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Institutional industry herding: Intentional or spurious?

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ABSTRACT

This paper investigates the extent to which institutional herding at the industry level is motivated by intent. We assess intent using both market and sector states based on three variables (returns; volatility; volume), in order to gauge whether herding intent is more relevant to conditions prevailing in a sector or the market as a whole. Using a unique database of quarterly portfolio holdings of Spanish funds, we produce evidence that institutional herding in the Spanish market is intentional for most sectors, manifesting itself mainly during periods when the market as a whole or the specific sector under examination has underperformed, generated rising/high volatility and exhibited rising/high volume.

1. Introduction

The possibility of fund managers herding at the industry level has been explored by a series of studies, with evidence from the extant research confirming the presence of institutional industry

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herding for several markets internationally (e.g. Voronkova and Bohl, 2005; Choi and Sias, 2009; Chen et al., 2012). An interesting question here is whether the observed industry herding results from funds following each other intentionally into and out of industries or not. A second question arising from the above is whether the presence of intent in industry herding is related to the specific conditions of each industry or whether the conditions of the market as a whole are also capable of promoting it. It is these two issues the present study aims at addressing.

From a theoretical perspective, herd behaviour involves the propensity of investors towards mimicking the trades of their peers following observation of their actions and their actions' payoffs (Hirshleifer and Teoh, 2003). Although retail investors would be expected to be more susceptible to behavioural biases in their trades, there exists ample evidence in the literature lending support to the existence of herding on behalf of professional investors which has been attributed to both *intentional* and *spurious* motives (Bikhchandani and Sharma, 2001). For a professional investor to herd *intentionally*, his herding needs to be motivated through (a) a relative view of his position versus his peers and (b) the anticipation of a positive externality (i.e. a payoff). It is possible, for example, that fund managers choose to herd because they expect to reap *informational payoffs* (Devenow and Welch, 1996); this is the case when an investor follows others because he thinks that they are in possession of better information or better information-processing skills. If this becomes widespread practice, it can compromise a market's informational efficiency, since it will result in temporary blockades in the aggregation of information into prices (those herding are not trading on their information, hence the latter is not reflected into securities' prices) and, in the extreme, lead to informational cascades (Banerjee, 1992; Bikhchandani et al., 1992). It is also possible that investment professionals herd intentionally motivated by *career/reputational payoffs* (Trueman, 1994; Clement and Tse, 2005). With the performance of fund managers being assessed relatively (i.e. versus their peers), a fund manager lacking confidence in his skills has every interest in copying the trades of his better able peers, since this will allow him to conceal his low ability. Such behaviour distorts the assessment process, with those in charge of it finding it difficult to decipher whether a fund manager's good performance is due to his skills or due to him mimicking his "good" peers (Scharfstein and Stein, 1990). However, the presence of factors common among investment professionals may lead fund managers to exhibit correlation in their trades, thus generating the impression of herding, without the latter being due to intent (*spurious herding*). Such correlation can be the result of fund managers being characterized by *relative homogeneity* (De Bondt and Teh, 1997) given their common features (similarities in their educational background, investment experience, the signals they receive and their processing) and the common regulatory framework they are subject to (Voronkova and Bohl, 2005). Another possibility is that what comes across as herding may in fact be the result of *style investing* (e.g. Bennett et al., 2003); if several funds, for example, are momentum-trading, it is likely that they herd into recent winners and out of recent losers.

The identification of the above motives underlying institutional herding prompted a surge in the number of studies undertaken with the purpose of establishing its presence empirically, with evidence denoting that fund managers herd to varying degrees internationally.[1] Earlier evidence from the US (Lakonishok et al., 1992; Grinblatt et al., 1995; Wermers, 1999) indicated that US fund managers herded to a limited extent, while recent studies (Sias, 2004; Choi and Sias, 2009) report findings suggesting that their herding is far from negligible. Wylie (2005) shows that herding is not widespread among UK funds, while a similar observation is made by Goodfellow et al. (2009) for Polish institutional investors. Significant herding is reported by Walter and Weber (2006) and Kremer and Nautz (2013) for German mutual funds, Olivares (2008) for Chilean pension funds, Voronkova and Bohl (2005) for Polish pension funds and Holmes et al. (2013) for Portuguese equity funds.

However, the bulk of empirical herding research has treated the above mentioned (intentional and spurious) herding motives as a set of theoretical explanations underlying the herding of fund managers, with very little attention having been devoted to the empirical identification of intent itself. Holmes et al. (2013) first proposed an approach aiming at deciphering empirically whether fund managers

[1] The lack of uniformity in herding significance worldwide is further illustrated by studies investigating herding at the market level (e.g. Christie and Huang, 1995; Chang et al., 2000; Blasco et al., 2012; Gebka and Wohar, 2013).

herd intentionally or not. The crux of their argument was that if institutional herding were intentional, its significance would exhibit variations between different states of the market; conversely, if fund managers herded spuriously, their herding would be expected to be significant irrespective of the market's state. To that end, they put forward a series of hypotheses linking herding intent with specific market conditions related to variables such as market returns, market volatility and regulatory changes and tested them in the context of the Portuguese market. The findings they reported indicated that Portuguese fund managers did not herd indiscriminately but rather that their herding grew in significance when the market underwent specific conditions (i.e. they herded intentionally). Holmes et al.'s (2013) results demonstrated how herding intent could be traced in the market environment through the impact of this environment's variations over herding significance. However, institutional herding need not take place exclusively at the market level or be solely driven by the conditions prevailing at that level. An example is the ample evidence (Voronkova and Bohl, 2005; Choi and Sias, 2009; Chen et al., 2012) indicating that fund managers herd significantly when investing in industries. Since the key herding motives (intentional and spurious) mentioned previously are as much influential on fund managers' decision to herd at the industry level as they are at the individual stock level (Choi and Sias, 2009), the Holmes et al. (2013) approach described above can be applied to assess the presence of intent in institutional industry herding. Nevertheless, the assessment of intent at the industry level requires the identification of environmental states upon which institutional herding will be conditioned. Holmes et al. (2013) tested for intent on the premises of different *market* states because their study investigated herding at the *market* level; testing for intent at the industry level requires that one takes into consideration the specific conditions of each industry as well as those of the market, since industries are subject both to their own dynamics (due e.g. to their specific structure, regulatory environment or fundamentals) as well as to the market's (they constitute parts of it). Resorting to market conditions alone to detect herding intent at the industry level is bound to miss out on important information conveyed through sector conditions, since the latter are more representative of the activity surrounding an industry (Demirer and Kutan, 2006) and should be more relevant to the investments of fund managers relative to that sector (Frazzini and Lamont, 2008).

The present paper tests whether institutional industry herding[2] is intentional or not for the first time in the literature controlling for a variety of states corresponding to both the market as a whole as well as each individual sector. We explore the presence of institutional herding intent at the sector level in the context of the Spanish market using quarterly portfolio-holdings data of the country's mutual funds. Specifically, the states we control for to test for intent are based on three variables (returns; volatility; volume), each pertaining to each sector separately and the market as a whole. Our research aims at addressing the following two questions:

- Do fund managers herd intentionally at the industry level?
- Is the intent underlying their industry herding related to the specific conditions of each industry or are market conditions also capable of promoting it?

In summary, our results indicate that Spanish fund managers herd significantly at the overall market level, while the interactions of their herding in each sector with these states reveal that fund managers herd significantly in most industries mainly during periods when the market as a whole or the specific sector under examination has underperformed, generated rising/high volatility and exhibited rising/high volume. These findings denote the presence of intent in institutional industry herding and we show how this is linked to informational and career-related herding motives. With Spain being a middle-tier equity market in terms of its capitalization,[3] the evidence presented here

[2] The term "industry herding" is employed here to denote the herding undertaken towards stocks within a given industry (e.g. whether funds herd in their trades in stocks belonging to sector A) and is not used to refer here to herding taking place across industries (the case of funds herding into sector A stocks and out of sector B stocks).

[3] Standing at $1031 billion by year-end 2011 (source: 2011 Annual Statistics of the World Federation of Stock Exchanges).

contributes to our better understanding of institutional herding in a category of equity markets that has received relatively little attention by researchers.[4]

Our research contributes to the existing herding literature by providing evidence for the first time on institutional industry herding being intent-driven and demonstrating that it is both market as well as sector conditions underlying this intent. This is interesting from an investor's viewpoint, since being aware of the conditions that promote herding among funds investing in a sector can constitute a potentially useful input to any sector-style strategy. Regarding regulators, these results denote that the intent underlying institutional industry herding is versatile in nature, motivated by different market and sector conditions for each sector; such knowledge can be important to them when considering measures aiming at curtailing fund managers' herding tendencies in order to avoid their potentially destabilizing effects. The next section will provide a detailed presentation of the market/sector variables used to control for herding intent and describe the database employed in our research and the methodology used. Section 3 presents and discusses the results and Section 4 concludes.

2. Data and methodology

Our study is based on a unique database of quarterly portfolio holdings of Spanish mutual funds covering the June 1995–September 2008 period, obtained from the Spanish Securities Markets Commission (Comisión Nacional del Mercado de Valores – CNMV). Our sample consists of 1543 mutual funds which have invested in 245 domestic (i.e. Spanish) stocks at any point in time during our sample period. The dataset at hand provides us with information on the code and name of each fund, the code and name of its portfolio's assets each quarter and the number of shares of each asset it holds. Table 1 presents some descriptive statistics regarding Spanish funds' holdings both for the full sample as well as each of the nine sectors we have identified. As the table shows, the average number of stocks traded actively by at least one fund is 79.9 for the whole period, peaking in 1999 to 100.1 and declining to 83.2 by 2010. Likewise, the average number of active funds per stock for the whole period is 136.6, reaching a peak in 1999 (156) and falling to 135.3 by 2010. This pattern tracks the course of the Spanish stock market (which peaked in early 2000 only to crash later following the Dot Com bubble's burst in spring 2000 in the US) and is encountered in most of our sample's sectors.

