theoretical expectations, institutional herding is found to be insignificantly different across various mood states, thus denoting that mood does not impact the propensity of fund managers to herd.

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* Corresponding author. Email: V.Kallinterakis@liverpool.ac.uk

1. Introduction

Institutional investors constitute by far the most dominant investor group in contemporary financial markets, accounting for the bulk of the market capitalization and trading volume of the latter (Choi and Sias, 2009; Stambaugh, 2014). Although their sophisticated nature would presume the prevalence of rationality in their trades, international evidence suggests their particular susceptibility to behaviourally biased trading patterns[1], the most widely documented of those being herding.[2] Extant research has denoted the importance of several "rational" factors underlying the propensity of institutional investors to herd, including informational asymmetries (Gelos and Wei, 2005; Choi and Skiba, 2015), career concerns (Holmes et al., 2013; Jiao and Ye, 2014), style investing (Sias, 2004; Choi and Sias, 2009; Celiker et al., 2015) and their regulatory framework (Voronkova and Bohl, 2005), to mention but a few. However, the effect of mood (a less-than-perfectly rational factor) over institutional herding has not been investigated to date, despite the recent surge in research (Goetzmann et al., 2015; Kaustia and Rantapuska, 2016) on mood's impact over the trading behaviour of institutional investors.

Our study aims at filling this gap in the literature by investigating the relationship between mood and institutional herding in the context of the Turkish equity market drawing on a unique database of daily portfolio holdings of the market's domestic funds covering the January 2002 – August 2008 window. Utilizing various established mood proxies (weekend effect; holidays; Ramadan; sunshine; new/full moon) this research addresses two specific issues. First, we examine whether various mood states are related to the *presence* of institutional herding (i.e. its statistical significance), in general. Second, in view of literature evidence (e.g. Kamstra et al., 2003) on the propensity of mood to affect the direction of investors' trades, we assess whether these mood states are associated with the *direction* of institutional herding (i.e. whether it is buy- or sell-herding that is observed during their occurrence).

[1] Examples of such patterns include home bias (Coval and Moskowitz, 1999, 2001; Hong et al, 2005; Baik et al, 2010) and the disposition effect (Frazzini, 2006; Jin and Scherbina, 2011).

[2] See, for example, the survey papers on herding by Hirshleifer and Teoh (2003) and Spyrou (2013) as well as the recent global evidence by Choi and Skiba (2015).

Overall, we produce results showcasing the presence of significant herding among Turkish fund managers whose magnitude increases with the number of active funds per stock and which appears stronger on the buy- than the sell-side. As regards the relationship between mood and institutional herding *presence*, our results appear inconclusive. We report evidence in support of funds herding more on Mondays, during Ramadan and on days of decreased sunshine, without however that herding being significantly different from that manifested on Fridays, outside Ramadan and on days of increased sunshine, respectively. Results further suggest the presence of some pre holiday herding, with no clear relationship emerging between funds' herding and new/full moon days.

Turning now to the relationship between mood and institutional herding *direction*, we find Ramadan-days presenting us with evidence of buy-herding only (which - for those cases when it is present - is always stronger, compared to that of non-Ramadan days), while sell-herding appears exclusively present outside Ramadan. What is more, buy- (sell-) herding is stronger on increased (decreased) sunshine days; buy-herding appears stronger compared to sell-herding on increased sunshine days, while decreased sunshine days present us with no consistent pattern on whether it is buy- or sell-herding that is stronger for them. Evidence of buy-herding for Mondays and Fridays is rather limited (surfacing relatively more on Mondays than Fridays), with its magnitude being larger for Mondays compared to Mondays' sell-herding (for those cases where both buy- and sell-herding are significant on Mondays). Conversely, sell-herding appears consistently present on Fridays and always stronger than sell-herding on Mondays (when the latter is present). The stronger buy-herding on Mondays is qualitatively interesting, running counter to expectations related to "Monday Blues", according to which one would expect more selling activity on Mondays (see e.g. Gondhalekar and Mehdian, 2003). With returns for Turkish stock indices having been documented as being the lowest on Mondays compared to other days of the week (Demirer and Karan, 2002; Oğuszoy and Güven, 2003; Cinko and Avci, 2009), it is entirely plausible that Turkish fund managers are aware of the Monday effect's presence in their market and are, thus aiming at buying more on Monday in order to take advantage of the day's low prices. With regards to the sell-herding observed on Fridays, it may well be due to profit taking of a short term nature, since stock index returns in Turkey have traditionally been found to be the highest on Fridays.[3] New/full moon days present us with very mixed evidence of buy-/sell-herding, while very little evidence of herding of either direction surfaces around holidays. However, aside from very few exceptions (identified mainly with some significant herding differences between Mondays and Fridays) most differences in both buy- and sell-herding are statistically insignificant across various mood states, thus indicating that mood does not shape institutional herding direction significantly.

We further test for the robustness of our results by performing a series of tests. First, we repeat all estimations excluding tracker funds (whose trades are, by definition, motivated by benchmark-tracking) from the sample and report results near-identical to those from the full-sample estimations. Second, we control for possible size effects by sorting stocks in quintiles based on previous-year market capitalization rankings; results again indicate that institutional herding is insignificantly different across various mood states irrespective of stock-size (and appearing the least strong for stocks of the lowest capitalization). Third, because our results are based on univariate tests, where only a single mood proxy is accounted for at a time, we perform multivariate analyses by regressing institutional herding over all the mood proxies simultaneously; results again denote the absence of any significant relationship between mood and institutional herding.

Our work contributes significantly to behavioural finance research in distinct ways. To begin with, it assesses the relationship between mood and institutional herding for the first time in the literature and produces evidence suggesting that this relationship is insignificant, thus denoting that mood states do not significantly bias the propensity of sophisticated investors to herd. Compared to extant research on mood effects over institutional trading behaviour, the evidence we present in this study is in line with the findings reported by Kaustia and Rantapuska (2016) on the weak effect of weather-related mood proxies over the trading behaviour of institutional investors in Finland[4], yet runs counter to Goetzmann et al. (2015) who find that cloud cover affects mispricing perceptions and trading

[3] For more on this, see Demirer and Karan (2002), Oğuszoy and Güven, (2003) and Cinko and Avci (2009).

[4] Kaustia and Rantapuska (2016) report similarly weak weather-related mood effects over retail investors' trades in Finland as well. Evidence on mood effects over retail investors' trading behaviour appears rather mixed to date, with Goetzmann and Zhu (2005) finding that cloud cover does not affect US retail investors' trading decisions (although they did report such an effect over NYSE market makers) and Schmittmann et al. (2015) concluding that good (bad) weather prompts German retail investors to buy (trade) more.

decisions of US institutional investors. Second, our findings suggest that the pursuit of a behaviourally biased trading pattern (in our case, herding) by fund managers does not necessarily render them susceptible to mood effects in their trading conduct. Third, given that mood as a factor is far from strictly rational, we contribute to the ongoing debate on the effect of less-than-perfectly rational factors over herd behaviour in general, a debate that has to date welcomed inputs from areas as diverse as biology (Stallen et al., 2012), culture (Beckmann et al., 2008; Chang and Lin, 2015; Eun et al., 2015) and socio-economics (Prechter and Parker, 2007).[5]

Our study bears important implications for researchers, as it highlights the need for a more comprehensive investigation of the relationship between mood and institutional herding at a wider cross market level internationally, in order to establish whether it reveals any patterns and whether it varies among markets at different stages of financial development (considering that our evidence emanates from the asset management industry of an emerging market). It would be interesting, for example, to gauge whether mood-factors common to several countries (such as, for example, the Ramadan month in majority Muslim countries) produce similar effects over their funds' herding. Another possibility would be to examine whether funds investing in the same market but hailing from different countries exhibit differences in their herding contingent on the different weather conditions prevailing in their country of origin (given the mood-related role of weather). What is more, it would be interesting to investigate whether, herding aside, mood is related to other behavioural investment patterns popular among fund managers, such as momentum trading (Choi and Skiba, 2015).

As far as the wider investment community is concerned, the study of mood-related patterns in the herding of fund managers should be of key interest, since the emergence of any such patterns would suggest the potential for them forming the basis for *ad hoc* trading strategies. If, for example, a robustly significant relationship between a weather mood-proxy (e.g. sunshine) and institutional herding were to be established for a market, one could theoretically trade in/against the anticipated direction of funds' herding given that proxy's forecasts while at the same time hedge their position via

[5] Although the role of *social mood* in market-wide herding has been discussed in past research, both from a theoretical (Prechter, 2001; Olson, 2006) and an empirical (Gavriilidis et al., 2016) perspective, no prior research exists on the link between mood *per se* and institutional herding. A closely related – yet by no means identical – factor whose relationship to herding (market-wide and institutional) has been studied is sentiment; for more on this, see section 2.2.

weather derivatives. Although we are not aware of such a strategy having ever been formally proposed (be it by researchers or practitioners), the popularity of weather derivatives as hedging instruments since the mid 1990s (Pérez-González and Yun, 2013) renders it theoretically feasible.

The rest of the paper is structured as follows: section 2 presents an overview of the research surrounding herding (section 2.1) and the role of mood in financial markets (section 2.2). Section 3 describes the data set utilized (section 3.1) and outlines the empirical design employed (section 3.2). Section 4 presents and discusses the results and section 5 concludes.

2. Theoretical background

2.1 Herd behaviour

Herding refers to the situation whereby investors exhibit similarity in their behaviour following interactive observation of each other's actions or action-payoffs, while at the same time sidelining their private information or fundamentals (Hirshleifer and Teoh, 2003; Hwang and Salmon, 2004). Contingent on whether investors herd in anticipation of a benefit from engaging into said behaviour or whether their herding is the product of a common factor fostering correlation in their trades, herding is classified as *intentional* or *spurious* (Bikhchandani and Sharma, 2000; Holmes et al., 2013; Gavriilidis et al., 2013; Galariotis et al., 2015).

The roots of intentional herding can be traced in the presence of (actual or perceived) asymmetries in the market environment which prompt some investors to view themselves as disadvantaged; in this case, mimicking the behaviour of their ("better") peers offers them the opportunity to improve their position. Such asymmetries could be of an *informational* nature, whereby individuals with no access to information, or whose quality of information or information processing skills is low, are tempted to track the trades of their better informed peers in order to free ride on their information (Devenow and Welch, 1996). If the number of investors choosing to copy their peers' trades grows over time, it will lead the majority of market participants to either discard their private signals or refrain altogether from obtaining any in the first place[6], thus gradually rendering the public pool of information poorer and giving rise to informational cascades (Banerjee, 1992; Bikhchandani et al., 1992; Lee, 1998). The latter can be cause for concern, since the fact that they are based on very little information renders them fragile to the arrival of new information, thus increasing the likelihood of excess volatility being exacerbated in the market (Moscarini et al., 1998). Although one would expect less sophisticated investors to be more prone to herding in anticipation of informational externalities, evidence suggests that institutional investors can also herd due to such concerns; as Gelos and Wei (2005) and Choi and Skiba (2015) have shown, foreign funds investing in markets characterized by opaque transparency tend to engage in herding in their flows into and out of these markets due to the latter's higher information risk.

Intentional herding can further be incited by *reputational* asymmetries; these are associated with the fact that investment professionals (e.g. fund managers or financial analysts) of differential skills and abilities are subject to a performance assessment of a relative nature, as they are assessed versus the performance of their peers (Scharfstein and Stein, 1990). A key concern for less able/reputed professionals in this context is to avoid underperforming their industry average in order to ensure that their low quality is not detected and one way to achieve this is by imitating the trades of their better-quality peers (Truman, 1994; Welch, 2000; Clement and Tse, 2005). This is particularly important for fund managers during down market periods, since the higher likelihood of losses during the latter entails graver professional implications for fund managers, enhancing their risk aversion levels. Should a "bad" manager choose to mimic a "good" one's trades during such a period, he could claim his trading decisions were prudent (since they would tally with those of "good" managers) and attribute any losses to the adverse market conditions prevailing during that period. Reputational considerations, can, however, promote similar behaviour during market upswings as well, since underperforming his peers during positive market periods would only help cast a professional stigma

[6] High information costs further contribute to the evolution of cascades. If information is costly to obtain, investors will rationally choose to infer it via the trades of their informed peers, rather than devote resources to its collection; this is more so, if the number of investors anticipated to act on that information is limited, in which case acquiring it yields little benefit (the one "buying" that information cannot expect it to have a price impact large enough to allow him to profit from it). These considerations culminate in what is known as "investigative cascades", which are presented in good detail in Hirshleifer and Teoh (2003). Of course, since monitoring others' trades can be costly in itself, an investor may choose to observe his peers' trades indirectly at the aggregate level simply by examining past price sequences (Hirshleifer and Teoh, 2003).

over a "bad" manager. From an empirical perspective, evidence (Sias, 2004; Choi and Sias, 2009; Holmes et al., 2013; Gavriilidis et al., 2013; Jiao and Ye, 2014) suggests that reputational reasons constitute, to varying degrees, important drivers of institutional herding.[7]

On the other hand, spurious herding refers to the similarity in investors' responses to commonly observed signals; unlike intentional herding, investors herd spuriously due to the influence of a common factor to which they are all exposed, without interactive observation among them being present. Key to spurious herding, particularly among investment professionals, is *relative homogeneity*, the latter referring to features most of them share in common and which lead to similarities in their decisions (De Bondt and Teh, 1997). Such features can include, for example, the similar educational backgrounds and professional qualifications of most fund managers and the similarities in the micro/macro indicators they monitor and their processing (Froot et al., 1992; Hirshleifer et al., 1994; Wermers, 1999). In addition, the regulatory framework to which they are commonly subject can further reinforce commonality in their portfolio structures, something particularly evident among pension funds (Voronkova and Bohl, 2005; Olivares, 2008; Blake et al., 2017), whose managers are subject to strict regulatory requirements regarding minimum performance and stock selection profiles.

Spurious herding can also be motivated via *style investing* ("characteristic trading"; Sias, 2004), the latter referring to strategies involving stock selection on the premises of specific stock characteristics, such as past performance, value, size and industry. Style investing is particularly popular among institutional investors (Bennett et al., 2003) and, if a sufficiently large number of them follow a particular style, this can lead them to trade similar stocks and generate the impression of them herding.[8] The latter, however, would be spurious, since the correlation in their trades would not be the

[7] It is also possible that a well reputed professional will prefer to follow the consensus of her industry, if the reputational costs of a wrong decision exceed the reputational benefits of a correct one, in case she reaches that decision on her own (Graham, 1999).
[8] Empirical research (Grinblatt et al., 1995; Nofsinger and Sias, 1999; Wermers, 1999; Sias, 2004; Choi and Sias, 2009; Choi and Skiba, 2015) has confirmed that mutual funds that herd often exhibit momentum trading in their trades; however, their evidence is far from conclusive regarding the significance of the herding-momentum relationship, nor does it allow us to infer any causality effects between the two.

product of interactive observation among them, but rather the result of them following the same strategy.

Specifically with respect to institutional investors (who constitute the focus of our study), any herding (be it intentional or spurious) on their part can raise issues regarding their portfolio structures, in terms of the efficiency of their allocation and their congruence to their clients' risk preferences (Economou et al., 2015b), in effect raising the potential for moral hazard in their industry. What is more, the dominance of institutional investors in modern financial markets and the increasingly globalized financial environment in which they operate imply that any herding on their behalf is capable of fomenting new and exacerbating existing financial episodes, both within and across markets, thus contributing to systemic risk. The above issues have prompted a large amount of empirical research on whether fund managers herd internationally, with much of the discussion on explaining their herding hinging on the aforementioned intentional (informational/reputational asymmetries) and spurious (relative homogeneity/style investing) herding drivers, all of which are of a rational nature.[9] In this study we examine whether fund managers' herding is mood-driven (based on various mood proxies) and it is mood as a (less-than-perfectly rational) concept that we now turn to discuss.

