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International herding: Does it differ across sectors?☆

Bartosz Gębka^{a,*}, Mark E. Wohar^{b,1}

^a University of Newcastle upon Tyne, Newcastle University Business School, 5 Barrack Road, Newcastle upon Tyne NE1 4SE, United Kingdom

^b Department of Economics, Mammel Hall 332S, University of Nebraska at Omaha, Omaha, NE 68182-0286, United States

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ABSTRACT

This paper investigates the existence of herding in the global equity market. We apply a methodology which utilises cross-country dispersion in index returns. An analysis of national indices world-wide unveils virtually no instances of global information cascades, as price patterns largely adhere to the predictions of the rational pricing models. However, some sector-specific indices reveal price patterns indicative of traders' irrationality, especially in basic materials, consumer services, and oil and gas. This can be driven by a group of investors following each other in and out of markets, overconfidence, or excessive flight to quality. These irrational patterns decline over time.

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1. Introduction

This paper analyses the existence of cross-country herding behaviour and its impact on stock prices, both on the level of national indices and in different industries. Periods of financial turmoil, with large movements in asset prices worldwide and abrupt changes in capital flows across borders, have traditionally drawn the attention of academics, practitioners, and politicians. Herding by financial investors

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* Corresponding author. Tel.: +44 191 208 1578; fax: +44 191 208 1735.

E-mail addresses: bartosz.gebka@ncl.ac.uk, b.t.gebka@ncl.ac.uk (B. Gębka), mwohar@mail.unomaha.edu (M.E. Wohar).

¹ Tel.: +1 402 554 3712; fax: +1 402 554 2853.

is considered one of the most important causes of financial distress. Herding, broadly understood as the excessive and irrational tendency of traders to ignore fundamental information and flock together, can destabilise markets, lead to inefficiency, cause excess volatility, increase the fragility of financial systems, and induce systemic risk (Bikhchandani and Sharma, 2001). In the globalised world, these phenomena are not tamed by national borders but are likely to spread around the globe, with international investors moving in and out of countries in a synchronised fashion, or due to herding in one country giving rise to contagious crises in other markets (e.g., Borensztein and Gelos, 2003; Kaminsky et al., 2004). This paper investigates whether herding is indeed a world-wide phenomenon, and how it differs from herding within national borders, for different economic sectors, and over time.

Although widely discussed, herding is anything but clearly defined. Bikhchandani and Sharma (2001) offer a taxonomy of patterns in the behaviour of financial actors wearing the common name of herding. Firstly, not all instances of simultaneous and similar actions lead to inefficiencies and excess volatility: spurious, or unintentional, herding emerges when investors, independently of each other, react in a similar manner to common news. Such behaviour can result in efficient price reactions to news about fundamentals and is therefore desirable. However, if knowledge about other investors' decisions affects one's own actions, intentional herding takes place and can result in inefficient outcomes. Suppressing one's prior judgments and following the crowd, however, does not have to be irrational on the level of an individual trader. In the case of informational cascades, trading by other parties can be considered to contain superior information about assets, hence it may be a rational strategy to suppress one's prior beliefs and follow the market (e.g., Banerjee, 1992; Calvo and Mendoza, 2000). Similarly, fund managers' career concerns can cause them to mimic the investment decisions of their peers, as this strategy is likely to generate returns at least comparable with the competitors' outcomes and provide a signal of satisfactory skills and ability to the manager's employer (Scharfstein and Stein, 1990; Graham, 1999). Thirdly, if a fund manager's compensation depends on his performance relative to the industry's average outcome, and the penalty for being below average is more painful than the benefits of beating the peers, he may rationally decide to aim at average profits and follow the investment decisions of his peers to achieve this aim (Maug and Naik, 1996; Admati and Pfleiderer, 1997). Lastly, intentional herding can also be driven by irrational motives, i.e., sentiment.

As most reasons for herding are impossible to observe, empirical studies analyse the magnitude to which the market outcomes, such as simultaneity of trading decisions across investors or patterns in price behaviour, are in line with the theory of herding. We review the relevant literature in Section 2, and its main findings are as follows. Firstly, studies investigating transactions of investors suggest more herding to occur among individuals than institutions, with different types of institutional investors prone to herding to various degrees (e.g., pension funds seem to herd less into and out of positions than mutual funds do). Secondly, research using patterns in asset prices to detect herding seems to indicate that mature markets are less affected by herding than their emerging counterparts. Lastly, numerous studies deliver both theoretical arguments and empirical evidence linking financial contagion to herding by international investors and show the global nature of herding. However, none of these findings is entirely conclusive, as arguments to the contrary also exist.