To measure institutional herding we adopt the approach proposed by Sias (2004) which identifies herding through the intertemporal dependence of institutional demand, the latter being calculated as the raw fraction of funds increasing their position in security k during period (in our case, quarter) t:

$$Raw\Delta_{k,t} = \frac{\text{No. of Funds Buying Security } k \text{ in quarter } t}{\text{No. of Funds Buying Security } k \text{ in quarter} + \text{No. of Funds Selling Security } k \text{ in quarter } t} \tag{1}$$

Sias (2004) then standardizes $Raw\Delta_{k,t}$:

$$\Delta_{k,t} = \frac{Raw\Delta_{k,t} \overline{Raw\Delta}_t}{\sigma(Raw\Delta_{k,t})} \tag{2}$$

where $\overline{Raw\Delta}_t$ is the cross-sectional average raw fraction of institutions buying in quarter t and $\sigma(Raw\Delta_{k,t})$ is the cross-sectional standard deviation of the raw fraction of institutions buying in quarter t. To test for the existence of herding, Sias (2004) assumes institutional demand to follow an autoregressive process of order one:

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

[4] As shown previously, the bulk of research on institutional herding has focused on the US and a few other large capital markets (UK; Germany), while several small capital markets (e.g. Chile; Poland, Portugal) have also been investigated. Markets standing in the middle of these two capitalization-extremes have not been widely explored, exceptions being South Korea during the Asian crisis (e.g. Choe et al., 1999) and Taiwan (e.g. Chen et al., 2012).

Table 1
Descriptive statistics.

	Total market	Basic Materials	Consumer Goods	Consumer Services	Financials	Healthcare	Industrials	Oil and Gas	Technology	Utilities					
Panel A: Sample statistics															
No. of stocks	245	23	33	28	65	10	54	6	6	20					
No. of funds	1543	1003	874	1189	1241	839	1176	1235	967	1409					
No. of quarter-holdings positions	635,749	36,512	25,472	75,717	148,810	12,804	123,648	41,477	19,394	151,915					
No. of stock-quarters	15,032	1426	2046	1708	4030	620	3348	372	242	1240					
Panel B: Equity statistics															
Average number of active stocks per quarter traded by at least one fund	June 1995–September 2008	1995	1996	1997	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008
Total market	79.9	36.8	40.6	66.8	82.1	100.1	94.2	81.5	81.3	77.3	85.3	94.8	96.1	98.0	83.2
Basic Materials	15.6	15.7	15.5	16.3	18.5	18.5	17.0	17.0	15.5	14.8	14.3	14.3	13.8	14.0	14.0
Consumer Goods	19.1	20.0	17.5	21.3	24.0	23.8	21.0	20.5	18.5	17.0	17.0	16.8	17.0	16.5	16.3
Consumer Services	12.4	6.0	7.5	9.5	11.3	12.5	15.0	16.5	15.8	15.0	14.5	13.5	12.0	12.0	12.3
Financials	34.2	30.7	33.0	33.3	37.3	38.0	34.3	34.0	33.8	33.5	33.0	31.0	33.3	37.5	36.3
Healthcare	4.7	3.0	3.3	4.0	4.0	4.0	4.0	4.0	4.0	4.0	4.0	4.5	5.8	7.8	9.0
Industrials	31.4	33.7	33.3	36.3	35.5	37.3	33.5	31.8	31.8	29.8	27.8	28.8	28.0	25.8	26.8
Oil and Gas	3.8	2.7	3.3	4.0	3.3	3.0	3.3	4.0	4.0	4.0	4.0	4.0	4.0	4.8	5.0
Technology	3.5	1.3	1.0	1.0	1.8	3.5	5.0	5.0	4.8	4.5	5.0	4.8	4.0	4.0	4.0
Utilities	11.3	14.0	14.5	14.5	15.0	14.5	9.0	8.5	9.0	9.0	9.0	9.0	9.5	10.3	11.8
Panel C: Funds' statistics															
Average no. of active funds per stock per quarter traded by ≥1 fund	June 1995–September 2008	1995	1996	1997	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008
Total market	136.6	128.0	129.8	141.0	151.5	156.0	143.0	142.3	138.0	132.3	128.5	126.5	127.3	132.5	135.3
Basic Materials	43.0	26.9	23.6	50.8	52.1	55.9	50.8	38.8	30.0	25.3	32.7	49.0	64.5	58.7	43.9
Consumer Goods	25.9	14.2	14.4	27.2	32.0	33.4	25.4	21.5	20.9	21.3	24.9	32.9	32.4	34.1	28.0
Consumer Services	113.6	54.9	53.7	114.5	123.4	156.7	139.6	107.6	103.7	110.2	130.2	150.5	135.3	119.5	90.7
Financials	38.1	21.8	21.0	42.4	50.7	56.9	35.9	24.1	34.2	34.2	39.9	52.1	51.9	43.1	25.9
Healthcare	40.3	2.7	3.1	19.9	31.2	32.7	64.4	64.0	56.3	45.9	40.6	35.6	42.2	65.0	61.2
Industrials	46.2	37.0	36.8	48.7	69.7	82.0	46.2	25.1	28.8	29.0	33.8	48.8	56.6	55.4	48.2
Oil and Gas	182.2	71.5	81.1	116.6	161.8	269.6	198.5	221.2	197.5	195.3	210.1	233.6	229.8	189.3	175.7
Technology	94.2	16.8	54.0	137.3	62.0	109.3	166.7	151.4	119.0	96.8	64.4	68.0	101.8	97.2	74.8
Utilities	248.5	89.9	117.3	159.1	198.3	217.1	345.3	317.2	303.6	317.2	318.2	312.5	273.6	271.3	238.5

Sample data include quarterly holdings of funds from Spain for the June 1995–September 2008 period. For each quarter we calculate the number of stocks traded by at least one fund; for each quarter we also calculate the number of funds active in each stock for stocks traded by at least one fund. Panels B and C provide the time series' averages of these figures for each year as well as their total average throughout the sample period, both for the total market as well as for each sector separately.

The first-order autocorrelation coefficient (β_1) reflects the quarter-on-quarter cross-sectional correlation between institutional demand in quarter t and quarter $t-1$, since both sides of Eq. (3) are standardized and there is only one independent variable ($\Delta_{k,t-1}$) on the right-hand side of the equation. Sias (2004) decomposes β_1 into that part due to funds following their own trades and another one due to funds following the trades of other funds. More specifically, β_1 is decomposed as follows:

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

$N_{k,t}$ is the number of funds actively trading security k in quarter t and $D_{n,k,t}$ is a dummy variable taking the value of one when fund n is a buyer of security k in quarter t and zero when fund n is a seller of security k in quarter t. Likewise, $N_{k,t-1}$ is the number of funds actively trading security k in quarter $t-1$ and $D_{n,k,t-1}$ is a dummy variable equal to one when fund n is a buyer of security k in quarter $t-1$ and zero when fund n is a seller of security k in quarter $t-1$. $D_{m,k,t-1}$ is a dummy variable that equals one when fund m ($m \neq n$) is a buyer of security k in quarter $t-1$ and zero when fund m ($m \neq n$) is a seller of security k in quarter $t-1$. The first term on the right-hand side of the above equation is the portion of the correlation due to funds following their own trades; if it is positive (negative), then funds tend to follow (reverse) their trades over adjacent quarters. The second term on the right-hand side of the above equation is the portion of the correlation due to funds following the trades of other funds; if it is positive (negative), then funds tend to follow (trade against) each other over adjacent quarters.

Eqs. (3) and (4) are estimated both for the universe of our sample's stocks as well as for each of our nine sectors. To gauge now whether institutional industry herding is intentional or not, we follow the approach of Holmes et al. (2013) which traces intent through the interaction of institutional herding with different states of the trading environment. We examine the presence of intent in our paper using three variables (returns; volatility; volume) in both their market and sector expressions.[5,6]

Market/sector returns: the relative nature of institutional investors' performance assessment (they are normally assessed versus their peers) renders herding a viable option for "bad" (i.e. low quality) fund managers as it allows them to conceal their weak ability by imitating the actions of their "good" counterparts. The importance of this is expected to be more pronounced during periods of declining prices, since it is during those periods that investors are more likely to generate losses and, consequently, face assessment issues. Since bearish conditions lead everyone in the market to perform poorly, herding on the trades of "good" managers allows "bad" managers to share the blame: despite them making "good" decisions (in the sense that, they traded the same stocks as their "good" peers),

[5] Data used to calculate the market/sector expressions of the three variables were obtained from Thomson-Reuters DataStream. The Madrid Stock Exchange General Price Index (MADRIDI) is used to calculate all market expressions of these variables; their sector expressions are calculated using the following indices (DataStream mnemonics in brackets): Basic Materials (BMATRES); Consumer Goods (CNSMGES); Consumer Services (CNSMSES); Financials (FINANES); Healthcare (HLTHCES); Industrials (INDUSES); Oil and Gas (OILGSES); Technology (TECNOES); Utilities (UTILSES).

[6] Central to the following arguments is the view that spurious herding will not be affected by factors related to market/sector states. While there exists some evidence which identifies a relationship between market states and characteristic trading (e.g. Cooper et al., 2004), there are three reasons why we believe the extent of unintentional herding will not vary with market/sector states: (a) while there is some evidence that market states and momentum profits are linked, the evidence is mixed (e.g. in contrast to Cooper et al., 2004, Griffin et al., 2003, 2005 find there is no such relationship); (b) the limited evidence which does suggest such a relationship, relates to profits from momentum trading, rather than the extent of such trading; and (c) if market states do impact on the extent of characteristic trading, this will manifest itself within periods (as is the case for profits), but not across periods. The measure of herding used in this paper relates to behaviour across periods in that it captures investors in one period following the trades of investors from previous periods.

they still underperformed as a result of the prevailing bearish conditions. Such behaviour obviously jams the assessment process, rendering it difficult for the assessors to distinguish between high- and low-quality managers, while on the other hand giving "bad" managers the opportunity to conceal their low quality. Bullish conditions can, however, also prompt "bad" managers to herd intentionally, since underperforming during periods of rising prices is more easily associated to low ability. If institutional industry herding is intentional, we would expect to trace a relationship between market/sector returns and institutional industry herding (i.e. institutional industry herding would exhibit differences between bearish and bullish periods); if fund managers herded spuriously, no such differences would be expected to arise.[7] More formally, we distinguish between two hypotheses:

H_1: institutional industry herding is intentional (i.e. it depends on market/sector returns)
H_2: institutional industry herding is spurious (i.e. it does not depend on market/sector returns)

To test for the effect of market/sector returns over institutional industry herding we use the quarter-end closing prices of the Madrid Stock Exchange General Price Index and our nine sector indices for the June 1995–September 2008 period, calculate their quarterly log-differenced returns and rank the return-series of each index in ascending order. We then split the return-series of each index in two different ways, one relative and one absolute. In the former case, we split each return-series into two parts, contingent upon whether a quarter's returns are positive or negative (i.e. whether the market/sector index has risen/declined in quarter t compared to quarter $t-1$) and then split β_1 and its two components (funds following their own trades; funds following the trades of other funds) of each sector accordingly. In the latter case, we break up each return-series into three parts, namely "high" (the top third of the market/sector index returns), "mid" (the middle third of the market/sector index returns) and "low" (the bottom third of the market/sector index returns) and then break up β_1 and its two components of each sector accordingly.