2.2 Mood and investment decisions

Mood, as a concept, refers to a pre rational state of affective content experienced internally by an individual and motivated by both exogenous (e.g. environmental conditions), as well as endogenous (such as a person's earlier emotional experiences) factors (Frijda, 1993). Mood-states can be both global (e.g. positive versus negative mood) as well as specific (e.g. euphoria versus anger) and are of a transient nature, thus constituting short-lived phenomena (Frijda, 1994) with no conscientious cognitive effort mediating their appearance and evolution (given mood's pre rational nature). Mood can be perceived individually (a person who has just lost a loved one will, for example, experience

[9] We have cited several of these studies in this section; for a more comprehensive review of the herding literature, see Spyrou (2013). With the exception of a few studies exploring the role of culture (Beckmann et al., 2008) and sentiment (Liao et al., 2011; Celiker et al., 2015) on institutional herding, we are aware of no other studies investigating the role of less-than-perfectly rational factors over the propensity of fund managers to herd.

feelings of loss) as well as collectively (a natural disaster befalling a city will induce negative emotions to its inhabitants), the latter also known as social mood (Nofsinger, 2005; Olson, 2006).

The impact of mood can be felt in various cognitive functions, including attention, encoding of information, forecasting, memory, motivation and perception, thus being expected to be present in individuals' judgement-formation and decision-making (Schwarz and Bohner, 1996; Isen, 2000; Forgas and George, 2001; Lowenstein and Lerner, 2002). As a general observation, the onset of a given mood tends to prompt mood-congruent cognitive processes and decisions (Schwarz and Clore, 1983; Schwarz, 2002); a person in a positive mood is likely to view the world as a better place (whereas a person with negative mood will probably not share that view) and a person in a happy (sad) state of mind will probably view the decision to engage in equity trading as less (more) risky. Associative memory processes are also important in enhancing this congruence, since positive (negative) mood tends to lead people toward recalling more positive (negative) past experiences, while also searching more actively for positive (negative) stimuli that will reinforce their affective state (Bower, 1981).

In the specific context of financial markets, mood has been associated with the promotion of mood-congruent perceptions of risk and direction of investors' trades. Positive mood tends to reduce an investment's perceived riskiness, prompting people to be less averse towards engaging in it and rendering them more likely to resort to heuristics in its analysis (its lower perceived risk reduces the necessity for analytical processing; Forgas, 1998), with people in a negative mood tending to view investments as riskier than they actually are and devoting more time in trying to detect their possible pitfalls (Park et al., 2005; Schwarz and Bless, 1991; Schwarz, 2000; Slovic and Peters, 2006). Therefore, investors in a positive (negative) state of mood would be expected to be more (less) overconfident (Au et al., 2003), engage in more (less) risk-seeking behaviour (Forgas, 1995; Isen, 2000; Yuen and Lee, 2003; Chou et al., 2007; Knutson et al., 2008; Kuhnen and Knutson, 2011; Bassi et al., 2013) and view equity investing as an opportunity (a threat). As a result, they would be more likely to misattribute their mood state for information and be more inclined towards buying (selling) stocks when being under the influence of positive (negative) mood (Mano, 1994; Mittal and Ross, 1998).[10]

Extant empirical research in finance has examined the impact of mood over asset returns on the premises of a wide array of mood-proxies, including sunshine (Saunders, 1993; Hirshleifer and Shumway, 2003), temperature (Cao and Wei, 2005), lunar phases (Yuan et al., 2006), biorhythms (Kamstra et al., 2000), holidays (Meneu and Pardo, 2004), religious celebrations (Białkowki et al., 2012), sports events (Edmans et al., 2007), aviation disasters (Kaplansky and Levi, 2010) and terrorist attacks (Brounen and Derwal, 2010), with results to date suggesting that events/situations with positive (negative) emotional content are associated with positive (negative) equity returns, on average. With regards to investors' behaviour, Goetzmann and Zhu (2005) showed that cloud cover bore little effect over US retail investors' trades (although they did report such an effect among NYSE market makers), while Schmittmann et al. (2015) documented how good (bad) weather conditions led German retail investors to buy (trade) more. Goetzmann et al. (2015) found cloud cover to affect US institutional investors in terms of their equity valuations and the direction of their trades, with more (less) cloud cover increasing (decreasing) their perceived overpricing of stocks and prompting them to buy less (more); conversely, Kaustia and Rantapuska (2016) reported evidence of a very weak effect of various weather-related mood proxies over domestic (retail and institutional) investors' trades in Finland. The above suggest that evidence on mood-effects over investors' behaviour is both limited and inconclusive and it is to that end that our study contributes to the literature by assessing the relationship between several mood-proxies (see section 3.2 for a more detailed discussion) and institutional investors' herd behaviour.

[10] A term often used interchangeably with mood (despite it not entailing the same content as mood) in the finance literature is "sentiment" (Baker and Wurgler, 2007); the latter pertains to extrapolative beliefs about future cash flows and risks, based on the perception of a trend being at works (e.g. that an up/downward trend in earnings will persist). Unlike mood, sentiment is "fundamentals-plus", in the sense that the beliefs underlying it are founded on existing fundamentals which are then extrapolated upon to project future trends. Furthermore, unlike mood, sentiment involves cognitive effort (its formulation merits some processing of the information available) and tends to be of longer duration (as it relates to wider market trends). A final, and most important, difference between mood and sentiment is that, whereas mood bears no causal relationship to economic/financial indicators (stock returns, for example, do not cause changes in sunshine levels), sentiment does (as it can be reflected through various market indicators, including, for example, consumer confidence indices, IPOs' first-day returns and trading volume, to mention a few). With respect to sentiment's relationship to herding, Liao et al. (2011) and Celiker et al. (2015) find that US funds herd significantly on the sell-side when trading stocks subject to highly optimistic sentiment, while a series of studies (Chiang et al., 2013; Economou et al., 2015a; Philippas et al., 2013) report a significant relationship between market-wide herding and the US CBOE VIX index ("fear index") in the US and internationally.

3. Data and methodology

3.1 Data

We test empirically for the effect of mood over institutional herding on the premises of a unique data set entailing the daily portfolio holdings of all "Type A" Turkish funds active during the period between January 2nd, 2002 and August 14th, 2008. Funds formally designated as "Type A" are required by law to invest at least 25% of their portfolio assets in domestic equities, i.e. stocks issued by Turkish publicly listed companies (with funds not subject to said requirement designated as "Type B"[11] ones).[12] The database was obtained from the Capital Markets Board of Turkey and includes information on the: code and name of each fund; code and name of each asset in each fund's portfolio; end-of-day number of units, price and market value (all expressed in Turkish Lira) of each asset held. The advantage of using daily institutional holdings to examine whether funds herd due to mood effects rests on the fact that mood in itself is a short term phenomenon (Ekman and Davidson, 1994) and using daily funds' data enables us to track any effects of mood changes over funds' herding more accurately (compared for example to data of lower frequency).

As the descriptive statistics presented in Table 1 illustrate, our sample comprises of all 134 "Type A" funds active at any point during our sample period, a fact which allows our sample to be free from survivorship bias; these funds invested in a total of 419 domestic stocks throughout that period. Of those 134 funds, 35 are equity funds, 21 are balanced/mixed funds, 64 are variable funds[13] and 14 are index funds. The average number of active stocks per day traded by at least one fund is 75 (or approximately 18% of the total number of stocks our sample funds invested in during the sample

[11] "Type B" funds are not legally required to invest in equities, the result being their portfolios are dominated by fixed income instruments, such as bonds and repos.

[12] Both "Type A" and "Type B" funds in Turkey are incorporated as open ended funds and their investments are not allowed to exceed 9% of the total shares outstanding of any single company, while they are also not allowed to invest more than 10% of their net asset value in any single company's shares. Depending on their investment scope, funds of both types can be classified as Variable, Balanced/Mixed, Affiliate Companies, Sector, Equity, Private, Index, Notes and Bonds, Liquid and Foreign Securities Funds. In general, "Type A" funds are dwarfed by "Type B" ones in terms of their portfolios' value (expressed in Turkish Lira): "Type B" funds' total portfolio value has historically been, on average, around 20 times larger than that of "Type A" funds. What is more, equity investments constitute only a small fraction of Turkish mutual funds' investments, with government bonds and repos commanding a key position in their portfolios, while, overall, the size of the Turkish mutual fund market corresponds to only a very small fraction of the country's GDP (2.7%, as of 2010; see Białkowski et al., 2013). For more on the above, see the Annual Reports of the Capital Markets Board of Turkey (http://www.cmb.gov.tr/indexcont.aspx?action=showpage&menuid=3&pid=1&submenuheader=-1).

[13] Variable funds are funds which, aside from the 25%-threshold on equity investments pertaining to "Type A" funds mentioned above, are not subject to any further restrictions on their portfolio allocation.

period), with the average number of active funds per stock per day being 3. When looking at the corresponding figures for stocks traded by at least 2, 3 and 4 funds, we notice that the average number of stocks per day actively traded by funds falls substantially (reaching only 23 stocks for stocks traded by at least 4 funds), while the average number of active funds per stock per day for stocks traded by at least 4 funds is 7. Overall, these figures indicate a rather concentrated daily equity trading activity on behalf of "Type A" funds in the Turkish stock market that clearly has the potential of encouraging herding; with 3-7 funds, on average, being active per stock each day, this helps facilitate observation among them, thus rendering herding more feasible – and likely.

3.2 Methodology

To measure institutional herding – and later assess its relationship with mood – we employ the measure proposed by Sias (2004), which aims at extracting herding via the intertemporal dependence in the structure of institutional demand for stocks; more formally, institutional demand is proxied via the raw fraction of funds buying stock *k* in period (in our case, day) *t* ($\mathrm{Raw}\Delta_{k,t}$), which is calculated as:

$$Raw\Delta_{k,t} = \frac{Number\ of\ funds\ buying\ stock\ k\ on\ day\ t}{Total\ number\ of\ funds\ active\ in\ stock\ k\ on\ day\ t} \tag{1}$$

The total number of active funds in the denominator of Equation (1) is the sum of all funds that have either increased ("buyers") or decreased ("sellers") their position in stock *k* on day *t* compared to day *t-1*. $Raw\Delta_{k,t}$ is then standardized by subtracting on each day from each stock's $Raw\Delta_{k,t}$ its cross sectional (across all active stocks on that day) mean ($\overline{\mathrm{Raw}\Delta_t}$) and dividing it by its cross sectional standard deviation ($\sigma(\mathrm{Raw}\Delta_{k,t})$):

$$\Delta_{k,t} = \frac{\mathrm{Raw}\Delta_{k,t} - \overline{\mathrm{Raw}\Delta_t}}{\sigma(\mathrm{Raw}\Delta_{k,t})} \tag{2}$$

To assess the temporal dependence of institutional demand, Sias (2004) proposed a first order autoregressive structure for $\Delta_{k,t}$, as follows:

$$\Delta_{k,t} = \beta_t \Delta_{k,t-1} + \varepsilon_{k,t} \tag{3}$$

With both sides of Equation (3) being standardized (and since $\Delta_{k,t-1}$ is its sole independent variable), its slope (β_t) represents the cross sectional correlation of institutional demand between day *t* and day *t-1*. Sias (2004) then partitioned β_t as follows:

$$\beta_t = \rho(\Delta_{k,t}, \Delta_{k,t-1}) =$$
$$\left[\frac{1}{(K-1)\sigma(Raw\Delta_{k,t})\sigma(Raw\Delta_{k,t-1})}\right] x \sum_{k=1}^{K}\left[\sum_{n=1}^{N_{k,t}} \frac{(D_{n,k,t} - \overline{Raw\Delta_t})(D_{n,k,t-1} - \overline{Raw\Delta_{t-1}})}{N_{k,t}N_{k,t-1}}\right] \tag{4}$$
$$+\left[\frac{1}{(K-1)\sigma(Raw\Delta_{k,t})\sigma(Raw\Delta_{k,t-1})}\right] x \sum_{k=1}^{K}\left[\sum_{n=1}^{N_{k,t}} \sum_{m=1,m\neq n}^{N_{k,t-1}} \frac{(D_{n,k,t} - \overline{Raw\Delta_t})(D_{m,k,t-1} - \overline{Raw\Delta_{t-1}})}{N_{k,t}N_{k,t-1}}\right]$$

In the above equation, the first additive component represents the part of the slope due to funds following their own lagged trades and the second one the part of the slope due to funds following the lagged trades of other funds (herding). Positive (negative) values for the first component would suggest that funds trade on day *t* in (against) the direction of their trades in day *t-1*; positive (negative) values for the second component would indicate that funds on day *t* trade toward (away from) other funds' trades of day *t-1*. From the perspective of notation: $N_{k,t}$ is the total number of active funds in stock *k* on day *t*; $D_{n,k,t}$ is a dummy variable assuming the value of unity (zero) if fund *n* increases (decreases) its position in stock *k* on day *t*; and $D_{m,k,t-1}$ is a dummy variable assuming the value of unity (zero) when fund *m* (*m≠n*) increases (decreases) its position in stock *k* on day *t-1*.

Since our study investigates the effect of mood not only over institutional herding presence but also institutional herding direction, we account for the latter by partitioning our sample stocks each day into two groups (see Holmes et al., 2013), a buy-herd (comprised of stocks predominantly bought, i.e. whose $Raw\Delta_{k,t} > 0.5$) and a sell-herd (comprised of stocks predominantly sold, i.e. whose $Raw\Delta_{k,t} < 0.5$) one and estimate the Sias (2004) measure for each.

We investigate the relationship between mood and institutional herding by assessing the interactions of the latter with five mood-proxies (weekend effect; holidays; Ramadan; sunshine; new/full moon) which have been established as such in the literature. In the remainder of this section, we delineate how each of those proxies affects mood and how we would theoretically expect it to relate to institutional herding presence and direction.

Weekend effect: this effect is one of the oldest documented in finance (Cross, 1973; French, 1980; Gibbons and Hess, 1981) and refers to stock returns being, on average, negative on Mondays and rising as one moves from Tuesday to Friday (with Friday's returns being the highest of the week). Despite the wealth of rational explanations[14] proposed to account for it, a significant number of studies have attributed the effect to investors' mood being negative on Mondays ("Monday Blues") and the most positive on Fridays, among all working days.[15] With respect, specifically, to institutional investors, evidence on the connection of their trades to the weekend effect is rather mixed (Sias and Starks, 1995; Chan et al., 2004; Venezia and Shapira, 2007). Assuming that fund managers are affected by mood in their trading conduct, the fact that positive (negative) mood enhances (depresses) risk taking tendencies (Forgas, 1995; Isen, 2000; Yuen and Lee, 2003; Chou et al., 2007; Knutson et al., 2008; Kuhnen and Knutson, 2011; Bassi et al., 2013) suggests that their herding would be theoretically expected to manifest itself more strongly when mood is negative, as a response towards the greater risk aversion (seeking "safety in numbers") induced by negative mood.[16] If so, this would translate into lower (higher) institutional herding levels on Fridays (Mondays). However, although the hypothetically higher risk taking of Fridays would, in principle, be likely to prompt fund managers to go-it-alone (e.g. due to overconfidence prompting them to follow their private signals; Daniel et al, 2001), it is also possible that it might lure them into herding. This may be either because high risk

[14] For a presentation of the rational explanations proposed for the weekend effect, see the recent study by Birru (2016).