Part of the ambiguity about the existence of herding in research using price patterns may be due to two opposite ways information cascades can manifest themselves in price behaviour. Traditionally, following Christie and Huang (1995), herding was seen as a market-wide feature dominating the price behaviour of at least a large majority of assets. These authors reasoned that, at times of extreme price movements, investors would suppress their private information and judgments and follow the market in their asset valuation and investment decisions. Hence, herding here is not about a group of investors following each other into and out of positions. Rather, herding affects the valuation of all assets, causing their prices to excessively move together, rather than to display heterogeneous reactions to common information and to company-specific news about their fundamentals. Hence, Christie and Huang (1995) proposed that excessively low values of cross-sectional dispersion in individual stocks' returns will be indicative of herding.

On the other hand, studies employing transaction data understand herding differently, as correlated actions of a group of investors which go beyond their joint responses to common news. Clearly, in this case, herding is a feature of a subset of assets rather than a market-wide characteristic, as the herd abandons one subset of stocks/markets and moves into another subset. When an irrational herd

moves into (out of) a position, this causes the price of the target stocks to move up (down) too much compared to their respective fundamentals, resulting in stock price movements in opposite directions. Hence, this localised, as opposite to market-wide, herding increases the cross-sectional dispersion of returns beyond its rational level. Therefore, rather than being characterised by market-wide information cascades inducing insufficient levels of return dispersion, herding can also be indicated by excessive dispersion of returns. The existing literature largely ignores the latter case and speaks of herding only if returns are excessively homogenous.

The contributions of this paper are as follows. First, we utilise the methodology by [Christie and Huang \(1995\)](#) and [Chang et al. \(2000\)](#) to study herding on a global scale, rather than on different national markets separately. As this method only requires information on prices but not on transactions by investors, it is not limited by data availability issues to a subset of trades or countries and can be employed to analyse herding on a truly global scale. Second, we also investigate how international herding differs across industries, as some can be more prone to flocking together by investors than others, and over time. Further, we analyse the exact nature of international herding: is it due to global information cascades affecting all countries to a similar degree (market-wide herding), or does it rather manifest itself in joint actions of a subgroup of investors moving in and out of selected countries (localised herding)?

To preview our main findings, we disclose that investor behaviour on the international scale is of a completely different character than that dominant on the national markets. Namely, whereas the latter is argued in the literature to be herding of the market-wide type, i.e., with all assets moving excessively together as a result of all-encompassing information cascades, our analysis of international markets reveals excessive heterogeneity in returns across countries. This pattern in international return behaviour may be indicative of localised herding (herds simultaneously moving into and out of markets), excessive “flight to quality” during market stress, or investor overconfidence. Our findings are most pronounced for the basic materials, consumer services, and oil and gas sectors, and are robust across different model specifications and estimation techniques. We also observe that this apparent irrationality has been declining since the late 1990s.

The remainder of this paper is organised as follows: Section 2 reviews the relevant literature. Section 3 describes data and methodology. Results are presented in Section 4, and Section 5 offers an interpretation of our findings and conclusions.

2. Literature review

In this section, we offer a brief insight into three strands of the voluminous literature on herding in financial markets: studies of localised herding using data on portfolio holdings or transactions of investors, usually restricted to one country; studies employing patterns in return dispersion to infer about the existence of market-wide herding, and research attributing financial contagions to international herding.

2.1. National studies based on transaction data

One branch of the literature, of which the paper by [Lakonishok, Shleifer, and Vishny \(1992\)](#) (LSV) is an early prominent example, utilises low frequency portfolio holdings data and investigates the degree of correlation in trades by investors and the extent to which they follow each other in and out of positions, i.e., localised herding. As for the institutional investors, the evidence is mixed, as some studies report only modest levels of herding ([Lakonishok et al., 1992](#); [Grinblatt et al., 1995](#)) and others show significant herding ([Nofsinger and Sias, 1999](#); [Dennis and Strickland, 2002](#)). The picture is further mixed as herd behaviour differs across institution types ([Lakonishok et al., 1992](#)), e.g., pension funds are less likely to herd than other institutions ([Badrinath and Wahal, 2002](#)), but most institutional herding can be spurious ([Wermers, 1999](#); [Sias et al., 2001](#); [Bushee and Goodman, 2007](#); [Schmeling, 2007](#)). Individual investors are seen as more irrational and prone to follow the market in a herd-like manner ([Kim and Wei, 2002](#)), but evidence of the contrary behaviour is also available: [Ekholm and Pasternack \(2008\)](#) show Finnish individuals to be driven by overconfidence, hence more likely to go their individual ways rather than follow the crowd. Hence, the overall evidence on localised herding is

differentiated at best and maybe the most robust conclusion remains that of Griffin et al. (2003) that the nature of herding is not universal and differs across exchanges and countries.