Market/sector volatility: the presence of high or increased volatility in a market has been associated (Ross, 1989) with an increase in informed trading, in the sense that a higher flow of information to the market leads prices to be more volatile as this information is incorporated to them. A highly informative environment is obviously not conducive to herding, since there exists more information on which investors can trade. However, "bad" managers may view such a situation from a different perspective, as an increase in information-flow can lead the market environment to grow in complexity; in that case, deciphering the content of information may require skills that "bad" managers are not expected to possess, thus ending up mimicking their "good" peers. However, tranquil periods can also prompt "bad" managers to resort to herding, as the lack of turbulence renders it easier for them to visualize the trades of their "good" peers. If fund managers herd intentionally at the industry level, we would expect a relationship to evolve between market/sector volatility and their herding (institutional industry herding would exhibit differences between more volatile and less volatile periods); if fund managers herd spuriously, one would expect no such differences.[8] More formally, we distinguish between the following hypotheses:

H_3: institutional industry herding is intentional (i.e. it depends on market/sector volatility)
H_4: institutional industry herding is spurious (i.e. it does not depend on market/sector volatility)

To test for the effect of market/sector volatility over institutional industry herding we use the daily closing prices of the Madrid Stock Exchange General Price Index and our nine sector indices for the June 1995–September 2008 period, calculate the volatility of each index every quarter using Schwert's (1989) approach and rank these quarterly volatility observations of each index in ascending order. We

[7] If relative homogeneity drives herding and changes in the market's/sector's return quarter-on-quarter affect herding, this would suggest that the composition of institutional investors as a group varies significantly from one quarter to the next, something probably unrealistic to assume. If style investing drives herding, we would expect market/sector performance to affect the profitability of style strategies, yet not the level of style investing (i.e. the tendency of investors to style-invest).

[8] The quarterly variations in market/sector volatility would not be expected to lead to variations in either the relative homogeneity among fund managers, or the level of style investing practiced.

then split each volatility-series in two different ways, one relative and one absolute. In the former case, we split each volatility-series into two parts, contingent upon whether a quarter's volatility has risen/declined in quarter t compared to quarter $t-1$ and then split β_1 and its two components of each sector accordingly. In the latter case, we break up each volatility-series into three parts, namely "high" (the top third of the market/sector volatility values), "mid" (the middle third of the market/sector volatility values) and "low" (the bottom third of the market/sector volatility values) and then break up β_1 and its two components of each sector accordingly.

Market/sector volume: the presence of increased/high volume suggests the trading environment grows more liquid and higher liquidity encourages the participation of informed investors, as it allows them to see their trades more easily executed (Romano, 2007). From the perspective of "bad" managers, high liquidity facilitates peer-mimicking, as it enables them to herd on their "good" peers without their herding strategy being inhibited by trading frictions (such as e.g. thin trading, which would be expected to be more pronounced during periods of lower trading activity).[9] Consequently, if there is intent on behalf of fund managers in their industry herding, we would expect to find a relationship between their herding and trading volume (i.e. institutional industry herding would be expected to be more pronounced during periods characterized by higher trading activity); however, if their herding were spurious, one would not expect its significance to vary with trading volume.[10] More formally, we distinguish between two hypotheses:

H_5: institutional industry herding is intentional (i.e. it depends on market/sector volume)
H_6: institutional industry herding is spurious (i.e. it does not depend on market/sector volume)

To test for the effect of market/sector volume over institutional industry herding we use the daily volume observations of the Madrid Stock Exchange General Price Index and our nine sector indices for the June 1995–September 2008 period, aggregate the daily volume observations each quarter for each index and then rank the quarterly volume observations of each index in ascending order. We then split each volume-series in two different ways, one relative and one absolute. In the former case, we split each volume-series into two parts, contingent upon whether a quarter's volume has risen/declined in quarter t compared to quarter $t-1$ and then split β_1 and its two components of each sector accordingly. In the latter case, we break up each volume-series into three parts, namely "high" (the top third of the market/sector volume values), "mid" (the middle third of the market/sector volume values) and "low" (the bottom third of the market/sector volume values) and then break up β_1 and its two components of each sector accordingly.

3. Results – discussion

Before examining whether institutional industry herding is intentional or not, we will first take a look at our full-sample results, both for the market level as well as for each sector individually which are presented in Table 2. At the overall market level, the demand of Spanish funds for domestic stocks bears a significant[11] temporal dependence (reflected through the β_t coefficient) which is strongly motivated by herding (reflected through the "funds following the trades of other funds" part) rather than habit investing (the "funds following their own trades" part is insignificant). The only other occasion where β_t appears significant in Table 2 is for Technology, for which both β_t-components are significant, while significant herding is detected for Consumer Services and Industrials. The first

[9] Evidence of high volume promoting herding at the market level has been empirically documented by Tan et al. (2008) for the Chinese A shares' market and Economou et al. (2011) for the Spanish and Portuguese markets.

[10] Quarterly changes in market/sector volume would not be expected to lead to variations in the relative homogeneity among fund managers; it is unlikely that the composition of their ranks would vary quarter-on-quarter. Regarding style investing, changes in quarterly volume could affect the profitability, yet not the level of style investing; for example, although the US equity turnover has increased markedly over the decades, the propensity of US funds to momentum-trade appears consistent in several studies on institutional trading from the 1970s (e.g. Grinblatt et al., 1995) to more recent years (e.g. Sias, 2004).

[11] Any reference to statistical significance from now on will refer to estimates significant at either the 5 or 1 percent levels.

Table 2
Tests for herding – buyer if increased position.

	Average coefficient (β)	Funds following their own trades	Funds following the trades of other funds	Average R^2
All sectors	0.0426	−0.0112	0.0538	0.0181
	(0.0206)	(0.2005)	(0.0001)	
Basic Materials	0.0017	−0.0425	0.0442	0.0987
	(0.9687)	(0.0525)	(0.2619)	
Consumer Goods	0.0220	−0.0484	0.0704	0.0867
	(0.5967)	(0.2430)	(0.1456)	
Consumer Services	0.1052	−0.0439	0.1492	0.1673
	(0.0658)	(0.0694)	(0.0045)	
Financials	0.0376	0.0004	0.0372	0.0525
	(0.2466)	(0.9820)	(0.0612)	
Healthcare	0.0324	0.0724	−0.0400	0.3318
	(0.6894)	(0.1416)	(0.6113)	
Industrials	0.0572	−0.0062	0.0634	0.0463
	(0.0560)	(0.6878)	(0.0121)	
Oil and Gas	−0.0527	−0.0021	−0.0505	0.4401
	(0.5697)	(0.9446)	(0.5813)	
Technology	0.7775	−0.1013	0.8788	0.4275
	(0.0000)	(0.0146)	(0.0000)	
Utilities	0.0601	0.0105	0.0496	0.1538
	(0.2755)	(0.4736)	(0.3559)	

This table reports the results for the following equation: $\Delta_{k,t} = \beta_t \Delta_{k,t-1} + \varepsilon_{k,t}$. For each security and quarter between June 1995 and September 2008 we calculate the fraction of funds that increase their position in the security in the Spanish market. A fund is defined as increasing its position if it holds a greater fraction of the firm's shares at the end of the quarter than it held at the beginning. All data are standardized (i.e. rescaled to zero mean, unit variance) each quarter. We then estimate quarterly cross-sectional regressions of institutional demand on lagged institutional demand. Because there is a single independent variable in each regression and the data are standardized, these regression coefficients are also the cross-sectional correlations between institutional demand and lagged institutional demand. The first column reports the time-series' averages of these 52 correlation coefficients and associated p-values (in parentheses) for the total market and each sector separately. The second and third columns report the portion of the correlation that results from funds following their own lagged trades and the portion that results from funds following the previous trades of other funds (herding) for the total market and each sector separately.

picture therefore obtained from our full-sample results is that Spanish funds herd significantly, with their herding significance identified with Consumer Services, Industrials and Technology.[12]

We now move on to assess whether institutional herding at the sector level is due to intent or not by examining its interactions with a series of market and sector states based on three variables (returns; volatility; volume). To begin with, we first assess the impact over institutional industry herding of the relative change in the quarterly returns of both the market index as well as the index of the sector under consideration. Results are reported in Table 3, where it appears that β_t is significant mostly during quarters of negative market (Financials; Oil and Gas; Technology) and sector (Consumer Services; Financials; Industrials; Technology) performance.[13] Habit investing seems stronger during underperforming sector quarters (the "funds following their own trades" part is significant for Oil and Gas and Technology for those quarters) while for Oil and Gas it is also significant during negative market quarters. In terms of herding, the "funds following the trades of other funds" part is significant for Consumer Services during quarters of positive market returns and negative sector returns; for both Financials and Industrials, the estimates of that part are significant during quarters of negative market returns and negative sector returns. The above indicate that the significance of institutional industry herding is stronger during quarters when either the market or the sector have performed poorly,

[12] The overall significant herding Spanish funds exhibit at the market level is due to their strong herding in Consumer Services, Industrials and Technology, since the values of the "funds following the trades of other funds" part are higher than the value of its corresponding part at the market-level (0.0538) for these three sectors: 0.8788 for Technology (16 times higher), 0.1492 for Consumer Services (almost three times higher) and 0.0634 for Industrials. The only case of a sector exhibiting a value for that part above the market's level yet with no significance is Consumer Goods (0.0704).

[13] For Technology stocks, β_t is also significant during quarters of positive market and sector performance.

Table 3
Tests for herding – controlling for market and sector returns (positive–negative).