[15] For more on the negative (positive) mood content of Mondays (Fridays), see Larsen and Kasimatis (1990), Reis et al. (2000) and Croft and Walker (2001). For more on research on mood motivating the weekend effect in capital markets, see the literature overviews by Abu Bakar et al. (2014) and Birru (2016).

[16] With negative mood leading individuals to perceive bad outcomes as more likely (Johnson and Tversky, 1983; Wright and Bower, 1992), it is possible that it can prompt, for example, "bad" fund managers to view their low stock picking skills as lower than they actually are, leading them to track the trades of their better able peers even more intensively.

taking leads them to underweight the risk associated with herding[17], or because positive mood prompts people to resort to heuristics (Forgas, 1998) in their decision making (by offering investors the opportunity to substitute analytical evaluation with consensus-tracking, herding tacitly functions as a heuristic *per se*). The above suggest that a clear relationship between institutional herding presence and the weekend effect is far from straightforward; however, the same cannot be argued regarding the relationship between the weekend effect and institutional herding direction. Since positive (negative) mood has been found to encourage purchases (sales) of stocks (Goetzmann et al., 2015), if fund managers were to be subject to weekend-related mood effects, they would be expected to buy (sell) more on Fridays (Mondays). As a result, one would expect buy-side (sell-side) institutional herding on Fridays (Mondays) to be: a) stronger than sell-side (buy-side) institutional herding on Fridays (Mondays) and b) stronger compared to buy-side (sell-side) institutional herding of Mondays (Fridays). In view of the above, we propose the following hypotheses regarding the relationship of the weekend effect as a mood factor with institutional herding presence and direction in Turkey:

$H_{0,1,1}$ (institutional herding presence hypothesis): Institutional herding is expected to be significantly different between Fridays and Mondays, though the sign of this relationship is ambiguous.

$H_{0,1,2}$ (institutional herding direction hypothesis 1): Institutional herding on the buy-side (sell-side) is expected to be stronger on Fridays (Mondays) as opposed to Mondays (Fridays).

$H_{0,1,3}$ (institutional herding direction hypothesis 2): Institutional herding on the buy-side (sell-side) is expected to be stronger on Fridays (Mondays) than herding on the sell-side (buy-side) on Fridays (Mondays).

We test empirically for the above hypotheses by partitioning β_t and its two components (funds following their own trades; funds following the trades of other funds) into two groups corresponding to Mondays and Fridays, respectively.

Holidays: empirical research (Lakonishok and Smidt, 1988; Ariel, 1990; Cadsby and Ratner, 1992) has shown that pre holiday returns are significantly positive and account for a considerable portion of

[17] The case of positive mood leading investors to perceive negative outcomes as less likely – see Johnson and Tversky (1983) and Wright and Bower (1992).

each year's total rate of return; conversely, post holiday returns are found to be insignificantly different from average ordinary day returns. Considering that holidays allow individuals the opportunity for relaxation via distraction from their daily routine and are associated with a sense of euphoria ("holiday euphoria"; for an excellent review, see Lahav et al, 2016), it has been suggested (Fabozzi et al, 1994) that the abnormally high pre holiday returns are motivated by investors' positive mood prior to a holiday.[18] The holiday effect bears some similarities to the weekend effect, in the sense that both involve a trading break (weekend; holiday), with people's mood being positive in anticipation of it on its eve (Friday; pre holiday) and reversing (Monday) or dissipating (post holiday) on the day following it. As a result, similar to the discussion above on the weekend effect (based on positive/negative mood enhancing/depressing risk taking tendencies), if institutional investors' trades are subject to mood effects, it would be impossible to assert whether these would lead them to herd more pre or post holiday, thus again allowing for no clear relationship between the holiday effect and institutional herding presence. Given, however, that positive mood amplifies the propensity for equity purchases (Goetzmann et al., 2015), assuming that fund managers are subject to holiday-related mood effects, they would be expected to buy more pre holidays. As a result, one would expect fund managers pre holidays to: a) exhibit stronger buy- than sell-herding and b) exhibit stronger buy-herding compared to post holidays. In view of the above, we propose the following hypotheses regarding the relationship of the holiday effect with institutional herding presence and direction in Turkey:

$H_{0,2,1}$ (institutional herding presence hypothesis): Institutional herding is expected to be significantly different pre versus post holidays, though the sign of this relationship is ambiguous.

$H_{0,2,2}$ (institutional herding direction hypothesis 1): Institutional herding on the buy-side is expected to be stronger pre holidays as opposed to post holidays.

[18] Alternative – though not necessarily more "rational" – explanations for the holiday effect include the overlap of the holiday effect with other calendar anomalies (such as the weekend effect and the January effect; see e.g. Liano et al., 1992), the size effect (Petengill, 1989; Marquering, 2006), market structure (Chong et al., 2005) and the trading preferences of investor groups (Ariel, 1990; Meneu and Pardo, 2004).

$H_{0,2,3}$ (institutional herding direction hypothesis 2): Institutional herding on the buy-side is expected to be stronger than herding on the sell-side pre holidays.[19]

We test empirically for the above hypotheses by first identifying the major national and religious holidays celebrated in the Republic of Turkey[20] and then partitioning β_t and its two components (funds following their own trades; funds following the trades of other funds) into two groups corresponding to pre holiday and post holiday days, respectively.

Ramadan: it is the ninth month of the Islamic calendar, central to which is the requirement for Muslims to engage in prayers, fast during day light and refrain from smoking and sensual pleasures (Al-Hajieh et al., 2011). Ramadan's atmosphere is characterized by spiritual elation and positive mood (Daradkeh, 1992; Knerr and Pearl, 2008), culminating in a common euphoric state of religion-induced experience to which individuals in majority Muslim countries are collectively subject. This, in turn, promotes relative homogeneity of an emotional content in society (Gavriilidis et al., 2016), which, coupled with the enhanced social interaction levels observed during that month (Białkowski et al., 2012), increase the potential for commonality in behaviour. Specifically with respect to these markets' institutional investors, such conditions would be expected to enhance their already existent relative homogeneity levels as an industry (see the discussion in section 2.1), thus increasing the likelihood of them engaging in stronger herding[21] during Ramadan compared to the rest of the year's months.[22] Given Ramadan's positive mood content (and in view of positive mood encouraging investors to engage in equity purchases[23]; see e.g. Goetzmann et al., 2015) one would expect institutional herding during that month to be strongly buy-side driven. In view of the above, we

[19] Unlike for hypotheses $H_{0,1,2}$ and $H_{0,1,3}$ for the weekend effect proposed previously, we cannot make any predictions regarding the strength of buy- or sell-herding post holiday. This is because, although post holiday mood is assumed to be negative, evidence to date (see the literature cited here) has indicated that post holiday returns are insignificantly different from ordinary day ones, thus rendering investors' behaviour post holidays inconclusive in its direction (contrary to the weekend effect, where the clear psychological prediction of negative Monday mood is confirmed empirically by negative, on average, Monday returns).

[20] These include: New Year (January 1st), Children's Day (April 23rd), Labour Day (May 1st), Youth and Sports Day (May 19th), Victory Day (August 30th), Republic Day (October 29th), Kurban Bayrami and Ramazan Bayrami.

[21] If so, that herding would be spurious, given the typology presented in section 2.1.

[22] In the seminal study on the relationship between herding and the Ramadan, Gavriilidis et al. (2016) present evidence suggesting that market-wide herding is indeed stronger during, compared to outside, Ramadan in several majority Muslim markets (Turkey included).

[23] Indeed, average market returns during Ramadan have been found to be the highest among all other months of the year in several studies investigating the Ramadan effect in stock exchanges of majority Muslim markets (Turkey included); see Białkowski et al. (2012).

propose the following hypotheses regarding the relationship of Ramadan to institutional herding presence and direction in Turkey:

$H_{0,3,1}$ (institutional herding presence hypothesis): Institutional herding is expected to be stronger during, compared to outside, Ramadan.

$H_{0,3,2}$ (institutional herding direction hypothesis 1): Institutional herding on the buy-side is expected to be stronger during, compared to outside, Ramadan.

$H_{0,3,3}$ (institutional herding direction hypothesis 2): Institutional herding on the buy-side is expected to be stronger compared to herding on the sell-side during Ramadan.

We test empirically for the relationship between Ramadan and institutional herding presence/direction in our study by first identifying (based on the approach proposed by Białkowski et al., 2012) the Ramadan months (6/11-4/12/2002; 27/10-21/11/2003; 18/10-12/11/2004; 5/10-2/11/2005; 25/9-20/10/2006; and 13/9-11/10/2007) during our sample period (2/1/2002 – 14/8/2008) and then partitioning β_t and its two components (funds following their own trades; funds following the trades of other funds) into two groups corresponding to within and outside Ramadan, respectively.

Sunshine: a large volume of research (see Goetzmann et al., 2015 for an overview of the relevant literature) has confirmed the effect of sunshine over mood and the effect's implications for medical science; all in all, sunshine has been found to boost mood, whereas overcast weather tends to dampen it. In the financial context, research to date has investigated the effect of sunshine over equity returns (Saunders, 1993; Hirshleifer and Shumway, 2003), risk tolerance (Bassi et al., 2013) and investors' trading behaviour (Goetzmann and Zhu, 2005; Goetzmann et al., 2015; Schmittmann et al., 2015; Kaustia and Rantapuska, 2016). Although the evidence presented is not necessarily consistent, sunshine, generally, tends to be associated with positive returns in equity markets and a stronger buy-propensity on behalf of investors. With regards specifically to institutional investors, research is limited and inconclusive in its results: whereas Goetzmann et al. (2015) find that more (less) cloud cover increases (decreases) the perceived overpricing of stocks among US institutional investors and prompts them to buy less (more), Kaustia and Rantapuska (2016) report a weak effect of several weather-related mood proxies (sunshine included) over the trading behaviour of institutional investors in Finland. In line with the previous discussion on the weekend/holiday effects (where we associated positive/negative mood with enhanced/depressed risk taking tendencies), if sunshine does indeed affect institutional investors' trades, it would be impossible to assert whether this would lead them to herd more during days of increased or decreased sunshine. As a result, there exists no clear relationship between sunshine and institutional herding presence, although the same cannot be argued regarding the role of sunshine in institutional herding direction. With sunshine being associated with positive mood, fund managers' propensity to buy (sell) would be expected to increase on increased (decreased) sunshine days, thus raising the possibility of buy-(sell-) herding also rising on those days. In view of the above, we propose the following hypotheses regarding the relationship of sunshine with institutional herding presence and direction in Turkey:

$H_{0,4,1}$ (institutional herding presence hypothesis): Institutional herding is expected to be significantly different between days of increased and days of decreased sunshine, though the sign of this relationship is ambiguous.

$H_{0,4,2}$ (institutional herding direction hypothesis 1): Institutional herding on the buy-side (sell-side) is expected to be stronger on days of increased (decreased) sunshine as opposed to days of decreased (increased) sunshine.

$H_{0,4,3}$ (institutional herding direction hypothesis 2): Institutional herding on the buy-side (sell-side) is expected to be stronger than herding on the sell-side (buy-side) on days of increased (decreased) sunshine.

We test empirically for the relationship between sunshine and institutional herding presence/direction in our study by identifying the hours of sunshine every day during our sample period (2/1/2002 – 14/8/2008) utilizing data from the Turkish State Meteorological Service; we then partition β_t and its two components (funds following their own trades; funds following the trades of other funds) into two groups corresponding to days of increased and days of decreased sunshine, respectively, contingent on whether day *t* entails more or fewer hours of sunshine compared to day *t-1*.

New/full moon: the effects of lunar phases on individuals' mood have been examined in a variety of studies (see Yuan et al., 2006 for a comprehensive review of the relevant literature), with evidence suggesting an adverse effect of the full moon over human mood and well being, with the effect reversing around the new moon. The presence of such an effect in asset returns has been empirically confirmed by Dichev and Janes (2003) and Yuan et al. (2006), who showed that the average equity return within a 7-/15-day window around a full moon is significantly lower compared to the one within a similar window around a new moon.[24] However, Keef and Khaled (2011) found evidence denoting that average new (full) moon period returns are larger than (insignificantly different from) the returns falling within neither - new or full moon - period[25], arguing in favour of a new moon effect in returns, rather than a full moon one. Evidence from other studies is either mixed (finding both new and full moon effects of either direction in international stock returns; see Floros and Tan, 2013), or dismissive of the presence of any lunar effects altogether (Herbst, 2007). Although we are aware of no research on lunar effects over the trades of institutional investors, if the latter were to be subject to such effects, one would expect their mood to improve (deteriorate) during the new (full) moon period. Similar to the previous discussion on the weekend/holiday/sunshine effects (where we associated positive/negative mood with enhanced/depressed risk taking tendencies), if institutional investors are subject to lunar effects in their trading, it would be impossible to assert whether these would lead them to herd more during the full or new moon period, thus again allowing for no clear relationship between the new/full moon and institutional herding presence. However, since the new (full) moon has been related to positive (negative) mood (and in view of positive/negative mood fostering equity purchases/sales), one would expect institutional investors to buy (sell) more during the new (full) moon period. This, in turn, would raise the possibility of their buy-side (sell-side) herding being: a) stronger during the new (full) moon period compared to the full (new) moon period and b) stronger than their sell-side (buy-side) herding during the new (full) moon period. We, therefore, propose the following hypotheses regarding the relationship of the new/full moon with institutional herding presence and direction in Turkey:

[24] The 7- (15-) day window is constructed by assuming +/-3 (+/-7) days around the new/full moon day plus the new/full moon day, in line with Yuan et al. (2006).
[25] Those are the returns falling into the first and third quarter periods of the moon.

$H_{0,5,1}$ (institutional herding presence hypothesis): Institutional herding is expected to be significantly different between the new and full moon periods, though the sign of this relationship is ambiguous.

$H_{0,5,2}$ (institutional herding direction hypothesis 1): Institutional herding on the buy-side (sell-side) is expected to be stronger during the new (full) moon period as opposed to the full (new) moon period.

$H_{0,5,3}$ (institutional herding direction hypothesis 2): Institutional herding on the buy-side (sell-side) is expected to be stronger than herding on the sell-side (buy-side) during the new (full) moon period.

We test empirically for the relationship between the new/full moon and institutional herding presence/direction in our study by first identifying the new/full moon phases during our sample period (2/1/2002 – 14/8/2008) following the approach outlined in Yuan et al. (2006) and then partitioning β_t and its two components (funds following their own trades; funds following the trades of other funds) into two groups corresponding to the new and the full moon period[26], respectively.

4. Results – Discussion

4.1 Do fund managers herd in Turkey?

We begin the presentation of our results with the estimates from Equation (3) and the concomitant decomposition of β_t into its two components (funds following their own trades; funds following the trades of other funds) as per Equation (4) for the full sample period; results are presented in Table 2 for stocks traded by at least one (Panel A), two (Panel B), three (Panel C) or four (Panel D) funds. The employment of those four thresholds is appropriate here in view of the low average daily number (three) of active funds per stock, thus allowing us to assess whether our findings are robust to different levels of institutional equity trading activity. The results outlined in Table 2 suggest that Turkish funds' equity demand is characterized by significant temporal dependence, as evidenced

[26] We construct these periods by assuming 7-day windows (corresponding to +/-3 days around the new/full moon day plus the new/full moon day), in line with Yuan et al. (2006); we do not assume 15-day windows (unlike Yuan et al., 2006), in order to avoid the contamination of the new/full moon window with days falling within other lunar phases (first quarter; third quarter).

through the significantly[27] positive β_t values; the latter exhibit a declining trend as the number of active funds per stock increases, ranging from 0.0631 for the ≥1 funds' threshold to 0.0471 for the ≥4 funds' threshold.[28] These findings suggest that the day-on-day cross correlation of Turkish institutional demand at the market level is around 4.7-6.3%, thus placing our findings in between the cross correlations reported for other markets[29] for various frequencies.