	Panel A: Market returns split								Panel B: Sector returns split							
	Average coefficient (β)		Funds following their own trades		Funds following the trades of other funds		Average R^2		Average coefficient (β)		Funds following their own trades		Funds following the trades of other funds		Average R^2	
	Positive	Negative	Positive	Negative	Positive	Negative	Positive	Negative	Positive	Negative	Positive	Negative	Positive	Negative	Positive	Negative
Basic Materials	−0.0401	0.0687	−0.0580	−0.0177	0.0179	0.0864	0.1028	0.0877	−0.0231	0.0450	−0.0471	−0.0346	0.0240	0.0796	0.1132	0.0689
	(0.5065)	(0.3055)	(0.0751)	(0.4622)	(0.7080)	(0.2178)			(0.7080)	(0.4708)	(0.1434)	(0.1427)	(0.6201)	(0.2576)		
Consumer Goods	0.0537	−0.0287	−0.0533	−0.0404	0.1070	0.0118	0.0810	0.0960	−0.0033	0.0455	−0.0878	−0.0120	0.0845	0.0575	0.0592	0.1123
	(0.2976)	(0.6924)	(0.4133)	(0.1948)	(0.1350)	(0.8267)			(0.9482)	(0.4942)	(0.2746)	(0.7045)	(0.3440)	(0.2136)		
Consumer Services	0.1478	0.0371	−0.0198	−0.0825	0.1676	0.1196	0.1908	0.1299	0.0666	0.1540	−0.0462	−0.0411	0.1128	0.1951	0.1887	0.1405
	(0.0605)	(0.6490)	(0.4023)	(0.1063)	(0.0259)	(0.0840)			(0.4250)	(0.0475)	(0.2288)	(0.1296)	(0.1263)	(0.0112)		
Financials	−0.00716	0.1094	−0.0237	0.0392	0.0166	0.0702	0.0499	0.0567	−0.0142	0.1207	−0.0337	0.0550	0.0194	0.0657	0.0491	0.0581
	(0.8628)	(0.0369)	(0.3359)	(0.2342)	(0.5258)	(0.0224)			(0.7274)	(0.0224)	(0.1665)	(0.0922)	(0.4782)	(0.0191)		
Healthcare	−0.0021	0.0878	0.0964	0.0341	−0.0986	0.0537	0.3651	0.3319	0.0390	0.0210	0.0773	0.0641	−0.0383	−0.0430	0.3618	0.2799
	(0.9840)	(0.4708)	(0.1842)	(0.5512)	(0.3485)	(0.6546)			(0.7169)	(0.8674)	(0.2601)	(0.3379)	(0.6875)	(0.7647)		
Industrials	0.0403	0.0841	−0.0004	−0.0154	0.0408	0.0995	0.0517	0.0379	0.0341	0.0974	0.0021	−0.0206	0.0320	0.1179	0.0461	0.0469
	(0.3200)	(0.0586)	(0.9832)	(0.4785)	(0.2461)	(0.0040)			(0.3717)	(0.0490)	(0.9219)	(0.3627)	(0.3218)	(0.0034)		
Oil and Gas	0.0839	−0.2714	0.0169	−0.0328	0.0669	−0.2386	0.4885	0.3627	0.0039	−0.1511	0.0169	−0.0352	−0.0129	−0.1159	0.4417	0.4373
	(0.5030)	(0.0397)	(0.7371)	(0.0140)	(0.5952)	(0.0601)			(0.9734)	(0.3308)	(0.7287)	(0.0479)	(0.9136)	(0.4320)		
Technology	0.8350	0.6962	−0.0908	−0.1162	0.9258	0.8125	0.4068	0.4569	0.9857	0.5978	−0.0724	−0.1264	1.0581	0.7241	0.4341	0.4079
	(0.0002)	(0.0047)	(0.0630)	(0.1233)	(0.0001)	(0.0056)			(0.0004)	(0.0020)	(0.1742)	(0.0473)	(0.0004)	(0.001)		
Utilities	0.0232	0.1193	0.0160	0.0017	0.0071	0.1175	0.1295	0.1928	0.0752	0.0342	0.0133	0.0058	0.0618	0.0285	0.1459	0.1676
	(0.7325)	(0.2150)	(0.4324)	(0.9321)	(0.9185)	(0.1679)			(0.2834)	(0.7137)	(0.5038)	(0.7910)	(0.3930)	(0.7226)		

This table reports the results for the following equation: $\Delta_{k,t} = \beta_t \Delta_{k,t-1} + \varepsilon_{k,t}$. For each security and quarter between June 1995 and September 2008 we calculate the fraction of funds that increase their position in the security in the Spanish market. A fund is defined as increasing its position if it holds a greater fraction of the firm's shares at the end of the quarter than it held at the beginning. All data are standardized (i.e. rescaled to zero mean, unit variance) each quarter. We then estimate quarterly cross-sectional regressions of institutional demand on lagged institutional demand. Because there is a single independent variable in each regression and the data are standardized, these regression coefficients are also the cross-sectional correlations between institutional demand and lagged institutional demand. We then average our results across two distinctive groups, contingent upon whether the quarterly market/sector return is positive or negative. The Madrid Stock Exchange General Price Index and our nine sectors' indices are used here to calculate market and sector returns, respectively. Returns here are calculated every quarter as the first logarithmic differences of the quarterly closing prices of the Madrid Stock Exchange General Price Index and our nine sectors' indices. The first column reports the time-series' averages of these correlation coefficients and associated p-values (in parentheses) for each of the two groups and for each sector, controlling for market (panel A) and sector (panel B) returns separately. The second and third columns report the portion of the correlation that results from funds following their own lagged trades and the portion that results from funds following the previous trades of other funds (herding) for each of the two groups and for each sector, controlling for market (panel A) and sector (panel B) returns separately.

suggesting that it is intentional in line with what we mentioned in the previous section. Technology stocks exhibit significant institutional herding irrespective of the quarterly performance of the market or their sector (the "funds following the trades of other funds" part is significant in all tests) thus denoting the absence of herding intent there; no herding significance is detected for the other sectors.

The link between institutional industry herding and negative market/sector returns is further confirmed in Table 4 which presents the estimates from the break-up of β_t and its two components into three parts (high–mid–low market/sector index returns). We begin from the Technology sector, whose β_t-estimates and "funds following the trades of other funds" estimates are significant for all tests, indicating that the demand of Spanish funds for Technology stocks is strongly herding-driven, again without intent underlying their herding. Aside from Technology, the significance of β_t is manifested only for Consumer Services during quarters of low market returns; the "funds following their own trades" part is significant for Basic Materials (mid market returns), Consumer Services (mid sector returns) and Technology (mid market returns and low sector returns). Regarding herding, the "funds following the trades of other funds" estimates exhibit significance during quarters of low market returns for Consumer Services, Financials and Industrials, during quarters of mid sector returns for Consumer Services and during quarters of low sector returns for Industrials. The significance of institutional herding in these sectors during quarters characterized mostly by low market/sector returns (i.e. relatively underperforming quarters) implies a relationship between market/sector performance and institutional industry herding, thus reflecting the latter's intentional nature.

We now turn to assess the interaction between institutional industry herding and market/sector volatility, beginning from the impact over institutional industry herding of the relative change in the quarterly volatility of both the market index as well as the index of the sector under consideration. As Table 5 illustrates, the Technology sector continues to maintain the significance of both its β_t-estimates and the "funds following the trades of other funds" estimates irrespective of whether the quarterly market/sector volatility has increased or decreased, again indicating that the demand of Spanish funds for Technology stocks is due to herding, which nevertheless produces no signs of intent. Aside from Technology, the significance of β_t is manifested only for Industrials during quarters where sector volatility has decreased; the "funds following their own trades" part is significant only for Basic Materials (increased market volatility quarters) and Utilities (increased sector volatility quarters). The "funds following the trades of other funds" estimate is significant for Consumer Services (increased market and sector volatility quarters) and Industrials (decreased sector volatility quarters),[14] indicating that institutional herding for these sectors is intentional.

Table 6 presents the estimates from the break-up of β_t and its two components into three parts (high–mid–low market/sector volatility). The Technology sector retains the significance of both its β_t-estimates and the "funds following the trades of other funds" estimates in all tests performed, confirming once more that Spanish funds herd significantly in this sector. The significance of β_t is evident during high market volatility quarters for the Industrials and Oil and Gas sectors and during high sector volatility quarters for Industrials. Regarding the "funds following their own trades" part, it appears significant for Oil and Gas during high market/sector volatility quarters and Technology (low sector volatility quarters). The picture emanating from the "funds following the trades of other funds" part indicates the presence of significant herding mostly during high market (Financials; Industrials) and sector (Consumer Services; Industrials) volatility quarters; it also appears significant during mid market (Basic Materials) and sector (Consumer Services) volatility quarters. The above indicate a relationship between institutional industry herding and market/sector volatility (herding is stronger when market/sector volatility is not low), confirming the presence of intentional herding.

The interaction between institutional industry herding and market/sector volume is first illustrated controlling for the impact of the relative change in the quarterly volume of both the market index as well as the index of the sector under consideration over institutional industry herding. The relevant results are presented in Table 7, where again we notice the pattern of uniform significance for all tests of the β_t-estimates and the "funds following the trades of other funds" estimates for the Technology sector. Aside from Technology, β_t exhibits significance only for Consumer Services during

[14] For Industrials this part is negatively significant during decreased market volatility quarters, indicative of counter-herding.

Table 4
Tests for herding – controlling for market and sector returns (high–mid–low).

	Average coefficient (β)			Funds following their own trades			Funds following the trades of other funds			Average R^2		
	High	Mid	Low	High	Mid	Low	High	Mid	Low	High	Mid	Low
Panel A: Market returns												
Basic Materials	0.0044	−0.0380	0.0411	−0.0246	−0.1003	0.0008	0.0291	0.0622	0.0403	0.1470	0.0601	0.0861
	(0.9648)	(0.5369)	(0.5730)	(0.5732)	(0.0255)	(0.9668)	(0.7101)	(0.3456)	(0.5445)			
Consumer Goods	0.0359	0.1010	−0.0754	0.0153	−0.1096	−0.0473	0.0206	0.2106	−0.0281	0.0835	1.1022	0.0938
	(0.6281)	(0.1457)	(0.3231)	(0.7218)	(0.3246)	(0.1440)	(0.6550)	(0.0851)	(0.6211)			
Consumer Services	0.0547	0.0511	0.2131	−0.0921	−0.0131	−0.0283	0.1468	0.0642	0.2415	0.2244	0.1008	0.1810
	(0.6459)	(0.4994)	(0.0454)	(0.1732)	(0.1904)	(0.3762)	(0.1812)	(0.1812)	(0.0112)			
Financials	−0.0213	0.0359	0.0984	−0.0262	−0.0047	0.0326	0.0049	0.0407	0.0658	0.0559	0.0519	0.0497
	(0.7271)	(0.5332)	(0.0630)	(0.4400)	(0.8971)	(0.3301)	(0.8953)	(0.2402)	(0.0481)			
Healthcare	−0.0557	0.0434	0.1089	0.1061	0.0586	0.0534	−0.1619	−0.0151	0.0555	0.4458	0.2299	0.3260
	(0.7441)	(0.7106)	(0.4480)	(0.3623)	(0.4498)	(0.3862)	(0.2915)	(0.9035)	(0.6931)			
Industrials	0.0734	0.0200	0.0803	0.0062	−0.0109	−0.0136	0.0672	0.0309	0.0093	0.0517	0.0459	0.0416
	(0.1816)	(0.7071)	(0.1168)	(0.8604)	(0.5960)	(0.5924)	(0.1195)	(0.5397)	(0.0166)			
Oil and Gas	0.0345	0.0258	−0.2231	0.0659	−0.0425	−0.0276	−0.0314	0.0683	−0.1955	0.4430	0.5114	0.3617
	(0.8403)	(0.8809)	(0.1276)	(0.4797)	(0.0747)	(0.0520)	(0.8546)	(0.6894)	(0.1684)			
Technology	0.9726	0.8415	0.5085	−0.0227	−0.1673	−0.1038	0.9953	1.0089	0.6123	0.4145	0.4752	0.3857
	(0.0066)	(0.0093)	(0.0000)	(0.5870)	(0.0286)	(0.2584)	(0.0077)	(0.0059)	(0.0009)			
Utilities	0.0229	0.0571	0.1006	0.0093	0.0265	−0.0051	0.0136	0.0305	0.1057	0.1362	0.1232	0.2039
	(0.8240)	(0.4971)	(0.3499)	(0.7825)	(0.2249)	(0.8130)	(0.9005)	(0.7024)	(0.2761)			
Panel B: Sector returns												
Basic Materials	−0.0665	0.0559	0.0127	−0.0489	−0.0534	−0.0247	−0.0176	0.1092	0.0374	0.1228	0.1077	0.0600
	(0.4696)	(0.4929)	(0.8381)	(0.3180)	(0.2060)	(0.2006)	(0.8275)	(0.0982)	(0.5454)			
Consumer Goods	0.0213	0.0088	0.0369	−0.1169	−0.0267	−0.0029	0.1382	0.0355	0.0398	0.0768	0.0674	0.1172
	(0.7605)	(0.8902)	(0.6777)	(0.3212)	(0.4262)	(0.9452)	(0.2899)	(0.3973)	(0.5348)			
Consumer Services	0.0604	0.1506	0.1022	−0.0411	−0.0733	−0.0157	0.1015	0.2239	0.1178	0.1909	0.1718	0.1391
	(0.6039)	(0.1016)	(0.2918)	(0.5129)	(0.0270)	(0.5185)	(0.2689)	(0.0229)	(0.1899)			
Financials	−0.0189	0.0520	0.0823	−0.0178	−0.0172	0.0448	−0.0011	0.0691	0.0375	0.0541	0.0518	0.0517
	(0.7551)	(0.3807)	(0.1512)	(0.5932)	(0.6495)	(0.2318)	(0.9779)	(0.0664)	(0.1701)			
Healthcare	−0.0033	0.0494	0.0503	0.1298	0.0598	0.0285	−0.1331	−0.0104	0.0218	0.3779	0.3535	0.2630
	(0.9833)	(0.7364)	(0.6977)	(0.3242)	(0.2425)	(0.6417)	(0.3461)	(0.9442)	(0.8646)			
Industrials	0.0332	0.0495	0.0893	0.0236	−0.0132	−0.02879	0.0096	0.0627	0.1180	0.0557	0.0354	0.0487

Table 4 (*Continued*)

	Average coefficient (β)			Funds following their own trades			Funds following the trades of other funds			Average R^2		
	High	Mid	Low	High	Mid	Low	High	Mid	Low	High	Mid	Low
	(0.5825)	(0.2783)	(0.0953)	(0.4867)	(0.5579)	(0.2449)	(0.8514)	(0.0948)	(0.0074)			
Oil and Gas	0.0639	−0.0663	−0.1550	0.0656	−0.0321	−0.0383	−0.0017	−0.0343	−0.1167	0.5254	0.4015	0.3957
	(0.7274)	(0.6672)	(0.3223)	(0.4849)	(0.0630)	(0.0544)	(0.9926)	(0.8277)	(0.4270)			
Technology	0.9419	0.6935	0.7101	−0.0359	−0.0726	−0.2000	0.9778	0.7661	0.9101	0.3886	0.4635	0.4250
	(0.0084)	(0.0007)	(0.0279)	(0.3902)	(0.3320)	(0.0309)	(0.0088)	(0.0012)	(0.0167)			
Utilities	0.0627	0.0804	0.0363	0.0164	0.0106	0.0047	0.0463	0.0698	0.0316	0.1601	0.1168	0.1866
	(0.5698)	(0.3162)	(0.7280)	(0.5854)	(0.6632)	(0.8467)	(0.6925)	(0.3765)	(0.7243)			

This table reports the results for the following equation: $\Delta_{k,t} = \beta_t \Delta_{k,t-1} + \varepsilon_{k,t}$. For each security and quarter between June 1995 and September 2008 we calculate the fraction of funds that increase their position in the security in the Spanish market. A fund is defined as increasing its position if it holds a greater fraction of the firm's shares at the end of the quarter than it held at the beginning. All data are standardized (i.e. rescaled to zero mean, unit variance) each quarter. We then estimate quarterly cross-sectional regressions of institutional demand on lagged institutional demand. Because there is a single independent variable in each regression and the data are standardized, these regression coefficients are also the cross-sectional correlations between institutional demand and lagged institutional demand. We then average our results across three distinctive groups, namely "high", "mid" and "low" contingent upon whether the market's/sector's return during the contemporaneous quarter falls in the top, middle or bottom third of the sample period's quarterly market/sector return-values ranked in ascending order. Returns here are calculated as the first logarithmic differences of the quarterly closing prices of the Madrid Stock Exchange General Price Index and our nine sectors' indices. The first column reports the time-series' average of these correlation coefficients and associated *p*-values (in parentheses) for each of the three groups and for each sector, controlling for market (panel A) and sector (panel B) returns separately. The second and third columns report the portion of the correlation that results from funds following their own lagged trades and the portion that results from funds following the previous trades of other funds (herding) for each of the three groups and for each sector, controlling for market (panel A) and sector (panel B) returns separately.

Table 5
Tests for herding – controlling for market and sector volatility (positive–negative).

	Panel A: Market volatility split								Panel B: Sector volatility split							
	Average coefficient (β)		Funds following their own trades		Funds following the trades of other funds		Average R^2		Average coefficient (β)		Funds following their own trades		Funds following the trades of other funds		Average R^2	
	Increased	Decreased	Increased	Decreased	Increased	Decreased	Increased	Decreased	Increased	Decreased	Increased	Decreased	Increased	Decreased	Increased	Decreased
Basic Materials	0.0018	0.0016	−0.0812	−0.0067	0.0830	0.0083	0.0751	0.1060	−0.0363	0.0305	−0.0698	−0.0173	0.0334	0.0479	0.0897	0.1064
	(0.9740)	(0.9810)	(0.0149)	(0.8160)	(0.1472)	(0.8803)			(0.5714)	(0.6446)	(0.0615)	(0.5165)	(0.5728)	(0.3926)		
Consumer Goods	0.0524	−0.0060	−0.1003	−0.0003	0.1527	−0.0057	0.0987	0.0757	0.0693	−0.0099	−0.0974	−0.0152	0.1667	0.0053	0.1140	0.0683
	(0.4123)	(0.9132)	(0.2147)	(0.9905)	(0.0936)	(0.8869)			(0.3619)	(0.8388)	(0.3223)	(0.5171)	(0.1150)	(0.8925)		
Consumer Services	0.1382	0.0747	−0.0826	−0.0080	0.2209	0.0827	0.1725	0.1627	0.1472	0.0564	−0.0717	−0.0116	0.2188	0.0680	0.2041	0.1246
	(0.0939)	(0.3589)	(0.0747)	(0.6633)	(0.0029)	(0.2735)			(0.1017)	(0.4111)	(0.0833)	(0.5854)	(0.0080)	(0.2767)		
Financials	0.0656	0.0118	0.0195	−0.0172	0.0460	0.0291	0.0601	0.0455	0.0848	0.0003	0.0331	−0.0254	0.0518	0.0257	0.0688	0.0396
	(0.1907)	(0.7840)	(0.5256)	(0.5014)	(0.1110)	(0.3021)			(0.1270)	(0.9938)	(0.2943)	(0.3146)	(0.1119)	(0.3095)		
Healthcare	0.0779	−0.0096	0.0787	0.0666	−0.0007	−0.0763	0.3504	0.3147	0.0419	0.0231	0.0751	0.0698	−0.0333	−0.0467	0.3084	0.3554
	(0.5213)	(0.9308)	(0.3865)	(0.1573)	(0.9947)	(0.5098)			(0.7087)	(0.8489)	(0.3651)	(0.2130)	(0.7579)	(0.6917)		
Industrials	0.0459	−0.0100	0.0075	0.0133	0.1284	−0.0233	0.0613	0.0326	0.0214	0.0930	−0.0250	0.0126	0.0464	0.0804	0.0472	0.0456
	(0.3631)	(0.0543)	(0.3700)	(0.8079)	(0.1272)	(0.0378)			(0.6331)	(0.0211)	(0.2121)	(0.5975)	(0.2006)	(0.0261)		
Oil and Gas	0.0176	−0.1179	0.0121	−0.0153	0.0055	−0.1025	0.3508	0.5228	0.0333	−0.1264	−0.0417	0.0317	0.0750	−0.1582	0.4144	0.4622
	(0.8837)	(0.4068)	(0.8512)	(0.2604)	(0.9650)	(0.4481)			(0.8064)	(0.3295)	(0.0594)	(0.5667)	(0.5667)	(0.2222)		
Technology	0.9125	0.6297	−0.1020	−0.1059	1.0145	0.7357	0.4069	0.4052	0.5600	0.8670	−0.0996	−0.1074	0.6596	0.9744	0.3339	0.4518
	(0.0047)	(0.0013)	(0.1739)	(0.0819)	(0.0060)	(0.0006)			(0.0102)	(0.0006)	(0.1672)	(0.0848)	(0.0092)	(0.0005)		
Utilities	0.1360	−0.1528	0.4544	0.5582	1.5786	−0.3435	0.1898	0.1205	0.0258	0.7159	0.0126	0.4701	0.0132	0.8428	0.1357	0.1734
	(0.1334)	(0.8798)	(0.6536)	(0.5815)	(0.1275)	(0.7340)			(0.0974)	(0.2666)	(0.0084)	(0.7352)	(0.0890)	(0.3091)		