A closer inspection of β_t's two components reveals interesting patterns; whereas the "funds following their own trades" part is significantly positive (denoting that funds follow their own lagged trades) for the ≥1 funds' threshold, it turns significantly negative (denoting that funds trade against the direction of their own lagged trades) for the rest three thresholds, with that part's value being the most negative for the ≥4 funds' threshold. On the other hand, the "funds following the trades of other funds" component is always significantly positive (indicative of significant herding), with its value rising (and from the ≥2 funds' threshold onward, exceeding the β_t value)[30] as we move toward the ≥4 funds' threshold. Overall, the evidence we report here strongly suggests the prevalence of herd behaviour among Turkish fund managers, with its magnitude rising as the average daily number of active funds per stock rises.

To assess whether herding varies contingent on its direction (buy; sell), we re-estimate Equation (3) and decompose β_t into its two components for predominantly bought ($Raw\Delta_{k,t}$ >0.5) and predominantly sold ($Raw\Delta_{k,t}$ <0.5) stocks (drawing on the previously mentioned definition of buy- and sell-herds), with results presented in Tables 3 and 4, respectively. β_t is always significantly positive for sell-herds and significantly positive for the first two thresholds' estimations for buy-herds. Both β_t components (funds following their own trades; funds following the trades of other funds) are mostly significant; the "funds following their own trades" ("funds following the trades of other

[27] For the purpose of brevity, any reference to statistical significance in this study will pertain to estimates whose p-values are less than 0.1.

[28] The ≥3 funds' threshold presents us with a marginally lower β_t value (0.0469) than the ≥4 funds' threshold; however, both thresholds' β_t values are well below those of the ≥1 and ≥2 funds' thresholds.

[29] The β_t values reported for the ≥1 funds' threshold (we only present those, since the rest of the thresholds used in the literature vary) are: 0.237 for Bulgaria (Economou et al., 2015b), 0.1642 for Germany (Kremer and Nautz, 2013), 0.743 for Montenegro (Economou et al., 2015b), 0.0424 for Portugal (Holmes et al., 2013), 0.0426 for Spain (Gavriilidis et al., 2013) and 0.1194 for the US (Sias, 2004). Since we study institutional herding at the market level, we do not include here β_t estimates from studies using the Sias (2004) model to measure industry herding (Choi and Sias, 2009; Celiker et al., 2015).

[30] The "funds following the trades of other funds" value amounts to 86%, 154%, 224% and 234% of β_t as we move from the ≥1 funds' to the ≥4 funds' threshold.

funds") component is almost always negative (positive), with its values being almost always smaller (larger) for the buy compared to the sell herd and almost always substantially smaller (larger) compared to its corresponding values per threshold in Table 2. As a result, funds trade away from their lagged trades more (less) strongly and follow the lagged trades of other funds more (less) when trading stocks that are predominantly bought (sold). With the two β_t components strongly countervailing each other, this leads β_t to assume lower values in Tables 3 and 4 compared to Table 2, thus indicating that the temporal dependence of directional (buy; sell) institutional demand is less pronounced compared to that of total institutional demand. The results reported in Tables 3 and 4 show that Turkish funds exhibit stronger buy- than sell-herding and it is possible that this is due to the asymmetry in complexity involved in a buy- compared to a sell-decision: when funds have to choose which stock/s to sell, they have to choose among the given number of stocks in their portfolio; by comparison, the decision to buy a stock is more taxing in terms of time, effort and attention, since it will involve choosing among the universe of listed stocks (Barber and Odean, 2009). Herding in this case can function as a useful heuristic, since monitoring the investments of their peers can inform/facilitate the stock selection process for fund managers.

4.2 Is Turkish fund managers' herding subject to the weekend effect?

Turning now to the empirical examination of the weekend effect over institutional herding, we present the estimates from Equation (3) and the components of β_t for all four thresholds for Fridays and Mondays in Table 5. As the results show, β_t is always significantly positive, without its magnitude exhibiting any regularity within each of (or between) the two days, aside from its highest value being observed for both days for the ≥2 funds' threshold. The "funds following their own trades" component is almost always negative (its significance being absent for the ≥1 funds' threshold), thus showcasing that Turkish funds tend to trade away from their lagged trades on both days, more so on Mondays (where the component's values are larger in absolute terms, i.e. more negative, than Friday's for the last three thresholds). This would indicate that the potential for funds' herding would be relatively greater for Mondays; indeed, the “funds following the trades of other funds” component (which is significantly positive in all cases) is larger for Mondays, with the exception of the ≥1 funds’ threshold. However, the difference in herding (indeed, any difference in estimates) between the two days is insignificant, denoting that, although Turkish fund managers herd more on Mondays, their herding is insignificantly different from Fridays’, thus, leading us to reject hypothesis $H_{0,1,1}$.

Regarding the relationship between the weekend effect and institutional herding direction, Tables 6 and 7 present some interesting findings. To begin with, the temporal dependence of directional institutional demand is much less pronounced for the buy- than the sell-herd (β_t is significant for the buy-herd on Fridays for the ≥1 funds’ threshold only, with its significance manifesting itself for both days[31] for the first three thresholds for the sell-herd). What is more, limited evidence of significance is further revealed for the β_t’s components for the buy-herd: the “funds following their own trades” (“funds following the trades of other funds”) part for the buy-herd is significantly negative (positive) for the ≥3 and 4 funds’ thresholds for Mondays and the ≥4 funds’ threshold for Fridays. Conversely, sell-herds present us with more widespread evidence of significance for both days. The “funds following their own trades” part for the sell-herd is significantly negative for the last three thresholds (the ≥3 funds’ threshold) for Fridays (Mondays), denoting that funds trade away from their lagged trades more strongly on the sell-side on Fridays. The “funds following the trades of other funds” part is significantly positive for all thresholds (the last two thresholds) for Fridays (Mondays); Mondays’ sell-herding (when significant) is always smaller in magnitude than Fridays’, with the difference between the two days’ estimates being significant for that part for the ≥2 and 3 funds’ thresholds. We also observe that for the ≥3 and 4 funds’ thresholds (i.e. when Mondays’ buy-herding is significant), buy-herding on Mondays is stronger than sell-herding on that day (the “funds following the trades of other funds” part is far more positive).

Overall, Turkish fund managers sell-herd consistently on Fridays and always more than on Mondays (when they do sell-herd on Mondays), while their buy-herding is limited, being relatively more present on Mondays (and stronger, when significant, than their Mondays’ sell-herding). These

[31] Except Mondays, for the ≥2 funds’ threshold.

findings run counter to our theoretical expectations; the positive (negative) mood associated with Friday (Monday) would be expected to boost buy- (sell-) herding on that day. Our results indicate the exact opposite, leading us to reject hypotheses $H_{0,1,2}$ and $H_{0,1,3}$, suggesting that mood is not what determines institutional herding direction in Turkey around the weekend. In view of the weekend effect (Monday's returns being the lowest and Friday's the highest in the week) having been established in Turkey (Demirer and Karan, 2002; Oğuszoy and Güven, 2003; Cinko and Avci, 2009), it is possible that what we observe here is Turkish fund managers buy-herding on Mondays in order to take advantage of the day's low prices and sell-herding on Fridays in order to book short term profits due to the day's high returns.

4.3 Is Turkish fund managers' herding subject to the holiday effect?

We now turn to assess whether the herding of Turkish fund managers exhibits any holiday effect; Table 8 presents the estimates from Equation (3) and the components of β_t for all four thresholds pre and post holiday. No evidence of β_t –significance surfaces whatsoever, with the two components of β_t demonstrating statistical significance primarily pre holiday; more specifically, the "funds following their own trades" ("funds following the trades of other funds") component is significantly negative (positive) for the ≥2 and 3 funds' thresholds pre holiday, without its difference from its corresponding post holiday values being statistically significant for those thresholds. The "funds following their own trades" part is also significantly negative both pre and post holiday for the ≥4 funds' threshold, with the difference between the two again being insignificant. Therefore, although we reveal some evidence indicating that institutional herding exists pre holiday, it is insignificantly different compared to post holiday, thus leading us to reject hypothesis $H_{0,2,1}$.

Tables 9 and 10 present the estimates from Equation (3) and the β_t components for buy- and sell-herds, respectively, pre and post holiday. Again here, we notice the notably limited evidence of statistical significance in our estimations; the β_t coefficients, for example are found to be significant only for the sell-herd for the ≥1 funds' threshold pre and post holiday. The "funds following their own trades” component is significantly negative for the ≥3 and 4 funds’ thresholds pre holiday for the buy-herd and significantly negative for the ≥4 funds’ threshold pre holiday for the sell-herd. With the “funds following the trades of other funds” component being significantly positive for the ≥2 and 3 funds’ thresholds pre holiday for the buy-herd and significantly positive for the ≥4 funds’ threshold pre holiday for the sell-herd, we reject hypothesis $H_{0,2,3}$ (since there exists no consistent evidence that buy-herding - when significant - is stronger than sell-herding pre holiday). The difference between the pre holiday estimates and their corresponding post holiday estimates is never found to be significant in any pre-post holiday pair of estimates for any threshold, thus leading us to reject hypothesis $H_{0,2,2}$.

4.4 Is Turkish fund managers’ herding subject to the Ramadan effect?

Table 11 presents the estimates from Equation (3) and the β_t components within and outside the month of Ramadan. As the results suggest, β_t is always significantly positive, assuming greater values during compared to outside Ramadan, with the difference of its estimates in- versus outside Ramadan being largely insignificant (with the exception of the ≥2 funds’ threshold). The “funds following their own trades” part is mostly negative (with the exception of the ≥1 funds’ threshold), with its values appearing consistently significant and negative during both Ramadan and non-Ramadan days for the ≥3 and 4 funds’ thresholds; for those two thresholds, its in-Ramadan estimates are larger (less negative) than the non-Ramadan ones, without their difference exhibiting any statistical significance, though. Similar to the pattern of β_t, the “funds following the trades of other funds” part is always significantly positive and assumes larger in-Ramadan values compared to non-Ramadan ones (with the exception of the ≥1 funds’ threshold); however, the difference between in- and non-Ramadan estimates for that part is never found to be significant. The above suggests that institutional herding is significant both during and outside Ramadan (tending to be of larger magnitude in-versus-outside Ramadan), yet insignificantly different between the two, thus denoting that hypothesis $H_{0,3,1}$ must be rejected.

Tables 12 and 13 present our empirical results for the buy- and sell-herd, respectively. As the estimates presented indicate, there is almost no evidence of statistical significance for either β_t or any of its two components for the sell-herd in-Ramadan, with non-Ramadan days dominating statistical significance in Table 13. As far as Table 12 is concerned, β_t appears significantly positive both within and outside Ramadan for the buy-herd for the ≥1 and 2 funds' thresholds (with the difference being significant for the ≥2 funds' threshold only), while, with the exception of the in-Ramadan estimate for the ≥2 funds' threshold, the "funds following their own trades" part is always significant (and mostly negative, except for the ≥1 funds' threshold). Regarding the "funds following the trades of other funds" part, it appears significantly positive during (outside) Ramadan for the ≥3 and 4 funds' thresholds (last three thresholds).

Overall, Ramadan is found to be associated with stronger buy-herd activity on behalf of Turkish fund managers (in line with theoretical expectations on the month's positive mood prompting equity purchases), without that activity being distinctively significant or consistent for that purpose. On the one hand, Ramadan is devoid of any sell-herding activity, with significant buy-herding emerging for that month for two (≥3 and 4 funds' thresholds) of the four thresholds; the fact that buy-herding is not consistently significant in-Ramadan leads hypothesis $H_{0,3,3}$ to be rejected here. On the other hand, buy-herding in-Ramadan (when significant) assumes always higher values compared to outside Ramadan; however, the in- versus non-Ramadan estimates for buy-herding (indeed, almost all in-versus-non-Ramadan pairs of estimates in Tables 12 and 13) are insignificantly different from each other, thus leading us to reject hypothesis $H_{0,3,2}$.[32]

4.5 Do changes in sunshine levels affect Turkish fund managers' herding?

[32] Białkowski et al. (2013) argued that market returns in majority Muslim countries tend to rise after the three-and-a-half day celebration (known as Ramazan Bayrami in Turkey, a public holiday for which we have already accounted in our holiday effect tests) following the Ramadan's completion and proposed an alternative identification of the Ramadan-period with one including not only the Ramadan-month in itself, but also the seven days following the Ramazan Bayrami. We explored whether our results vary when their definition of Ramadan is implemented, yet again produced evidence suggesting the absence of any significant difference in institutional herding in-versus-outside Ramadan. Results are not presented here in the interest of brevity and are available upon request.

Table 14 presents the results from the estimations of Equation (3) and the β_t components on days of increased and days of decreased sunshine. At first glance, there exists not a single insignificant estimate for any of the four thresholds examined, with β_t and its two components tending to exhibit larger values for decreased sunshine days (with the exception of the ≥1 funds' threshold); however, the difference of any pair of estimates between increased and decreased sunshine days is overall insignificant, leading us to reject hypothesis $H_{0,4,1}$.

Tables 15 and 16 present the estimates from Equation (3) and the β_t components on days of increased and days of decreased sunshine for the buy- and sell-herd, respectively. Regarding the buy-herd, the findings in Table 15 suggest that the temporal dependence of institutional demand is occasionally significant, as opposed to the "funds following their own trades" part which is always significant and almost always negative (with the exception of the first threshold). With the relevant coefficient being more negative for increased sunshine days compared to decreased sunshine ones for the last three thresholds, this denotes that fund managers in Turkey tend to trade against their own lagged trades more strongly on increased sunshine days, without, however, the difference between increased and decreased sunshine days appearing significant. The "funds following the trades of other funds" component is significantly positive for the last three thresholds (negative and insignificant for the first threshold), with buy-herding appearing stronger (yet insignificantly so) on increased as opposed to decreased sunshine days. As regards sell-herding, β_t is consistently positive and significant on decreased sunshine days (compared to it being significantly positive on increased sunshine days for the first two thresholds only). The "funds following their own trades" part exhibits a mixture of signs and significance, the latter clustering mainly on days of increased sunshine. The "funds following the trades of other funds" part is significantly positive for both increased and decreased sunshine days for the ≥2 and 3 funds' thresholds (and the ≥4 funds' threshold on increased sunshine days only). Sell-herding appears stronger on decreased sunshine days for the ≥2 and 3 funds' thresholds, without the difference in herding significance between increased and decreased sunshine days appearing significant for any threshold.