This table reports the results for the following equation: $\Delta_{k,t} = \beta_t \Delta_{k,t-1} + \varepsilon_{k,t}$. For each security and quarter between June 1995 and September 2008 we calculate the fraction of funds that increase their position in the security in the Spanish market. A fund is defined as increasing its position if it holds a greater fraction of the firm's shares at the end of the quarter than it held at the beginning. All data are standardized (i.e. rescaled to zero mean, unit variance) each quarter. We then estimate quarterly cross-sectional regressions of institutional demand on lagged institutional demand. Because there is a single independent variable in each regression and the data are standardized, these regression coefficients are also the cross-sectional correlations between institutional demand and lagged institutional demand. We then average our results across two distinctive groups, contingent upon whether the quarterly market/sector volatility has increased or decreased. The Madrid Stock Exchange General Price Index and our nine sectors' indices are used here to calculate market and sector returns, respectively. Market/sector volatility here is calculated every quarter using the standard deviation of daily index returns in quarterly intervals in line with Schwert (1989) on the basis of the Madrid Stock Exchange General Price Index and our nine sectors' indices. The first column reports the time-series' averages of these correlation coefficients and associated p-values (in parentheses) for each of the two groups and for each sector, controlling for market (panel A) and sector (panel B) volatility separately. The second and third columns report the portion of the correlation that results from funds following their own lagged trades and the portion that results from funds following the previous trades of other funds (herding) for each of the two groups and for each sector, controlling for market (panel A) and sector (panel B) volatility separately.

Table 6
Tests for herding – controlling for market and sector volatility (high–mid–low).

	Average coefficient (β)			Funds following their own trades			Funds following the trades of other funds			Average R^2		
	High	Mid	Low	High	Mid	Low	High	Mid	Low	High	Mid	Low
Panel A: Market volatility												
Basic Materials	−0.0400	0.0853	−0.0449	−0.0272	−0.0611	−0.0380	−0.0127	0.1465	−0.0069	0.0795	0.1243	0.0857
	(0.5781)	(0.3267)	(0.5618)	(0.3190)	(0.2085)	(0.3019)	(0.8720)	(0.0285)	(0.9089)			
Consumer Goods	0.0171	0.0165	0.0328	−0.0337	−0.0956	−0.0130	0.0509	0.1121	0.0458	0.1172	0.0535	0.0915
	(0.8434)	(0.7719)	(0.6745)	(0.3004)	(0.3897)	(0.7713)	(0.4538)	(0.3501)	(0.3496)			
Consumer Services	0.1019	0.1156	0.0975	−0.0278	−0.0263	−0.0786	0.1298	0.1419	0.1762	0.1011	0.1600	0.2416
	(0.1556)	(0.2278)	(0.4555)	(0.3491)	(0.4180)	(0.1958)	(0.0767)	(0.0976)	(0.1371)			
Financials	0.1085	0.0073	−0.0010	0.0458	−0.0279	−0.0149	0.0626	0.0353	0.0138	0.0640	0.0405	0.0538
	(0.0755)	(0.8858)	(0.9866)	(0.2921)	(0.2896)	(0.6519)	(0.0137)	(0.3469)	(0.7335)			
Healthcare	0.0847	0.0469	−0.0352	0.0512	0.1150	0.0486	0.0335	−0.0680	−0.0839	0.2069	0.4391	0.3434
	(0.4590)	(0.7730)	(0.8140)	(0.3200)	(0.3587)	(0.4285)	(0.7819)	(0.6641)	(0.5443)			
Industrials	0.1160	0.0226	0.0349	0.0050	−0.0162	−0.0068	0.1110	0.0388	0.0388	0.0369	0.0671	0.0339
	(0.0136)	(0.7246)	(0.4191)	(0.7759)	(0.6235)	(0.8117)	(0.0081)	(0.4258)	(0.3234)			
Oil and Gas	−0.2783	0.0845	0.0275	−0.0281	0.0368	−0.0175	−0.2501	0.0476	0.0450	0.3167	0.4386	0.5651
	(0.0361)	(0.6018)	(0.8845)	(0.0123)	(0.6804)	(0.4474)	(0.0531)	(0.7840)	(0.7977)			
Technology	0.5660	0.7402	0.9365	0.0114	−0.2244	−0.0999	0.5546	0.9647	1.0364	0.3351	0.4571	0.4256
	(0.0000)	(0.0040)	(0.0386)	(0.8315)	(0.0577)	(0.0567)	(0.0002)	(0.0026)	(0.0331)			
Utilities	−0.0002	0.1550	0.0205	−0.0215	0.0349	0.0168	0.0213	0.1200	0.0033	0.0827	0.2282	0.1462
	(0.9973)	(0.1867)	(0.8291)	(0.2775)	(0.1273)	(0.6139)	(0.7479)	(0.2835)	(0.9732)			
Panel B: Sector volatility												
Basic Materials	−0.0015	−0.0056	0.0128	−0.0305	−0.0710	−0.0245	0.0290	0.0654	0.0373	0.0704	0.1137	0.1060
	(0.9816)	(0.9490)	(0.8795)	(0.2125)	(0.1013)	(0.5877)	(0.7007)	(0.3890)	(0.5181)			
Consumer Goods	0.1443	−0.0318	−0.0431	−0.0894	−0.0319	−0.0249	0.2337	0.0000	−0.0181	0.1191	0.0632	0.0794
	(0.0856)	(0.6129)	(0.5458)	(0.4596)	(0.2696)	(0.5191)	(0.0681)	(0.9993)	(0.7212)			
Consumer Services	0.1345	0.1320	0.0477	−0.0148	−0.0509	−0.0657	0.1494	0.1828	0.1134	0.1067	0.1571	0.2389
	(0.0536)	(0.1937)	(0.7055)	(0.5851)	(0.1857)	(0.2589)	(0.0432)	(0.0470)	(0.3130)			
Financials	0.0763	0.0209	0.0168	0.0175	−0.0083	−0.0073	0.0589	0.0292	0.0241	0.0674	0.0308	0.0607
	(0.2415)	(0.6354)	(0.7913)	(0.7060)	(0.7180)	(0.8273)	(0.0691)	(0.3324)	(0.5747)			
Healthcare	−0.0089	0.0013	0.1068	0.0911	0.0561	0.0711	−0.1001	−0.0548	0.0357	0.1898	0.3846	0.4182
	(0.9352)	(0.9932)	(0.5140)	(0.1244)	(0.6373)	(0.3003)	(0.4955)	(0.7082)	(0.7757)			
Industrials	0.1054	0.0695	−0.0040	−0.0192	0.0087	−0.0090	0.1246	0.0608	0.0050	0.0351	0.0654	0.0376

	(0.0199)	(0.2668)	(0.9328)	(0.3599)	(0.7273)	(0.7968)	(0.0025)	(0.2513)	(0.8866)			
Oil and Gas	−0.0634	0.0041	−0.1023	−0.0240	0.0327	−0.0172	−0.0393	−0.0286	−0.0850	0.3602	0.4470	0.5127
	(0.6752)	(0.9800)	(0.5684)	(0.0267)	(0.7153)	(0.4560)	(0.7901)	(0.8701)	(0.6075)			
Technology	0.4795	0.9554	0.8080	−0.0052	−0.0247	−0.2831	0.4847	0.9801	1.0911	0.2808	0.3985	0.5384
	(0.0008)	(0.0123)	(0.0204)	(0.8969)	(0.5710)	(0.0207)	(0.0004)	(0.0136)	(0.0103)			
Utilities	0.0241	0.1085	0.0452	−0.0173	0.0129	0.0359	0.0413	0.0956	0.0093	0.1247	0.1862	0.1487
	(0.7790)	(0.3264)	(0.6356)	(0.4047)	(0.4877)	(0.3187)	(0.5847)	(0.3780)	(0.9248)			

This table reports the results for the following equation: $\Delta_{k,t} = \beta_t \Delta_{k,t-1} + \varepsilon_{k,t}$. For each security and quarter between June 1995 and September 2008 we calculate the fraction of funds that increase their position in the security in the Spanish market. A fund is defined as increasing its position if it holds a greater fraction of the firm's shares at the end of the quarter than it held at the beginning. All data are standardized (i.e. rescaled to zero mean, unit variance) each quarter. We then estimate quarterly cross-sectional regressions of institutional demand on lagged institutional demand. Because there is a single independent variable in each regression and the data are standardized, these regression coefficients are also the cross-sectional correlations between institutional demand and lagged institutional demand. We then average our results across three distinctive groups, namely "high", "mid" and "low" contingent upon whether the market's/sector's volatility during the contemporaneous quarter falls in the top, middle or bottom third of the sample period's quarterly market/sector volatility-values ranked in ascending order. Market/sector volatility here is calculated every quarter using the standard deviation of daily index returns in quarterly intervals in line with Schwert (1989) on the basis of the Madrid Stock Exchange General Price Index and our nine sectors' indices. The first column reports the time-series' average of these correlation coefficients and associated p-values (in parentheses) for each of the three groups and for each sector, controlling for market (panel A) and sector (panel B) volatility separately. The second and third columns report the portion of the correlation that results from funds following their own lagged trades and the portion that results from funds following the previous trades of other funds (herding) for each of the three groups and for each sector, controlling for market (panel A) and sector (panel B) volatility separately.

Table 7
Tests for herding – controlling for market and sector volume (positive–negative).