Overall, the results presented so far on the relationship between sunshine and institutional herding direction indicate that buy- (sell-) herding is stronger on increased (decreased) compared to decreased (increased) sunshine days. These results suggest that the sign of this relationship in the Turkish market is the correct one, in line with theoretical expectations, according to which fund managers would be expected to buy- (sell-) herd more on days of positive (negative) mood. Nevertheless, the differences in herding estimates between increased and decreased sunshine days appear consistently insignificant in Tables 15 and 16, implying that hypothesis $H_{0,4,2}$ cannot be accepted. Although the magnitude of buy-herding tends to be, overall, larger than that of sell-herding on increased sunshine days (as the results from the ≥2, 3 and 4 funds' thresholds indicate), the picture on decreased sunshine days is not consistent (buy-herding is stronger than sell-herding for the ≥3 and 4[33] funds' thresholds, while sell-herding stronger than buy-herding for the ≥2 funds' threshold), thus leading us to reject hypothesis $H_{0,4,3}$.

4.6 Does the new/full moon affect Turkish fund managers' herding?

Table 17 presents the estimates from Equation (3) and the β_t components for the new and full moon periods, respectively. All in all, almost all estimates are statistically significant, with β_t–values appearing significantly positive and higher during the new moon period; the "funds following their own trades" part is significantly negative for the ≥2, 3 and 4 funds' thresholds[34] for both lunar phases, being always smaller (i.e. more negative) during full moon periods compared to new moon ones. The "funds following the trades of other funds" part is always significantly positive, without its magnitude exhibiting any regularity, as it is greater during new (full) moon periods for the ≥2 and 3 funds' thresholds (≥1 and 4 funds' thresholds). With the difference between the new and full moon periods' estimates being always insignificant for that part, this suggests that Turkish fund managers' herding is

[33] For the ≥ 4 funds' threshold, the "funds following the trades of others funds" value is insignificant during decreased sunshine days for the sell-herd.

[34] For the ≥1 funds' threshold this part appears positive for both new and full moon periods, with the latter's estimate being insignificant.

insignificantly different between new and full moon periods, denoting that hypothesis $H_{0,5,1}$ should be rejected.

Tables 18 and 19 contain the estimates from Equation (3) and the β_t components for the buy- and sell-herd corresponding to the new and full moon periods. As the findings in Table 18 show, the two β_t components assume values (strongly positive for the "funds following the trades of other funds" part and strongly negative for the "funds following their own trades" part) that strongly countervail each other, resulting in very small and insignificant β_t-estimates (with the exception of the first threshold). Fund managers buy-herd during both new (≥2, 3 and 4 funds' thresholds) and full (≥3 and 4 funds' thresholds) moon periods as the "funds following the trades of other funds" part's estimates indicate. Their buy-herding appears stronger during full moon periods (the case of the ≥3 and 4 funds' thresholds, for which this part is significant for both lunar phases), with its difference between full and new moon periods being insignificant. Regarding the sell-herd (Table 19), β_t manifests itself significantly in more tests, with the significance of its components appearing rather mixed. The "funds following their own trades" part presents itself with mixed sign and significance across the four thresholds, while the "funds following the trades of other funds" part is almost always positive. The significance of that part is evident for the ≥2, 3 (both new and full moon periods) and 4 (full moon period only) funds' thresholds, with its magnitude exhibiting neither any clear pattern, nor statistical difference between full and new moon periods.[35] With the difference in herding between full and new moon periods being insignificant in all cases, we reject hypothesis $H_{0,5,2}$. Looking now at the buy- and sell-herding within each of the two lunar phases, we observe that buy-herding is stronger (the "funds following the trades of other funds" part assumes higher values) than sell-herding for the new moon period; however, buy-herding appears stronger than sell-herding for the full moon period as well, as the comparison between the "funds following the trades of other funds" parts that are significant for that period (≥3 and 4 funds' thresholds) in Tables 18 and 19 indicates. Although the former would be in line with theoretical expectations (new moon's positive mood would be expected

[35] The "funds following the trades of other funds" estimate is larger during the full moon period for the ≥2 funds' threshold and during the new moon period for the ≥3 funds' threshold.

to boost buy-herding), the latter is not (full moon's negative mood would be expected to be associated with sell-herding), thus leading hypothesis $H_{0,5,3}$ to be rejected.

4.7 Robustness tests

The evidence presented so far suggests that mood does not affect the propensity of Turkish fund managers to herd, with their herding found to be insignificantly different across various mood states in almost all cases. As a first robustness test of our findings, we first remove the 14 index funds of our data set from our sample and repeat all estimations from Tables 2-18. The reason for removing all index funds pertains to the fact that these funds are trackers in nature that rebalance their portfolios mechanically, aiming at replicating the composition and performance of the index they are benchmarked against. Including these funds in our estimations raises the possibility of our results being affected by the trades of funds motivated by passive investing and which, as a result, would not be expected to be related to mood *per se*. The estimates we obtain following the removal of those 14 funds from the sample are qualitatively similar to those reported in Tables 2-18 and confirm the absence of any mood-effects over Turkish fund managers' herding.[36]

We then explore whether our results are driven by the size effect, a well-known determinant of institutional herding internationally (Andrikopoulos et al., 2017).[37] To that end, we rank the universe of stocks that our sample funds have invested in each year into five quintiles (Q1 to Q5, with Q1 corresponding to the smallest and Q5 to the largest capitalization stocks) based on those stocks' market capitalization[38] at the end of the immediately preceding year and repeat all estimations from Tables 2-18. Results[39] confirm, by and large, the original full-sample results on institutional herding being insignificantly different across various mood states, thus indicating the absence of any size effect in our estimates. Moreover, the "funds following the trades of other funds" consistently

[36] Results are not reported here for reasons of brevity and are available from the authors on request.
[37] Funds have, generally, been observed in the literature to herd the most when trading very large or very small stocks. For a detailed discussion of the reasons pertaining to size-related herding, see Andrikopoulos et al. (2017).
[38] Data on our sample stocks' market capitalization was obtained from the Thomson Reuters Data Stream database.
[39] Results are not reported here for brevity reasons and are available from the authors on request.

assumes its lowest value for quintile 1, suggesting that Turkish fund managers herd the least in stocks of the smallest capitalization, irrespective of the mood state tested. A possible reason for this is that the relatively lower volumes typifying small stocks reduce the feasibility of herding by leading to delays in order-execution, thus rendering it more difficult for investors wishing to herd (indeed, to engage in any trading strategy) to do so uninhibitedly (Andrikopoulos et al., 2017).

With all our analyses so far having assessed the effect of single mood proxies over institutional herding, an issue worth exploring is whether our results hold when accounting for those proxies jointly; it may well be the case that the mood proxies employed here are related in some way, thus raising the possibility of our findings being cast in doubt. To assess the joint interactions of our mood proxies with institutional herding, we pool them together in a multivariate setting, as follows:

$$\beta_t = \alpha_0 + \alpha_1 Monday_t + \alpha_2 Holiday_t + \alpha_3 Ramadan_t + \alpha_4 Sunshine_t + \alpha_5 New_t + \varepsilon_t \quad (5)$$

In the above equation, $Monday_t$ is a dummy assuming the value of one on Mondays, zero otherwise; $Holiday_t$ is a dummy assuming the value of one pre holiday, zero otherwise; $Ramadan_t$ is a dummy assuming the value of one during Ramadan, zero otherwise; $Sunshine_t$ is a dummy assuming the value of one on increased sunshine days, zero otherwise; and New_t is a dummy assuming the value of one during new moon periods, zero otherwise. We also estimate Equation (5) using each of β_t's two components as dependent variable in turn. Results are presented in Table 20 for all four thresholds and, overall, denote the very limited presence of statistically significant estimates; these are predominantly detected when the "funds following their own trades" part is the dependent variable and always at the 10% level of significance.[40] No evidence of significance, whatsoever, surfaces when the "funds following the trades of other funds" part is used as dependent variable, thus denoting the absence of any significant relationship between institutional herding and mood.[41]

[40] More specifically, when the "funds following their own trades" part is used as dependent variable, the Ramadan and New Moon dummies are both significantly positive for the ≥1 funds' threshold and the Monday dummy is significantly negative for the ≥3 funds' threshold. We also observe that the Ramadan (pre holiday) dummy is significantly positive (negative) for the ≥4 funds' threshold when the β_t is used as dependent variable.

[41] Similar results were discovered when estimating Equation (5) using β_t and its two components from the buy- and sell-herds. Results are not reported here for brevity reasons and are available from the authors on request.

5. Conclusion

In this paper we empirically assess the relationship between mood and institutional investors' herding for the first time in the literature. Drawing on the daily portfolio holdings of Turkish funds for the 2/1/2002 – 14/8/2008 period, we study this relationship on the premises of a series of established mood proxies, including the weekend effect, the holiday effect, Ramadan, sunshine and the new/full moon. Overall fund managers in Turkey herd significantly, with their herding growing in magnitude as the number of active funds per stock rises and appearing stronger on the buy- than the sell-side. Regarding the relationship of mood with institutional herding, it occasionally assumes the correct sign as per theoretical expectations; however, institutional herding is found to be insignificantly different across various mood states, thus showcasing that the propensity of fund managers to herd is not subject to the impact of mood. These results further indicate that the pursuit of a behavioural trading pattern by institutional investors does not necessarily render them mood-prone in their trading conduct (more so given their sophisticated nature) and contribute to the debate on the role of less-than-perfectly rational factors over investors' herding, in general.

The evidence presented in our paper is of particular interest to researchers, since the lack of a significant effect of mood over institutional herding documented here raises the question of whether this holds internationally across markets with differences in their size, financial development, institutional design and asset management industry structure. Given the mixed extant evidence (Goetzmann et al., 2015; Kaustia and Rantapuska, 2016) on the role of weather-related mood proxies over institutional trading behaviour, it is not unlikely that the effect of mood over institutional herding may vary internationally. With the growth in international portfolio investments since the 1990s, it is also worth examining whether the differential weather conditions prevailing in the home countries of overseas fund managers are associated with any potential variations in their herding when trading in foreign markets (given the significant role of weather in shaping mood). Another issue arising is whether mood-factors commonly affecting many/all markets (such as Ramadan in majority Muslim markets and lunar phases for all markets) produce similar effects over fund managers' herding in different jurisdictions. Our findings are also of interest to investment practitioners keen on exploiting potential market inefficiencies; if, for example, institutional herding is found to be strongly related to a mood-factor, this could be used as input to inform their trading strategies. One such possibility would be the case whereby institutional herding interacts significantly with a weather-variable, such as rain or temperature; in the presence of such a relationship, an investor could rely on rain/temperature forecasts to trade in/against the anticipated direction of institutional herding while also employing weather derivatives to hedge their positions.

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Table 1: Descriptive statistics

Number of stocks	419
Number of funds	134
Number of day-holding positions	2,626,370
Average number of active stocks per day traded by ≥1 fund	74.6
Average number of active stocks per day traded by ≥2 funds	43.9
Average number of active stocks per day traded by ≥3 funds	30.8
Average number of active stocks per day traded by ≥4 funds	23.0
Average number of active funds per stock per day for stocks traded by ≥1 fund	3.2
Average number of active funds per stock per day for stocks traded by ≥2 funds	4.7
Average number of active funds per stock per day for stocks traded by ≥3 funds	5.8
Average number of active funds per stock per day for stocks traded by ≥4 funds	6.7

The table presents descriptive statistics on the data set of daily portfolio holdings of "Type A" Turkish funds for the 2/1/2002 – 14/8/2008 period obtained from the Capital Markets Board of Turkey. We report the average number of stocks traded by at least 1/2/3/4 funds every day; we also report the average number of active funds per stock each day for stocks traded by at least 1/2/3/4 funds.

Table 2: Tests for herding presence– Buyer if increased position

Average coefficient (β_t)	Partitioned slope coefficient: Funds following their own trades	Partitioned slope coefficient: Funds following the trades of other funds	Average R^2
Panel A: No of active funds per stock ≥ 1			
0.0631	0.0090	0.0541	0.0294
(0.0000)	(0.0501)	(0.0000)	
Panel B: No of active funds per stock ≥ 2			
0.0596	-0.0325	0.0920	0.0407
(0.0000)	(0.0000)	(0.0000)	
Panel C: No of active funds per stock ≥ 3			
0.0469	-0.0582	0.1051	0.0535
(0.0000)	(0.0000)	(0.0000)	
Panel D: No of active funds per stock ≥ 4			
0.0471	-0.0629	0.1100	0.0674
(0.0000)	(0.0000)	(0.0000)	

This table reports the estimates from the equation: $\Delta_{k,t} = \beta_t \Delta_{k,t-1} + \varepsilon_{k,t}$. For each security and day between January, 2nd 2002 and August 14th, 2008 we calculate the fraction of funds that increase their position in the security. A fund is defined as increasing its position if it holds a greater fraction of the firm's shares at the end of day *t* than it held at the end of day *t-1*. All data are standardized (i.e. rescaled to zero mean, unit variance) each day. We then estimate daily cross sectional regressions of institutional demand on lagged institutional demand. Because $\Delta_{k,t-1}$ is the sole 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 1659 correlation coefficients and associated p-values (in parentheses). The second and third columns report the portion of the correlation resulting from funds following their own lagged trades and the portion resulting from funds following the previous trades of other funds (herding).

Table 3: Tests for herding direction– buy herding

Average coefficient (β_t)	Partitioned slope coefficient: Funds following their own trades	Partitioned slope coefficient: Funds following the trades of other funds	Average R^2
Panel A: No of active funds per stock ≥ 1			
0.0318	0.0341	-0.0023	0.0520
(0.0000)	(0.0082)	(0.8640)	
Panel B: No of active funds per stock ≥ 2			
0.0222	-0.1777	0.1999	0.0950
(0.0042)	(0.0005)	(0.0001)	
Panel C: No of active funds per stock ≥ 3			
0.0137	-0.2519	0.2656	0.1174
(0.1249)	(0.0000)	(0.0000)	
Panel D: No of active funds per stock ≥ 4			
0.0053	-0.4075	0.4128	0.1627
(0.7435)	(0.0000)	(0.0000)	

This table reports the estimates from the equation: $\Delta_{k,t} = \beta_t \Delta_{k,t-1} + \varepsilon_{k,t}$ on the premises of stocks predominantly bought each day. For each security and day between January, 2nd 2002 and August 14th, 2008 we calculate the fraction of funds that increase their position in the security. A fund is defined as increasing its position if it holds a greater fraction of the firm's shares at the end of day *t* than it held at the end of day *t-1*. We then select only those stocks whose $Raw\Delta_{k,t}$ >0.5. All data are standardized (i.e. rescaled to zero mean, unit variance) each day. We then estimate daily cross sectional regressions of institutional demand on lagged institutional demand based on that truncated sample of stocks with $Raw\Delta_{k,t}$ >0.5. Because $\Delta_{k,t-1}$ is the sole 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 for that sample. The first column reports the time-series' average of these 1659 correlation coefficients and associated p-values (in parentheses). The second and third columns report the portion of the correlation resulting from funds following their own lagged trades and the portion resulting from funds following the previous trades of other funds (herding).

Table 4: Tests for herding direction– sell herding

	Partitioned slope coefficient		
Average coefficient (β_t)	Funds following their own trades	Funds following the trades of other funds	Average R²
Panel A: No of active funds per stock ≥ 1			
0.0492	0.0207	0.0285	0.0523
(0.0000)	(0.1208)	(0.0421)	
Panel B: No of active funds per stock ≥ 2			
0.0318	-0.1333	0.1651	0.0942
(0.0000)	(0.0003)	(0.0000)	
Panel C: No of active funds per stock ≥ 3			
0.0231	-0.1468	0.1699	0.1159
(0.0077)	(0.0000)	(0.0000)	
Panel D: No of active funds per stock ≥ 4			
0.0312	-0.0650	0.0962	0.1419
(0.0023)	(0.6914)	(0.5572)	

This table reports the estimates from the equation: $\Delta_{k,t} = \beta_t \Delta_{k,t\text{-}1} + \varepsilon_{k,t}$ on the premises of stocks predominantly sold each day. For each security and day between January, 2nd 2002 and August 14th, 2008 we calculate the fraction of funds that increase their position in the security. A fund is defined as increasing its position if it holds a greater fraction of the firm's shares at the end of day *t* than it held at the end of day *t-1*. We then select only those stocks whose $Raw\Delta_{k,t}$ <0.5. All data are standardized (i.e. rescaled to zero mean, unit variance) each day. We then estimate daily cross sectional regressions of institutional demand on lagged institutional demand based on that truncated sample of stocks with $Raw\Delta_{k,t}$ <0.5. Because $\Delta_{k,t-1}$ is the sole 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 for that sample. The first column reports the time-series' average of these 1659 correlation coefficients and associated p-values (in parentheses). The second and third columns report the portion of the correlation resulting from funds following their own lagged trades and the portion resulting from funds following the previous trades of other funds (herding).

Table 5: Tests for herding presence–herding and the weekend effect

Average coefficient (β_t)		Partitioned slope coefficient: Funds following their own trades		Partitioned slope coefficient: Funds following the trades of other funds		Average R²	
Friday	Monday	Friday	Monday	Friday	Monday	Friday	Monday
Panel A: No of active funds per stock ≥ 1							
0.0539	0.0585	-0.0088	0.0071	0.0627	0.0514	0.0280	0.0280
(0.0000)	(0.0000)	(0.3730)	(0.4992)	(0.0000)	(0.0000)		
0.7101		0.2698		0.3572			
Panel B: No of active funds per stock ≥ 2							
0.0583	0.0698	-0.0318	-0.0328	0.0901	0.1026	0.0395	0.0434
(0.0000)	(0.0000)	(0.0007)	(0.0023)	(0.0000)	(0.0000)		
0.4669		0.9384		0.4843			
Panel C: No of active funds per stock ≥ 3							
0.0405	0.0380	-0.0419	-0.0787	0.0823	0.1168	0.0481	0.0564
(0.0013)	(0.0049)	(0.0001)	(0.0000)	(0.0000)	(0.0000)		
0.8948		0.1089		0.1781			
Panel D: No of active funds per stock ≥ 4							
0.0354	0.0648	-0.0519	-0.0607	0.0873	0.1255	0.0629	0.0737
(0.0243)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)		
0.1753		0.5939		0.1266			

This table reports the estimates from the equation: $\Delta_{k,t} = \beta_t \Delta_{k,t\text{-}1} + \varepsilon_{k,t}$ for Mondays and Fridays. For each security and day between January, 2nd 2002 and August 14th, 2008 we calculate the fraction of funds that increase their position in the security. A fund is defined as increasing its position if it holds a greater fraction of the firm's shares at the end of day *t* than it held at the end of day *t-1*. All data are standardized (i.e. rescaled to zero mean, unit variance) each day. We then estimate daily cross sectional regressions of institutional demand on lagged institutional demand once for Mondays and once for Fridays only. Because $\Delta_{k,t-1}$ is the sole 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 for that sample on Mondays and Fridays, respectively. The first column reports the time-series' average of these correlation coefficients and associated p-values (in parentheses) for each of the two days. The second and third columns report the portion of the correlation resulting from funds following their own lagged trades and the portion resulting from funds following the previous trades of other funds (herding) for each of the two days. P-values of Wald test-statistics of difference between Friday-Monday estimates are included underneath each pair of estimates.

Table 6: Tests for herding direction–buy herding and the weekend effect

Average coefficient (β_t)		Partitioned slope coefficient: Funds following their own trades		Partitioned slope coefficient: Funds following the trades of other funds		Average R^2	
Friday	Monday	Friday	Monday	Friday	Monday	Friday	Monday
Panel A: No of active funds per stock ≥ 1							
0.0299	0.0090	0.0010	0.0089	0.0289	0.0001	0.0543	0.0551
(0.0166)	(0.4657)	(0.9746)	(0.7601)	(0.3661)	(0.9956)		
0.2338		0.8504		0.5027			
Panel B: No of active funds per stock ≥ 2							
0.0207	0.0276	-0.1090	-0.1558	0.1297	0.1835	0.0853	0.0965
(0.2075)	(0.1072)	(0.2199)	(0.2451)	(0.1486)	(0.1831)		
0.7712		0.7705		0.7434			
Panel C: No of active funds per stock ≥ 3							
0.0141	0.0372	-0.1030	-0.3104	0.1171	0.3477	0.1168	0.1347
(0.4650)	(0.1005)	(0.2193)	(0.0041)	(0.1703)	(0.0016)		
0.4358		0.1285		0.0974			
Panel D: No of active funds per stock ≥ 4							
-0.0055	0.0012	-0.1419	-0.6678	0.1364	0.6690	0.1754	0.1758
(0.8284)	(0.9650)	(0.0729)	(0.0023)	(0.0901)	(0.0026)		
0.8573		0.0231		0.0234			

This table reports the estimates from the equation: $\Delta_{k,t} = \beta_t \Delta_{k,t-1} + \varepsilon_{k,t}$ for Mondays and Fridays on the premises of stocks predominantly bought. For each security and day between January, 2nd 2002 and August 14th, 2008 we calculate the fraction of funds that increase their position in the security. A fund is defined as increasing its position if it holds a greater fraction of the firm's shares at the end of day *t* than it held at the end of day *t-1*. We then select only those stocks whose $Raw\Delta_{k,t} > 0.5$ for each of the two days separately. All data are standardized (i.e. rescaled to zero mean, unit variance) each day. We then estimate daily cross sectional regressions of institutional demand on lagged institutional demand once for Mondays and once for Fridays only, for stocks with $Raw\Delta_{k,t} > 0.5$. Because $\Delta_{k,t-1}$ is the sole 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 for that sample on Mondays and Fridays, respectively. The first column reports the time-series' average of these correlation coefficients and associated p-values (in parentheses) for each of the two days. The second and third columns report the portion of the correlation resulting from funds following their own lagged trades and the portion resulting from funds following the previous trades of other funds (herding) for each of the two days. P-values of Wald test-statistics of difference between Friday-Monday estimates are included underneath each pair of estimates.

Table 7: Tests for herding direction–sell herding and the weekend effect

Average coefficient (β_t)		Partitioned slope coefficient: Funds following their own trades		Partitioned slope coefficient: Funds following the trades of other funds		Average R^2	
Friday	Monday	Friday	Monday	Friday	Monday	Friday	Monday
Panel A: No of active funds per stock ≥ 1							
0.0506	0.0621	-0.0279	0.0272	0.0785	0.0348	0.0530	0.0522
(0.0000)	(0.0000)	(0.3057)	(0.3219)	(0.0073)	(0.2330)		
0.5128		0.1541		0.2899			
Panel B: No of active funds per stock ≥ 2							
0.0359	0.0085	-0.2118	-0.0020	0.2477	0.0105	0.0874	0.0941
(0.0333)	(0.6220)	(0.0021)	(0.9762)	(0.0005)	(0.8727)		
0.2560		0.0275		0.0140			
Panel C: No of active funds per stock ≥ 3							
0.0401	0.0418	-0.2399	-0.0890	0.2799	0.1308	0.1194	0.1079
(0.0389)	(0.0244)	(0.0003)	(0.0877)	(0.0000)	(0.0193)		
0.9473		0.0738		0.0960			
Panel D: No of active funds per stock ≥ 4							
0.0216	0.0355	-0.2941	-0.1150	0.3156	0.1506	0.1410	0.1426
(0.3589)	(0.1325)	(0.0291)	(0.1320)	(0.0180)	(0.0601)		
0.6748		0.2463		0.2869			

This table reports the estimates from the equation: $\Delta_{k,t} = \beta_t \Delta_{k,t-1} + \varepsilon_{k,t}$ for Mondays and Fridays on the premises of stocks predominantly sold. For each security and day between January, 2nd 2002 and August 14th, 2008 we calculate the fraction of funds that increase their position in the security. A fund is defined as increasing its position if it holds a greater fraction of the firm's shares at the end of day *t* than it held at the end of day *t-1*. We then select only those stocks whose $Raw\Delta_{k,t} < 0.5$ for each of the two days separately. All data are standardized (i.e. rescaled to zero mean, unit variance) each day. We then estimate daily cross sectional regressions of institutional demand on lagged institutional demand once for Mondays and once for Fridays only, for stocks with $Raw\Delta_{k,t} < 0.5$. Because $\Delta_{k,t-1}$ is the sole 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 for that sample on Mondays and Fridays, respectively. The first column reports the time-series' average of these correlation coefficients and associated p-values (in parentheses) for each of the two days. The second and third columns report the portion of the correlation resulting from funds following their own lagged trades and the portion resulting from funds following the previous trades of other funds (herding) for each of the two days. P-values of Wald test-statistics of difference between Friday-Monday estimates are included underneath each pair of estimates.

Table 8: Tests for herding presence–herding and the holiday effect

Average coefficient (β_t)		Partitioned slope coefficient: Funds following their own trades		Partitioned slope coefficient: Funds following the trades of other funds		Average R²	
Pre holiday	Post holiday	Pre holiday	Post holiday	Pre holiday	Post holiday	Pre holiday	Post holiday
Panel A: No of active funds per stock ≥ 1							
0.0150	0.0360	-0.0126	-0.0127	0.0276	0.0487	0.0265	0.0329
(0.6115)	(0.2403)	(0.7023)	(0.7307)	(0.2925)	(0.1325)		
0.6191		0.9983		0.6093			
Panel B: No of active funds per stock ≥ 2							
0.0304	0.0096	-0.0714	-0.0217	0.1018	0.0313	0.0446	0.0448
(0.4179)	(0.7816)	(0.0558)	(0.5350)	(0.0398)	(0.3211)		
0.6817		0.3237		0.2201			
Panel C: No of active funds per stock ≥ 3							
0.0032	-0.0286	-0.1094	-0.0469	0.1126	0.0183	0.0438	0.0649
(0.9342)	(0.5070)	(0.0032)	(0.1474)	(0.0174)	(0.7138)		
0.5809		0.1854		0.1643			
Panel D: No of active funds per stock ≥ 4							
-0.0316	-0.0391	-0.1165	-0.0490	0.0849	0.0099	0.0996	0.0712
(0.5705)	(0.3857)	(0.0035)	(0.0488)	(0.1917)	(0.8389)		
0.9158		0.1315		0.3487			

This table reports the estimates from the equation: $\Delta_{k,t} = \beta_t\Delta_{k,t-1} + \varepsilon_{k,t}$ for pre and post holiday days (defined as the day immediately preceding and the day immediately after a holiday, respectively). For each security and day between January, 2nd 2002 and August 14th, 2008 we calculate the fraction of funds that increase their position in the security. A fund is defined as increasing its position if it holds a greater fraction of the firm's shares at the end of day *t* than it held at the end of day *t-1*. All data are standardized (i.e. rescaled to zero mean, unit variance) each day. We then estimate daily cross sectional regressions of institutional demand on lagged institutional demand once for the pre holiday and once for the post holiday days only. Because $\Delta_{k,t-1}$ is the sole 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 for that sample pre and post holiday, respectively. The first column reports the time-series' average of these correlation coefficients and associated p-values (in parentheses) pre and post holiday. The second and third columns report the portion of the correlation resulting from funds following their own lagged trades and the portion resulting from funds following the previous trades of other funds (herding) for each of the two days. P-values of Wald test-statistics of difference between pre and post holiday estimates are included underneath each pair of estimates.

Table 9: Tests for herding presence–buy herding and the holiday effect

Average coefficient (β_t)		Partitioned slope coefficient: Funds following their own trades		Partitioned slope coefficient: Funds following the trades of other funds		Average R²	
Pre holiday	Post holiday	Pre holiday	Post holiday	Pre holiday	Post holiday	Pre holiday	Post holiday
Panel A: No of active funds per stock ≥ 1							
0.0031	0.0406	0.0099	-0.0056	-0.0068	0.0462	0.0607	0.0436
(0.9389)	(0.2599)	(0.9092)	(0.9457)	(0.9316)	(0.5890)		
0.4872		0.8963		0.6500			
Panel B: No of active funds per stock ≥ 2							
0.1088	-0.0600	-0.2110	-0.0085	0.3198	-0.0515	0.1866	0.0923
(0.2183)	(0.3111)	(0.1342)	(0.9712)	(0.0276)	(0.8278)		
0.1051		0.4593		0.1785			
Panel C: No of active funds per stock ≥ 3							
-0.0516	-0.0510	-0.6773	-0.4090	0.6257	0.3580	0.1125	0.1589
(0.6210)	(0.4488)	(0.0173)	(0.1699)	(0.0508)	(0.2431)		
0.9963		0.5059		0.5375			
Panel D: No of active funds per stock ≥ 4							
-0.0231	-0.0245	-0.3762	-1.5400	0.3531	1.5155	0.1299	0.1648
(0.7604)	(0.7681)	(0.0508)	(0.2599)	(0.1021)	(0.2715)		
0.9899		0.3962		0.4019			

This table reports the estimates from the equation: $\Delta_{k,t} = \beta_t\Delta_{k,t-1} + \varepsilon_{k,t}$ for pre and post holiday days (defined as the day immediately preceding and the day immediately after a holiday, respectively) on the premises of stocks predominantly bought. For each security and day between January, 2nd 2002 and August 14th, 2008 we calculate the fraction of funds that increase their position in the security. A fund is defined as increasing its position if it holds a greater fraction of the firm's shares at the end of day *t* than it held at the end of day *t-1*. We then select only those stocks whose $Raw\Delta_{k,t}$ >0.5 for pre and post holiday days separately. All data are standardized (i.e. rescaled to zero mean, unit variance) each day. We then estimate daily cross sectional regressions of institutional demand on lagged institutional demand once for the pre holiday and once for the post holiday days only, for stocks with $Raw\Delta_{k,t}$>0.5. Because $\Delta_{k,t-1}$ is the sole 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 for that sample pre and post holiday, respectively. The first column reports the time-series' average of these correlation coefficients and associated p-values (in parentheses) pre and post holiday. The second and third columns report the portion of the correlation resulting from funds following their own lagged trades and the portion resulting from funds following the previous trades of other funds (herding) for each of the two days. P-values of Wald test-statistics of difference between pre and post holiday estimates are included underneath each pair of estimates.