	Panel A: Market volume split								Panel B: Sector volume split							
	Average coefficient (β)		Funds following their own trades		Funds following the trades of other funds		Average R^2		Average coefficient (β)		Funds following their own trades		Funds following the trades of other funds		Average R^2	
	Increased	Decreased	Increased	Decreased	Increased	Decreased	Increased	Decreased	Increased	Decreased	Increased	Decreased	Increased	Decreased	Increased	Decreased
Basic Materials	−0.0435	0.0635	−0.0489	−0.0338	0.0053	0.0973	0.1002	0.0926	−0.0309	0.0297	−0.0545	−0.0323	0.0236	0.0620	0.1344	0.0650
	(0.4732)	(0.3471)	(0.1062)	(0.2989)	(0.9172)	(0.1201)			(0.6976)	(0.5522)	(0.1508)	(0.2061)	(0.7131)	(0.2156)		
Consumer Goods	0.0539	−0.0214	−0.0606	−0.0316	0.1146	0.0102	0.0955	0.0748	0.0840	−0.0270	−0.0612	−0.0383	0.1452	0.0112	0.1145	0.0648
	(0.3494)	(0.7265)	(0.3841)	(0.2594)	(0.1316)	(0.8385)			(0.2469)	(0.5781)	(0.4995)	(0.1087)	(0.1453)	(0.7649)		
Consumer Services	0.1825	−0.0001	−0.0145	−0.0840	0.1971	0.0838	0.1524	0.1879	0.1126	0.0945	−0.0555	−0.0269	0.1681	0.1214	0.1598	0.1785
	(0.0135)	(0.9985)	(0.5349)	(0.0798)	(0.0075)	(0.2680)			(0.1266)	(0.3155)	(0.1119)	(0.4007)	(0.0134)	(0.1614)		
Financials	0.0340	0.0426	−0.0006	0.0019	0.0347	0.0407	0.0519	0.0534	0.0200	0.0638	−0.0051	0.0086	0.0251	0.0552	0.0469	0.0608
	(0.4296)	(0.4062)	(0.9811)	(0.9438)	(0.1892)	(0.1936)			(0.6233)	(0.2482)	(0.8494)	(0.7705)	(0.3142)	(0.1015)		
Healthcare	−0.0075	0.0869	0.1184	0.0098	−0.1259	0.0771	0.3857	0.2585	−0.0272	0.0969	0.0540	0.0924	−0.0812	0.0045	0.3500	0.3123
	(0.9487)	(0.4353)	(0.1334)	(0.8337)	(0.3038)	(0.3594)			(0.8174)	(0.3957)	(0.4664)	(0.1639)	(0.4563)	(0.9692)		
Industrials	0.0555	0.0594	−0.0013	−0.0128	0.0569	0.0722	0.0585	0.0298	0.0672	0.0455	0.0216	−0.0386	0.0457	0.0841	0.0567	0.0344
	(0.2136)	(0.1167)	(0.9531)	(0.4942)	(0.0986)	(0.0590)			(0.1414)	(0.2371)	(0.3589)	(0.0417)	(0.2022)	(0.0208)		
Oil and Gas	0.0746	−0.2264	0.0284	−0.0439	0.0462	−0.1825	0.4213	0.4612	−0.0506	−0.0550	0.0319	−0.0390	−0.0825	−0.0161	0.4133	0.4691
	(0.5338)	(0.1222)	(0.5898)	(0.0200)	(0.6985)	(0.2098)			(0.6893)	(0.6949)	(0.5875)	(0.0202)	(0.5121)	(0.9071)		
Technology	0.6925	0.8861	−0.0838	−0.1238	0.7763	1.009	0.4206	0.4365	0.6455	0.8808	−0.0437	−0.1465	0.6892	1.0273	0.4331	0.4232
	(0.0001)	(0.0037)	(0.0732)	(0.1018)	(0.0001)	(0.0028)			(0.0003)	(0.0007)	(0.2293)	(0.0333)	(0.0003)	(0.0005)		
Utilities	0.0428	0.0838	−0.0055	0.0325	0.0484	0.0512	0.1228	0.1961	0.0286	0.6475	0.0027	0.8859	0.0259	0.6557	0.1107	0.2126
	(0.5394)	(0.3623)	(0.7525)	(0.2035)	(0.4735)	(0.5707)			(0.1033)	(0.3076)	(0.0213)	(0.3830)	(0.0820)	(0.4211)		

This table reports the results for the following equation: $\Delta_{k,t} = \beta_t \Delta_{k,t-1} + \varepsilon_{k,t}$. For each security and quarter between June 1995 and September 2008 we calculate the fraction of funds that increase their position in the security in the Spanish market. A fund is defined as increasing its position if it holds a greater fraction of the firm's shares at the end of the quarter than it held at the beginning. All data are standardized (i.e. rescaled to zero mean, unit variance) each quarter. We then estimate quarterly cross-sectional regressions of institutional demand on lagged institutional demand. Because there is a single independent variable in each regression and the data are standardized, these regression coefficients are also the cross-sectional correlations between institutional demand and lagged institutional demand. We then average our results across two distinctive groups, contingent upon whether the quarterly market/sector volume has increased or decreased. The Madrid Stock Exchange General Price Index and our nine sectors' indices are used here to calculate market and sector volumes, respectively. Market/sector volume here is calculated every quarter by aggregating the daily volume observations of the Madrid Stock Exchange General Price Index and our nine sectors' indices every quarter. The first column reports the time-series' averages of these correlation coefficients and associated p-values (in parentheses) for each of the two groups and for each sector, controlling for market (panel A) and sector (panel B) volume separately. The second and third columns report the portion of the correlation that results from funds following their own lagged trades and the portion that results from funds following the previous trades of other funds (herding) for each of the two groups and for each sector, controlling for market (panel A) and sector (panel B) volume separately.

increasing market volume quarters. Evidence in favour of significant habit investing is witnessed for Oil and Gas (during quarters of decreasing market/sector volume), Industrials (decreasing sector volume quarters), Technology (decreasing sector volume quarters) and Utilities (increasing sector volume quarters). Regarding herding, the "funds following the trades of other funds" part appears significant for Consumer Services (during increasing market/sector volume quarters) and Industrials (decreasing sector volume quarters), indicating that institutional herding in these sectors is intentional.

Table 8 presents the estimates from the break-up of β_t and its two components into three parts (high–mid–low market/sector volume). Once more, Technology generates significant estimates for β_t and the "funds following the trades of other funds" part. Evidence on the significance of β_t is documented for Consumer Goods (low market volume quarters and high/mid sector volume quarters) and Consumer Services (high market/sector volume quarters). Most "funds following their own trades" estimates are insignificant with the exception of Consumer Goods for mid sector volume quarters and Oil and Gas (low sector volume quarters). Conversely, the "funds following the trades of other funds" estimates provide us with more evidence in favour of herding significance, in particular for Basic Materials (high market/sector volume quarters), Consumer Goods (high sector volume quarters), Consumer Services (high market/sector volume quarters), Financials (mid sector volume quarters) and Industrials (low sector volume quarters). The above results show that institutional industry herding tends to be stronger during quarters when trading activity is high, indicating that it is driven by intent.

Overall, Tables 3–8 show that institutional industry herding interacts significantly with market/sector returns, volatility and volume; these interactions exhibit regularities we consider worth noting:

(a) Underperformance: herding is significant during quarters of negative market returns (Financials; Industrials), negative sector returns (Consumer Services; Financials; Industrials), low market returns (Consumer Services; Financials; Industrials) and low sector returns (Industrials) with very little evidence of significance during other market/sector returns' states. Since periods of price-declines lead most investors to realize losses, "bad" managers would prefer to mimic their "good" peers during such periods in order to claim that, despite having made good investment choices (those they mimicked), they underperformed due to adverse market conditions.
(b) Rising/high volatility: herding appears significant during quarters of increased market volatility (Consumer Services), increased sector volatility (Consumer Services), high market volatility (Financials; Industrials) and high sector volatility (Consumer Services; Industrials) with little evidence of significance during other market/sector volatility states. Volatile periods imply greater complexity which "bad" managers may find difficult to resolve due to their low processing skills, leading them to mimic their "good" peers instead.
(c) Rising/high volume: herding appears significant during quarters of increased market/sector volume (Consumer Services), high market volume (Basic Materials; Consumer Services) and high sector volume (Basic Materials; Consumer Goods; Consumer Services) with little evidence of significance during other market/sector volume states. High volume renders it easier for "bad" managers to copy their "good" peers, since highly liquid conditions allow them to engage in peer-mimicking without the latter being affected by the presence of market frictions (such as thin trading, which would be expected to be more evident during periods of low trading activity).

Our findings therefore suggest that Spanish fund managers industry-herd intentionally, motivated primarily by informational and professional considerations, with their intentional herding manifesting itself mainly for Consumer Services and Industrials (and to a lesser extent for Basic Materials, Financials and Consumer Goods). The fact that the most widespread evidence of intentional herding is reported for Consumer Services and Industrials is interesting, given that these are Spain's two dominant sectors, jointly comprising almost three quarters of the country's economic activity.[15] Fund managers lacking skills or information would be understandably very concerned about making bad investment decisions when trading in these sectors, as this would only render their low quality more

[15] *Source*: Financial Accounts of the Spanish Economy, Bank of Spain.

Table 8
Tests for herding – controlling for market and sector volume (high–mid–low).