Table 10: Tests for herding presence–sell herding and the holiday effect

Average coefficient (β_t)		Partitioned slope coefficient: Funds following their own trades		Partitioned slope coefficient: Funds following the trades of other funds		Average R^2	
Pre holiday	Post holiday	Pre holiday	Post holiday	Pre holiday	Post holiday	Pre holiday	Post holiday
Panel A: No of active funds per stock ≥ 1							
0.0849	0.1017	0.0031	-0.1962	0.0808	0.2979	0.0851	0.0748
(0.0973)	(0.0358)	(0.9666)	(0.2891)	(0.3263)	(0.1143)		
0.7941		0.3164		0.2857			
Panel B: No of active funds per stock ≥ 2							
-0.0459	0.0640	0.2097	-0.0584	-0.2557	0.1224	0.1293	0.0780
(0.5154)	(0.2144)	(0.7124)	(0.8413)	(0.6371)	(0.6846)		
0.2032		0.6742		0.5410			
Panel C: No of active funds per stock ≥ 3							
0.0142	0.0343	-0.0685	-0.2696	0.0827	0.3039	0.1239	0.1123
(0.8297)	(0.5860)	(0.7993)	(0.1674)	(0.7625)	(0.1612)		
0.8241		0.5393		0.5205			
Panel D: No of active funds per stock ≥ 4							
0.1006	0.0973	-0.3649	-0.6212	0.2643	0.7186	0.1567	0.0963
(0.2012)	(0.2578)	(0.0182)	(0.2642)	(0.0679)	(0.2489)		
0.0888		0.6530		0.4737			

This table reports the estimates from the equation: $\Delta_{k,t} = \beta_t \Delta_{k,t-1} + \varepsilon_{k,t}$ for pre and post holiday days (defined as the day immediately preceding and the day immediately after a holiday, respectively) on the premises of stocks predominantly sold. For each security and day between January, 2nd 2002 and August 14th, 2008 we calculate the fraction of funds that increase their position in the security. A fund is defined as increasing its position if it holds a greater fraction of the firm's shares at the end of day *t* than it held at the end of day *t-1*. We then select only those stocks whose $Raw\Delta_{k,t}$ <0.5 for pre and post holiday days separately. All data are standardized (i.e. rescaled to zero mean, unit variance) each day. We then estimate daily cross sectional regressions of institutional demand on lagged institutional demand once for the pre holiday and once for the post holiday days only, for stocks with $Raw\Delta_{k,t}$ <0.5. Because $\Delta_{k,t-1}$ is the sole 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 for that sample pre and post holiday, respectively. The first column reports the time-series' average of these correlation coefficients and associated p-values (in parentheses) pre and post holiday. The second and third columns report the portion of the correlation resulting from funds following their own lagged trades and the portion resulting from funds following the previous trades of other funds (herding) for each of the two days. P-values of Wald test-statistics of difference between pre and post holiday estimates are included underneath each pair of estimates.

Table 11: Tests for herding presence–herding and the Ramadan effect

Average coefficient (β_t)		Partitioned slope coefficient: Funds following their own trades		Partitioned slope coefficient: Funds following the trades of other funds		Average R^2	
Ramadan	Non-Ramadan	Ramadan	Non-Ramadan	Ramadan	Non-Ramadan	Ramadan	Non-Ramadan
Panel A: No of active funds per stock ≥ 1							
0.0749	0.0621	0.0324	0.0071	0.0425	0.0550	0.0297	0.0293
(0.0000)	(0.0000)	(0.0428)	(0.1359)	(0.0007)	(0.0000)		
0.4042		0.1495		0.3284			
Panel B: No of active funds per stock ≥ 2							
0.0900	0.0572	-0.0206	-0.0334	0.1106	0.0906	0.0456	0.0403
(0.0000)	(0.0000)	(0.1685)	(0.0000)	(0.0000)	(0.0000)		
0.0790		0.4531		0.3402			
Panel C: No of active funds per stock ≥ 3							
0.0661	0.0454	-0.0504	-0.0588	0.1165	0.1042	0.0513	0.0537
(0.0019)	(0.0000)	(0.0027)	(0.0000)	(0.0000)	(0.0000)		
0.3480		0.6349		0.6015			
Panel D: No of active funds per stock ≥ 4							
0.0854	0.0441	-0.0561	-0.0634	0.1415	0.1075	0.0664	0.0675
(0.0001)	(0.0000)	(0.0009)	(0.0000)	(0.0000)	(0.0000)		
0.1065		0.6731		0.1542			

This table reports the estimates from the equation: $\Delta_{k,t} = \beta_t \Delta_{k,t-1} + \varepsilon_{k,t}$ within and outside the month of Ramadan. For each security and day between January, 2nd 2002 and August 14th, 2008 we calculate the fraction of funds that increase their position in the security. A fund is defined as increasing its position if it holds a greater fraction of the firm's shares at the end of day *t* than it held at the end of day *t-1*. All data are standardized (i.e. rescaled to zero mean, unit variance) each day. We then estimate daily cross sectional regressions of institutional demand on lagged institutional demand within and outside Ramadan. Because $\Delta_{k,t-1}$ is the sole 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 for that sample within and outside Ramadan, respectively. The first column reports the time-series' average of these correlation coefficients and associated p-values (in parentheses) within and outside Ramadan. The second and third columns report the portion of the correlation resulting from funds following their own lagged trades and the portion resulting from funds following the previous trades of other funds (herding) within and outside Ramadan. P-values of Wald test-statistics of difference between within and outside Ramadan estimates are included underneath each pair of estimates.

Table 12: Tests for herding presence–buy herding and the Ramadan effect

Average coefficient (β_t)		Partitioned slope coefficient: Funds following their own trades		Partitioned slope coefficient: Funds following the trades of other funds		Average R²	
Ramadan	Non-Ramadan	Ramadan	Non-Ramadan	Ramadan	Non-Ramadan	Ramadan	Non-Ramadan
Panel A: No of active funds per stock ≥ 1							
0.0522	0.0302	0.0964	0.0292	-0.0442	0.0010	0.0508	0.0521
(0.0089)	(0.0000)	(0.0217)	(0.0305)	(0.2894)	(0.9434)		
0.2934		0.1252		0.3041			
Panel B: No of active funds per stock ≥ 2							
0.0967	0.0164	-0.3388	-0.1652	0.4355	0.1815	0.1124	0.0937
(0.0039)	(0.0388)	(0.4573)	(0.0000)	(0.3519)	(0.0000)		
0.0188		0.7043		0.5883			
Panel C: No of active funds per stock ≥ 3							
0.0447	0.0113	-0.2228	-0.2541	0.2675	0.2654	0.1126	0.1178
(0.2130)	(0.2207)	(0.0227)	(0.0000)	(0.0104)	(0.0000)		
0.3667		0.7806		0.9863			
Panel D: No of active funds per stock ≥ 4							
0.0556	0.0144	-0.5974	-0.3930	0.6530	0.3944	0.1264	0.1655
(0.1092)	(0.9333)	(0.0265)	(0.0000)	(0.0152)	(0.0000)		
0.1613		0.4550		0.2940			

This table reports the estimates from the equation: $\Delta_{k,t} = \beta_t \Delta_{k,t-1} + \varepsilon_{k,t}$ within and outside the month of Ramadan on the premises of stocks predominantly bought. For each security and day between January, 2nd 2002 and August 14th, 2008 we calculate the fraction of funds that increase their position in the security. A fund is defined as increasing its position if it holds a greater fraction of the firm's shares at the end of day *t* than it held at the end of day *t-1*. We then select only those stocks whose $Raw\Delta_{k,t}$ >0.5 within and outside Ramadan. All data are standardized (i.e. rescaled to zero mean, unit variance) each day. We then estimate daily cross sectional regressions of institutional demand on lagged institutional demand within and outside Ramadan, for stocks with $Raw\Delta_{k,t}$ >0.5. Because $\Delta_{k,t-1}$ is the sole 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 for that sample within and outside Ramadan, respectively. The first column reports the time-series' average of these correlation coefficients and associated p-values (in parentheses) within and outside Ramadan. The second and third columns report the portion of the correlation resulting from funds following their own lagged trades and the portion resulting from funds following the previous trades of other funds (herding) within and outside Ramadan. P-values of Wald test-statistics of difference between within and outside Ramadan estimates are included underneath each pair of estimates.

Table 13: Tests for herding presence–sell herding and the Ramadan effect

Average coefficient (β_t)		Partitioned slope coefficient: Funds following their own trades		Partitioned slope coefficient: Funds following the trades of other funds		Average R²	
Ramadan	Non-Ramadan	Ramadan	Non-Ramadan	Ramadan	Non-Ramadan	Ramadan	Non-Ramadan
Panel A: No of active funds per stock ≥ 1							
0.0463	0.0494	0.1151	0.0133	-0.0688	0.0361	0.0517	0.0524
(0.0192)	(0.0000)	(0.0166)	(0.3391)	(0.1633)	(0.0133)		
0.8843		0.0471		0.0512			
Panel B: No of active funds per stock ≥ 2							
0.0506	0.0303	-0.0388	-0.1406	0.0895	0.1709	0.1219	0.0921
(0.1010)	(0.0001)	(0.6920)	(0.0003)	(0.3308)	(0.0000)		
0.4930		0.3344		0.4140			
Panel C: No of active funds per stock ≥ 3							
0.0243	0.0230	0.0241	-0.1603	0.0002	0.1832	0.1169	0.1159
(0.4101)	(0.0111)	(0.9181)	(0.0000)	(0.9994)	(0.0000)		
0.9676		0.4366		0.4450			
Panel D: No of active funds per stock ≥ 4							
-0.0102	0.0344	2.7238	-0.2772	-2.7340	0.3116	0.1276	0.1430
(0.7619)	(0.0013)	(0.2192)	(0.0000)	(0.2168)	(0.0000)		
0.2633		0.1763		0.1694			

This table reports the estimates from the equation: $\Delta_{k,t} = \beta_t \Delta_{k,t-1} + \varepsilon_{k,t}$ within and outside the month of Ramadan on the premises of stocks predominantly sold. For each security and day between January, 2nd 2002 and August 14th, 2008 we calculate the fraction of funds that increase their position in the security. A fund is defined as increasing its position if it holds a greater fraction of the firm's shares at the end of day *t* than it held at the end of day *t-1*. We then select only those stocks whose $Raw\Delta_{k,t}$ <0.5 within and outside Ramadan. All data are standardized (i.e. rescaled to zero mean, unit variance) each day. We then estimate daily cross sectional regressions of institutional demand on lagged institutional demand within and outside Ramadan, for stocks with $Raw\Delta_{k,t}$ <0.5. Because $\Delta_{k,t-1}$ is the sole 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 for that sample within and outside Ramadan, respectively. The first column reports the time-series' average of these correlation coefficients and associated p-values (in parentheses) within and outside Ramadan. The second and third columns report the portion of the correlation resulting from funds following their own lagged trades and the portion resulting from funds following the previous trades of other funds (herding) within and outside Ramadan. P-values of Wald test-statistics of difference between within and outside Ramadan estimates are included underneath each pair of estimates.

Table 14: Tests for herding presence–herding and the sunshine effect

Average coefficient (β_t)		Partitioned slope coefficient: Funds following their own trades		Partitioned slope coefficient: Funds following the trades of other funds		Average R²	
Increased sunshine	Decreased sunshine	Increased sunshine	Decreased sunshine	Increased sunshine	Decreased sunshine	Increased sunshine	Decreased sunshine
Panel A: No of active funds per stock ≥ 1							
0.0683	0.0636	0.0126	0.0122	0.0557	0.0514	0.0282	0.0291
(0.0000)	(0.0000)	(0.0785)	(0.0876)	(0.0000)	(0.0000)		
0.5839		0.9638		0.6126			
Panel B: No of active funds per stock ≥ 2							
0.0569	0.0730	-0.0382	-0.0230	0.0951	0.0960	0.0373	0.0423
(0.0000)	(0.0000)	(0.0000)	(0.0008)	(0.0000)	(0.0000)		
0.1260		0.1107		0.9338			
Panel C: No of active funds per stock ≥ 3							
0.0487	0.0615	-0.0560	-0.0435	0.1047	0.1050	0.0481	0.0540
(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)		
0.2978		0.2347		0.9823			
Panel D: No of active funds per stock ≥ 4							
0.0479	0.0632	-0.0617	-0.0538	0.1095	0.1170	0.0604	0.0676
(0.0004)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)		
0.2852		0.4604		0.6474			

This table reports the estimates from the equation: $\Delta_{k,t} = \beta_t \Delta_{k,t-1} + \varepsilon_{k,t}$ during days of increased and decreased sunshine (having first identified the sunshine hours per day drawing on data obtained from the Turkish State Meteorological Service). For each security and day between January, 2nd 2002 and August 14th, 2008 we calculate the fraction of funds that increase their position in the security. A fund is defined as increasing its position if it holds a greater fraction of the firm's shares at the end of day *t* than it held at the end of day *t-1*. All data are standardized (i.e. rescaled to zero mean, unit variance) each day. We then estimate daily cross sectional regressions of institutional demand on lagged institutional demand for increased and decreased sunshine days. Because $\Delta_{k,t-1}$ is the sole 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 for that sample for increased and decreased sunshine days, respectively. The first column reports the time-series' average of these correlation coefficients and associated p-values (in parentheses) for increased and decreased sunshine days. The second and third columns report the portion of the correlation resulting from funds following their own lagged trades and the portion resulting from funds following the previous trades of other funds (herding) for increased and decreased sunshine days. P-values of Wald test-statistics of difference between increased and decreased sunshine days' estimates are included underneath each pair of estimates.

Table 15: Tests for herding presence–buy herding and the sunshine effect

Average coefficient (β_t)		Partitioned slope coefficient: Funds following their own trades		Partitioned slope coefficient: Funds following the trades of other funds		Average R²	
Increased sunshine	Decreased sunshine	Increased sunshine	Decreased sunshine	Increased sunshine	Decreased sunshine	Increased sunshine	Decreased sunshine
Panel A: No of active funds per stock ≥ 1							
0.0290	0.0370	0.0398	0.0564	-0.0108	-0.0194	0.0514	0.0515
(0.0009)	(0.0000)	(0.0386)	(0.0072)	(0.5880)	(0.3823)		
0.5038		0.5590		0.7745			
Panel B: No of active funds per stock ≥ 2							
0.0299	0.0166	-0.2428	-0.1011	0.2726	0.1177	0.0937	0.0922
(0.0130)	(0.1590)	(0.0096)	(0.0198)	(0.0044)	(0.0077)		
0.4291		0.1692		0.1407			
Panel C: No of active funds per stock ≥ 3							
0.0911	0.0231	-0.3196	-0.2121	0.3287	0.2351	0.1107	0.1155
(0.4957)	(0.1005)	(0.0032)	(0.0008)	(0.0028)	(0.0002)		
0.4727		0.3894		0.4596			
Panel D: No of active funds per stock ≥ 4							
-0.0248	0.0151	-0.4119	-0.3108	0.4094	0.3259	0.1729	0.1482
(0.9415)	(0.4114)	(0.0000)	(0.0003)	(0.0000)	(0.0003)		
0.6474		0.3913		0.5030			

This table reports the estimates from the equation: $\Delta_{k,t} = \beta_t \Delta_{k,t-1} + \varepsilon_{k,t}$ during days of increased and decreased sunshine (having first identified the sunshine hours per day drawing on data obtained from the Turkish State Meteorological Service) on the premises of stocks predominantly bought. For each security and day between January, 2nd 2002 and August 14th, 2008 we calculate the fraction of funds that increase their position in the security. A fund is defined as increasing its position if it holds a greater fraction of the firm's shares at the end of day *t* than it held at the end of day *t-1*. We then select only those stocks whose $Raw\Delta_{k,t}$ >0.5 for increased and decreased sunshine days. All data are standardized (i.e. rescaled to zero mean, unit variance) each day. We then estimate daily cross sectional regressions of institutional demand on lagged institutional demand for increased and decreased sunshine days, for stocks with $Raw\Delta_{k,t}$ >0.5. Because $\Delta_{k,t-1}$ is the sole 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 for that sample for increased and decreased sunshine days, respectively. The first column reports the time-series' average of these correlation coefficients and associated p-values (in parentheses) for increased and decreased sunshine days. The second and third columns report the portion of the correlation resulting from funds following their own lagged trades and the portion resulting from funds following the previous trades of other funds (herding) for increased and decreased sunshine days. P-values of Wald test-statistics of difference between increased and decreased sunshine days' estimates are included underneath each pair of estimates.

Table 16: Tests for herding presence–sell herding and the sunshine effect

Average coefficient (β_t)		Partitioned slope coefficient: Funds following their own trades		Partitioned slope coefficient: Funds following the trades of other funds		Average R²	
Increased sunshine	Decreased sunshine	Increased sunshine	Decreased sunshine	Increased sunshine	Decreased sunshine	Increased sunshine	Decreased sunshine
Panel A: No of active funds per stock ≥ 1							
0.0473	0.0517	0.0380	0.0222	0.0933	0.0295	0.0493	0.0498
(0.0000)	(0.0000)	(0.0598)	(0.2667)	(0.6566)	(0.1598)		
0.7111		0.5800		0.4972			
Panel B: No of active funds per stock ≥ 2							
0.0301	0.0327	-0.1435	-0.1502	0.1736	0.1829	0.0913	0.0922
(0.0109)	(0.0057)	(0.0030)	(0.0127)	(0.0004)	(0.0025)		
0.8780		0.9309		0.9052			
Panel C: No of active funds per stock ≥ 3							
0.0152	0.0266	-0.1225	-0.1524	0.1377	0.1789	0.1168	0.1139
(0.2725)	(0.0437)	(0.0125)	(0.0041)	(0.0054)	(0.0012)		
0.5531		0.6783		0.5762			
Panel D: No of active funds per stock ≥ 4							
0.0222	0.0487	-0.2600	0.1243	0.2822	-0.0756	0.1373	0.1299
(0.1597)	(0.0012)	(0.0004)	(0.7282)	(0.0001)	(0.8328)		
0.2217		0.2927		0.3280			

This table reports the estimates from the equation: $\Delta_{k,t} = \beta_t \Delta_{k,t-1} + \varepsilon_{k,t}$ during days of increased and decreased sunshine (having first identified the sunshine hours per day drawing on data obtained from the Turkish State Meteorological Service) on the premises of stocks predominantly sold. For each security and day between January, 2nd 2002 and August 14th, 2008 we calculate the fraction of funds that increase their position in the security. A fund is defined as increasing its position if it holds a greater fraction of the firm's shares at the end of day *t* than it held at the end of day *t-1*. We then select only those stocks whose $Raw\Delta_{k,t}$ <0.5 for increased and decreased sunshine days. All data are standardized (i.e. rescaled to zero mean, unit variance) each day. We then estimate daily cross sectional regressions of institutional demand on lagged institutional demand for increased and decreased sunshine days, for stocks with $Raw\Delta_{k,t}$ <0.5. Because $\Delta_{k,t-1}$ is the sole 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 for that sample for increased and decreased sunshine days, respectively. The first column reports the time-series' average of these correlation coefficients and associated p-values (in parentheses) for increased and decreased sunshine days. The second and third columns report the portion of the correlation resulting from funds following their own lagged trades and the portion resulting from funds following the previous trades of other funds (herding) for increased and decreased sunshine days. P-values of Wald test-statistics of difference between increased and decreased sunshine days' estimates are included underneath each pair of estimates.

Table 17: Tests for herding presence–herding and the new/full moon

Average coefficient (β_t)		Partitioned slope coefficient: Funds following their own trades		Partitioned slope coefficient: Funds following the trades of other funds		Average R²	
New Moon	Full Moon	New Moon	Full Moon	New Moon	Full Moon	New Moon	Full Moon
Panel A: No of active funds per stock ≥ 1							
0.0680	0.0548	0.0239	0.0060	0.0440	0.0488	0.0272	0.0300
(0.0000)	(0.0000)	(0.0054)	(0.5347)	(0.0000)	(0.0000)		
0.2510		0.1654		0.6509			
Panel B: No of active funds per stock ≥ 2							
0.0690	0.0414	-0.0270	-0.0405	0.0960	0.0819	0.0383	0.0452
(0.0000)	(0.0001)	(0.0026)	(0.0000)	(0.0000)	(0.0000)		
0.0559		0.2999		0.3774			
Panel C: No of active funds per stock ≥ 3							
0.0518	0.0384	-0.0547	-0.0665	0.1066	0.1050	0.0460	0.0528
(0.0000)	(0.0012)	(0.0000)	(0.0000)	(0.0000)	(0.0000)		
0.414		0.4962		0.9384			
Panel D: No of active funds per stock ≥ 4							
0.0495	0.0331	-0.0531	-0.0751	0.1026	0.1082	0.0628	0.0669
(0.0000)	(0.0180)	(0.0000)	(0.0000)	(0.0000)	(0.0000)		
0.3887		0.1840		0.8081			

This table reports the estimates from the equation: $\Delta_{k,t} = \beta_t \Delta_{k,t-1} + \varepsilon_{k,t}$ for the new and the full moon 7-day periods (calculated as +/-3 days around the new/full moon day plus the new/full moon day, in line with Yuen et al., 2006). For each security and day between January, 2nd 2002 and August 14th, 2008 we calculate the fraction of funds that increase their position in the security. A fund is defined as increasing its position if it holds a greater fraction of the firm's shares at the end of day *t* than it held at the end of day *t-1*. All data are standardized (i.e. rescaled to zero mean, unit variance) each day. We then estimate daily cross sectional regressions of institutional demand on lagged institutional demand for new moon periods and full moon periods. Because $\Delta_{k,t-1}$ is the sole 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 for that sample for new moon periods and full moon periods, respectively. The first column reports the time-series' average of these correlation coefficients and associated p-values (in parentheses) for new moon periods and full moon periods. The second and third columns report the portion of the correlation resulting from funds following their own lagged trades and the portion resulting from funds following the previous trades of other funds (herding) for new moon periods and full moon periods. P-values of Wald test-statistics of difference between new moon periods' and full moon periods' estimates are included underneath each pair of estimates.

Table 18: Tests for herding presence–buy herding and the new/full moon

Average coefficient (β_t)		Partitioned slope coefficient: Funds following their own trades		Partitioned slope coefficient: Funds following the trades of other funds		Average R²	
New Moon	Full Moon	New Moon	Full Moon	New Moon	Full Moon	New Moon	Full Moon
Panel A: No of active funds per stock ≥ 1							
0.04889	0.0219	0.0805	0.0311	-0.0315	-0.0092	0.0494	0.0539
(0.0000)	(0.0625)	(0.0013)	(0.2301)	(0.2190)	(0.7385)		
0.0894		0.1678		0.5521			
Panel B: No of active funds per stock ≥ 2							
0.0236	0.0262	-0.2469	-0.1188	0.2705	0.1451	0.0907	0.0962
(0.1281)	(0.1090)	(0.0020)	(0.2324)	(0.0009)	(0.1537)		
0.9071		0.3141		0.3334			
Panel C: No of active funds per stock ≥ 3							
0.0230	-0.0023	-0.2916	-0.3743	0.3146	0.3720	0.1127	0.1140
(0.2409)	(0.8973)	(0.0001)	(0.0284)	(0.0000)	(0.0315)		
0.3367		0.6567		0.7607			
Panel D: No of active funds per stock ≥ 4							
0.0325	0.0109	-0.3400	-0.4310	0.3725	0.4419	0.1604	0.1500
(0.1816)	(0.6288)	(0.0127)	(0.0000)	(0.0073)	(0.0000)		
0.5142		0.5630		0.6671			

This table reports the estimates from the equation: $\Delta_{k,t} = \beta_t \Delta_{k,t-1} + \varepsilon_{k,t}$ for the new and the full moon 7-day periods (calculated as +/-3 days around the new/full moon day plus the new/full moon day, in line with Yuen et al., 2006) on the premises of stocks predominantly bought. For each security and day between January, 2nd 2002 and August 14th, 2008 we calculate the fraction of funds that increase their position in the security. A fund is defined as increasing its position if it holds a greater fraction of the firm's shares at the end of day *t* than it held at the end of day *t-1*. We then select only those stocks whose $Raw\Delta_{k,t}$ >0.5 for the new and full moon periods. All data are standardized (i.e. rescaled to zero mean, unit variance) for each (new/full moon) period. We then estimate daily cross sectional regressions of institutional demand on lagged institutional demand for the new and full moon periods, for stocks with $Raw\Delta_{k,t}$ >0.5. Because $\Delta_{k,t-1}$ is the sole 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 for that sample for the new and full moon periods, respectively. The first column reports the time-series' average of these correlation coefficients and associated p-values (in parentheses) for the new and full moon periods. The second and third columns report the portion of the correlation resulting from funds following their own lagged trades and the portion resulting from funds following the previous trades of other funds (herding) for the new and full moon periods. P-values of Wald test-statistics of difference between the new and full moon periods' estimates are included underneath each pair of estimates.

Table 19: Tests for herding presence–sell herding and the new/full moon

Average coefficient (β_t)		Partitioned slope coefficient: Funds following their own trades		Partitioned slope coefficient: Funds following the trades of other funds		Average R²	
New Moon	Full Moon	New Moon	Full Moon	New Moon	Full Moon	New Moon	Full Moon
Panel A: No of active funds per stock ≥ 1							
0.0506	0.0509	0.0479	0.0165	0.0027	0.0344	0.0585	0.0527
(0.0000)	(0.0000)	(0.0450)	(0.6083)	(0.9197)	(0.2939)		
0.9818		0.4333		0.4518			
Panel B: No of active funds per stock ≥ 2							
0.0299	0.0245	-0.1633	-0.2174	0.1932	0.2419	0.0944	0.0877
(0.0713)	(0.0966)	(0.0493)	(0.0035)	(0.0182)	(0.0011)		
0.8042		0.6261		0.6579			
Panel C: No of active funds per stock ≥ 3							
0.0084	0.0156	-0.1852	-0.1299	0.1936	0.1455	0.1162	0.1117
(0.6432)	(0.3752)	(0.0115)	(0.1205)	(0.0078)	(0.0930)		
0.7744		0.6181		0.6699			
Panel D: No of active funds per stock ≥ 4							
0.0461	0.0311	0.6261	-0.1965	-0.5800	0.2276	0.1301	0.1470
(0.0228)	(0.1620)	(0.3567)	(0.0338)	(0.3927)	(0.0205)		
0.6177		0.2303		0.2390			

This table reports the estimates from the equation: $\Delta_{k,t} = \beta_t \Delta_{k,t-1} + \varepsilon_{k,t}$ for the new and the full moon 7-day periods (calculated as +/-3 days around the new/full moon day plus the new/full moon day, in line with Yuen et al., 2006) on the premises of stocks predominantly sold. For each security and day between January, 2nd 2002 and August 14th, 2008 we calculate the fraction of funds that increase their position in the security. A fund is defined as increasing its position if it holds a greater fraction of the firm's shares at the end of day *t* than it held at the end of day *t-1*. We then select only those stocks whose $Raw\Delta_{k,t}$ <0.5 for the new and full moon periods. All data are standardized (i.e. rescaled to zero mean, unit variance) for each (new/full moon) period. We then estimate daily cross sectional regressions of institutional demand on lagged institutional demand for the new and full moon periods, for stocks with $Raw\Delta_{k,t}$ <0.5. Because $\Delta_{k,t-1}$ is the sole 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 for that sample for the new and full moon periods, respectively. The first column reports the time-series' average of these correlation coefficients and associated p-values (in parentheses) for the new and full moon periods. The second and third columns report the portion of the correlation resulting from funds following their own lagged trades and the portion resulting from funds following the previous trades of other funds (herding) for the new and full moon periods. P-values of Wald test-statistics of difference between the new and full moon periods' estimates are included underneath each pair of estimates.

Table 20: Multivariate regression on the effect of mood proxies over institutional herding

	Dependent variable: β_t	Dependent variable: "Funds following their own trades"	Dependent variable: "Funds following the trades of other funds"
Panel A: No of active funds per stock ≥ 1			
Constant	0.0587	0.0002	0.0586
	(0.0000)	(0.9815)	(0.0000)
$Monday_t$	-0.0052	-0.0012	-0.0040
	(0.6025)	(0.9180)	(0.6754)
$Holiday_t$	-0.0462	-0.0139	-0.0323
	(0.1041)	(0.6701)	(0.2372)
$Ramadan_t$	0.0178	0.0296	-0.0118
	(0.2451)	(0.0931)	(0.4244)
$Sunshine_t$	0.0091	0.0072	0.0019
	(0.2653)	(0.4438)	(0.8076)
New_t	0.0077	0.0206	-0.0129
	(0.4081)	(0.0550)	(0.1516)
R^2	0.0035	0.0042	0.0027
Panel B: No of active funds per stock ≥ 2			
Constant	0.0537	-0.0308	0.0845
	(0.0000)	(0.0000)	(0.0000)
$Monday_t$	0.0132	-0.0004	0.0136
	(0.2764)	(0.9722)	(0.3196)
$Holiday_t$	-0.0305	-0.0378	0.0072
	(0.3797)	(0.2341)	(0.8532)
$Ramadan_t$	0.0285	0.0144	0.0141
	(0.1285)	(0.4010)	(0.5032)
$Sunshine_t$	-0.0028	-0.0088	0.0060
	(0.7775)	(0.3305)	(0.5903)
New_t	0.0110	0.0076	0.0034
	(0.3363)	(0.4669)	(0.7918)
R^2	0.0031	0.0021	0.0011
Panel C: No of active funds per stock ≥ 3			
Constant	0.0451	-0.0554	0.1005
	(0.0000)	(0.0000)	(0.0000)
$Monday_t$	-0.0103	-0.0254	0.0151
	(0.4711)	(0.0913)	(0.4055)
$Holiday_t$	-0.0520	-0.0562	0.0042
	(0.2049)	(0.1928)	(0.9360)
$Ramadan_t$	0.0229	0.0106	0.0123
	(0.3004)	(0.6485)	(0.6610)
$Sunshine_t$	0.0039	0.0037	0.0001
	(0.7410)	(0.7624)	(0.9920)
New_t	0.0072	0.0051	0.0020
	(0.5961)	(0.7179)	(0.9058)
R^2	0.0020	0.0029	0.0006
Panel D: No of active funds per stock ≥ 4			
Constant	0.0392	-0.0670	0.1062
	(0.0001)	(0.0000)	(0.0000)
$Monday_t$	0.0223	0.0030	0.0193
	(0.1799)	(0.8198)	(0.3129)
$Holiday_t$	-0.0828	-0.0526	-0.0302
	(0.0820)	(0.1654)	(0.5809)
$Ramadan_t$	0.0442	0.0095	0.0348
	(0.0853)	(0.6441)	(0.2390)
$Sunshine_t$	0.0027	0.0024	0.0003
	(0.8433)	(0.8231)	(0.9864)
New_t	0.0041	0.0131	-0.0091
	(0.7945)	(0.2936)	(0.6161)
R^2	0.0046	0.0019	0.0018

The table presents the estimates from the following multivariate regression: $\beta_t = \alpha_0 + \alpha_1 Monday_t + \alpha_2 Holiday_t + \alpha_3 Ramadan_t + \alpha_4 Sunshine_t + \alpha_5 New_t + \varepsilon_t$. $Monday_t$ is a dummy assuming the value of one on Mondays, zero otherwise; $Holiday_t$ is a dummy assuming the value of one pre holiday, zero otherwise; $Ramadan_t$ is a dummy assuming the value of one during Ramadan, zero otherwise; $Sunshine_t$ is a dummy assuming the value of one on increasing sunshine days, zero otherwise; and New_t is a dummy assuming the value of one during new moon periods, zero otherwise. The regressand in each of the three regressions is β_t, "Funds following their own trades" and "Funds following the trades of other funds". Parentheses include p-values.