	Average coefficient (β)			Funds following their own trades			Funds following the trades of other funds			Average R^2		
	High	Mid	Low	High	Mid	Low	High	Mid	Low	High	Mid	Low
Panel A: Market volume												
Basic Materials	0.0655	−0.0337	−0.0244	−0.0997	−0.0019	−0.0282	0.1653	−0.0317	0.0037	0.1293	0.0835	0.0791
	(0.4802)	(0.6384)	(0.7405)	(0.0646)	(0.9542)	(0.1525)	(0.0500)	(0.5515)	(0.9548)			
Consumer Goods	−0.0697	−0.0305	0.1696	−0.0689	−0.0026	−0.0763	−0.0008	−0.0279	0.2459	0.0843	0.0816	0.0946
	(0.3361)	(0.6634)	(0.0206)	(0.0614)	(0.9276)	(0.5292)	(0.9866)	(0.6188)	(0.0505)			
Consumer Services	0.2359	0.0289	0.0553	−0.0291	−0.0109	−0.0936	0.2651	0.0399	0.1490	0.1856	0.0961	0.2247
	(0.0271)	(0.6930)	(0.6426)	(0.3622)	(0.2971)	(0.1653)	(0.0050)	(0.5755)	(0.1757)			
Financials	−0.0064	0.0597	0.0584	−0.0164	0.0081	0.0091	0.0100	0.0515	0.0493	0.0555	0.0575	0.0443
	(0.9141)	(0.3192)	(0.2740)	(0.6459)	(0.8273)	(0.7731)	(0.7719)	(0.1428)	(0.1746)			
Healthcare	0.0687	0.0151	0.0144	0.0415	0.1190	0.0541	0.0272	−0.1039	−0.0396	0.2267	0.3362	0.4325
	(0.5680)	(0.9156)	(0.9313)	(0.2136)	(0.0663)	(0.6886)	(0.7827)	(0.5224)	(0.7891)			
Industrials	0.0518	0.0728	0.0459	0.0083	0.0112	−0.0392	0.0434	0.0616	0.0852	0.0451	0.0435	0.0507
	(0.3339)	(0.1569)	(0.4052)	(0.7762)	(0.6832)	(0.1085)	(0.4022)	(0.0785)	(0.0726)			
Oil and Gas	0.0650	−0.0991	−0.1213	−0.0113	−0.0145	0.0201	0.0763	−0.0845	−0.1414	0.4993	0.2797	0.5508
	(0.7123)	(0.4397)	(0.5187)	(0.2232)	(0.0907)	(0.8373)	(0.6587)	(0.5008)	(0.4511)			
Technology	0.6911	0.5421	1.1354	−0.0565	−0.0729	−0.1790	0.7476	0.6151	1.3144	0.3940	0.3560	0.5487
	(0.0035)	(0.0000)	(0.0120)	(0.1023)	(0.3358)	(0.0627)	(0.0031)	(0.0001)	(0.0082)			
Utilities	0.0416	0.0704	0.0678	0.0043	0.0439	−0.0186	0.0372	0.0264	0.0865	0.1695	0.1307	0.1626
	(0.6809)	(0.4264)	(0.5220)	(0.8695)	(0.1140)	(0.4086)	(0.7131)	(0.7789)	(0.3461)			
Panel B: Sector volume												
Basic Materials	0.0655	−0.0337	−0.0245	−0.0998	−0.0020	−0.0283	0.1653	−0.0317	0.0038	0.1293	0.0835	0.0791
	(0.4802)	(0.6384)	(0.7405)	(0.0646)	(0.9542)	(0.1525)	(0.0500)	(0.5515)	(0.9548)			
Consumer Goods	0.1906	−0.1305	0.0151	−0.0830	−0.0689	0.0078	0.2736	−0.0617	0.0073	0.1307	0.0719	0.0585
	(0.0268)	(0.0382)	(0.8025)	(0.4973)	(0.0127)	(0.8164)	(0.0327)	(0.2179)	(0.8694)			
Consumer Services	0.2362	0.0403	0.0431	−0.0170	−0.0237	−0.0922	0.2532	0.0641	0.1354	0.1873	0.1100	0.2083
	(0.0266)	(0.6000)	(0.7125)	(0.5086)	(0.2512)	(0.1725)	(0.0092)	(0.3775)	(0.2097)			
Financials	−0.0246	0.0509	0.0860	−0.0195	−0.0141	0.0358	−0.0050	0.0650	0.0502	0.0641	0.0483	0.0454
	(0.7030)	(0.3519)	(0.1045)	(0.5924)	(0.7164)	(0.2037)	(0.8946)	(0.0354)	(0.1686)			
Healthcare	0.0510	0.1245	−0.0836	−0.0061	0.0811	0.1419	0.0571	0.0434	−0.2255	0.1506	0.3879	0.4539
	(0.6004)	(0.4136)	(0.6256)	(0.8716)	(0.1214)	(0.3075)	(0.4758)	(0.7772)	(0.1708)			
Industrials	0.0378	0.0629	0.0706	−0.0072	0.0198	−0.0327	0.0450	0.0431	0.1033	0.0442	0.0422	0.0530

	(0.4866)	(0.2118)	(0.2047)	(0.8488)	(0.2770)	(0.1532)	(0.3361)	(0.2966)	(0.0263)			
Oil and Gas	0.0423	−0.0046	−0.1987	−0.0096	0.0671	−0.0681	0.0519	−0.0718	−0.1305	0.4783	0.2567	0.5960
	(0.8066)	(0.9702)	(0.3049)	(0.2801)	(0.4339)	(0.0389)	(0.7600)	(0.5941)	(0.4784)			
Technology	0.6911	0.5422	1.1355	−0.565	−0.0729	−0.1790	0.4760	0.6151	1.3145	0.3940	0.3516	0.5487
	(0.0035)	(0.0000)	(0.0120)	(0.1023)	(0.3358)	(0.0627)	(0.0031)	(0.0001)	(0.0082)			
Utilities	−0.0282	0.1222	0.0829	0.0026	0.0401	−0.0128	−0.0308	0.0821	0.0957	0.1586	0.1420	0.1616
	(0.7736)	(0.1785)	(0.4304)	(0.9239)	(0.1401)	(0.5738)	(0.7575)	(0.3884)	(0.2937)			

This table reports the results for the following equation: $\Delta_{k,t} = \beta_t \Delta_{k,t-1} + \varepsilon_{k,t}$. For each security and quarter between June 1995 and September 2008 we calculate the fraction of funds that increase their position in the security in the Spanish market. A fund is defined as increasing its position if it holds a greater fraction of the firm's shares at the end of the quarter than it held at the beginning. All data are standardized (i.e. rescaled to zero mean, unit variance) each quarter. We then estimate quarterly cross-sectional regressions of institutional demand on lagged institutional demand. Because there is a single independent variable in each regression and the data are standardized, these regression coefficients are also the cross-sectional correlations between institutional demand and lagged institutional demand. We then average our results across three distinctive groups, namely "high", "mid" and "low" contingent upon whether the market's/sector's volume during the contemporaneous quarter falls in the top, middle or bottom third of the sample period's quarterly market/sector volume-values ranked in ascending order. Market/sector volume here is calculated every quarter by aggregating the daily volume observations of the Madrid Stock Exchange General Price Index and our nine sectors' indices every quarter. The first column reports the time-series' average of these correlation coefficients and associated *p*-values (in parentheses) for each of the three groups and for each sector, controlling for market (panel A) and sector (panel B) volume separately. The second and third columns report the portion of the correlation that results from funds following their own lagged trades and the portion that results from funds following the previous trades of other funds (herding) for each of the three groups and for each sector, controlling for market (panel A) and sector (panel B) volume separately.

visible (by indicating, e.g. lack of proper understanding of the economy's fundamental sectors), thus being even more motivated to mimic their "good" peers intentionally. The case of a country's dominant economic sectors exhibiting more herding also surfaces in Zhou and Lai (2009), who reported significant herding in Hong Kong for Financials (a sector for which we found some evidence of intentional herding in our study) and Construction & Property. Furthermore, the significant herding we documented for Consumer Services is in line with Gebka and Wohar (2013), who also reported significant herding for Basic Materials (for which we found limited evidence of intentional herding) and Oil and Gas (for which we found no evidence of herding at all).[16] The case of Technology presenting us with overwhelming herding significance irrespective of the conditions tested should be attributed to the fact that the sector encompasses stocks mostly of moderate size (often falling under the classification of growth stocks), typified by high uncertainty and perceived as riskier, thus prompting fund managers to copy their peers' trades when investing in them to minimize the perceived risk (see e.g. Wermers, 1999).[17,18]

4. Conclusion

This paper investigates whether fund managers herd intentionally at the sector level and whether this intent is related to the specific conditions of each industry or whether the conditions of the market as a whole are also capable of promoting it. We examine the above drawing upon a unique database of quarterly portfolio holdings of Spanish mutual funds for the June 1995–September 2008 period. To gauge whether the observed herding in each sector is driven by intent or not we assess how it interacts with the performance (i.e. returns), volatility and volume of both that sector as well as the market as a whole. Our results indicate that Spanish fund managers herd significantly at the overall market level, while the interactions of their herding in each sector with these states reveal that fund managers herd significantly in a series of industries (this is the case mostly for Consumer Services and Industrials and to a lesser extent for Basic Materials, Financials and Consumer Goods) mainly during periods when the market as a whole or the specific sector under examination has underperformed, generated rising/high volatility and exhibited rising/high volume. These findings denote that Spanish fund managers herd in these sectors primarily motivated by informational and career-related reasons, consistent with the view that their herding is intentional.

Our results illustrate for the first time that institutional industry herding is intentional and that it is both market as well as sector conditions driving this intent. The above bear important implications for the investment community, particularly those investors engaged into sector styles, since being aware of the conditions that promote herding among funds investing in a sector can constitute a potentially useful input to their strategies. The intentional herding documented here is also of particular interest to regulators, since it implies that a non-negligible portion of fund managers lack information/skills (or choose not to rely on them), resorting to peer-mimicking instead when investing in various sectors; such behaviour is a cause for concern for two reasons. On the one hand, given the importance of industry in portfolio diversification (see e.g. Cavaglia et al., 2000), it can generate negative externalities

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[16] The study of Zhou and Lai (2009) is based on trade-and-quote data from the Hong Kong market; Gebka and Wohar's (2013) study employs the price-based frameworks proposed by Christie and Huang (1995) and Chang et al. (2000).

[17] To ensure the reliability of our estimates reported in Tables 3–8 given our relatively small sample size, we regress for each sector its β_t-series over all control factors (market/sector returns/volatility/volume) jointly; we repeat these regressions for each sector using each of the components of β_t of that sector as the dependent variable. The purpose of this test is to confirm the sign and significance of the relation between institutional herding and each of the control factors in order to assess whether the intent reported in Tables 3–8 is robust. Our regression estimates provide overall strong support for our original findings, confirming that funds herd intentionally in Consumer Services and Industrials (and to a lesser extent in Basic Materials, Consumer Goods and Financials). Results are not reported here for space reasons and are available upon request.

[18] Our results are based on the investigation of intent through domestic (Spanish) market/sector variables. Following the referee's suggestion, we control for the robustness of those findings by employing the European and World versions of these variables. We use the DS Europe/World indices to calculate their European/World market expressions while their sector expressions are calculated on the basis of the DataStream Europe/World sector-indices equivalents of our study's nine sectors. The picture emerging again indicates strong evidence of intentional herding for Consumer Services and Industrials with less evidence of intent for Basic Materials, Financials and Consumer Goods; Technology returns us with significant herding for all tests. Results are not presented here in the interest of brevity but are available upon request from the authors.

by giving rise to portfolio allocations which are neither optimal, nor in line with investors' preferences; on the other hand, if such practice is widespread, it can affect the overall market by amplifying systemic risk (given funds' leverage in equity volumes) and enhancing the potential for destabilization. The above suggest that regulators should encourage diversity in the sector investments of institutional investors; a possibility here would be to subject funds to periodic comparison of the correlations of their equity investments (at the market level as well as for each sector separately) and release this information (alongside with details of the fees each fund is charging) to the public in order to provide investors with insight into the extent of institutional herding and allow them to factor this knowledge in their fund-selection process.

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Appendix A. Supplementary data

Supplementary data associated with this article can be found, in the online version, at http://dx.doi.org/10.1016/j.intfin.2013.05.008.

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