2.2. *Studies based on cross sectional return dispersion*

Another branch of the literature aims at identifying market-wide information cascades resulting in herding by utilising the cross-sectional dispersion of stock returns, a methodology developed by Christie and Huang (1995) and Chang et al. (2000). In their study, Christie and Huang (1995) did not find any evidence of market-wide herding in the US. Chang et al. (2000) confirmed their finding of no herding for the US and Hong Kong, but reported herding to exist in South Korea, Taiwan and, to a lesser degree, Japan. Demirer et al. (2010) also found herding to prevail on the Taiwanese stock market, both when looking onto the overall market and each sector separately, especially during market downturns.

Evidence for the Chinese market, on the other hand, is mixed, with some studies finding no herding (Demirer and Kutan, 2006) and others reporting herding, even if they disagree on its exact nature: Chiang et al. (2010) find herding especially in A stocks and B stocks in down markets, whereas Tan et al. (2008) report herding in both A and B stocks, with the former more pronounced in up markets. The latter paper finds no evidence that herding spills over across Chinese markets. Goodfellow et al. (2009) report Polish institutional investors to be free from herding and their individual counterparts to herd mostly during market downswings and less over time. Chiang and Zheng (2010) analysed 18 countries around the globe and found herding to occur in advanced and Asian markets, especially when the market was moving up in the latter, but no (market-wide) herding in Latin American countries. Furthermore, they find herding to be more apparent during crisis periods, and many national markets to herd with the US market. However, Economou et al. (2011) tested for herding in Portuguese, Italian, Spanish and Greek markets and reported less, no more, herding in Greece and Spain during the recent crisis, as well as herding away from, rather than with, the US market. These authors also report herding to be consistently significant only in Greece, especially in up markets, and to be correlated across countries, the latter suggesting the existence of a common global component governing herding behaviour on national markets. The finding of existence of market-wide information cascades in Greece was confirmed by Caporale et al. (2008), and herding was also found on financial markets of Italy (Caparelli et al., 2004) and Turkey (Kapusuzoglu, 2011). For Australia, Henker et al. (2006) find evidence inconsistent with market-wide information cascades, i.e., excessive return dispersion, especially in industries such as “materials”, “consumer staples” and “financials”. Lastly, Blasco and Ferreuela (2008) analysed seven major stock markets and found herding only in Spain.

In summary, studies using return dispersion to detect market-wide herding seem to indicate that mature markets are less likely to be affected by this type of investor behaviour, but there are exceptions to this rule. Crisis periods and the overall movements of the market (bullish or bearish) seem to be relevant, too, even though their exact impact on herding is ambiguous. Lastly, there seems to exist a commonality in herding across markets.

2.3. *Studies on international financial contagion and herding*

Numerous studies investigate the notion that foreign investors behave in a herd-like manner and destabilise national markets around the world. Against popular belief, the evidence of irrational herding on the international scale is ambiguous at best. Choe et al. (1999) and Kim and Wei (2002) use transactions data from Korea and find strong evidence of positive-feedback trading and herding among foreign investors in 1997, especially compared to domestic institutional and individual investors who tend to be contrarian. Karolyi (2002) finds that foreigners became net sellers of Japanese equities during the Asian financial crisis in 1997. However, there is no evidence that this joint trading activity destabilised the market: he reports evidence of consistent positive-feedback trading among foreign investors, but the results are not supportive of intentional herding. Borensztein and Gelos (2000, 2003) studied the behaviour of emerging market funds. Applying the LSV measure some herding was found, but it was not severe: these investors follow each other into and out of countries, to some extent also in/out of regions. Open-end funds are followed by closed-end ones and country-specific by general funds, however these similarities in behaviour may be due to rational reactions to common news

rather than representing intentional herding. [Hernández et al. \(2001\)](#) find financial contagion to occur through trade and financial links and to be limited to one region, and hypothesise it to be due to herding. However, [Fazio et al. \(2003\)](#) investigated the impact of distance on correlations between markets as a measure of contagion and found the linkages between financial markets to be more, not less, reliant on fundamentals during crises, a result opposite to herding (herding takes place prior to the crises). [Froot and Tjornhom \(2002\)](#) study determinants of funds flows persistence for 21 developed countries and find that only 25% could be explained by herding, with the remaining 75% being due to stealth trading on private information.

On theoretical grounds, [Acharya and Yorulmazer \(2008\)](#) show that the likelihood of information contagion induces profit-maximising banks to herd with other banks. In their model, the costs of borrowing increase when there is negative news about other banks, as such news convey negative information about the common factor governing all banks' profits. When banks invest in the same industry, their returns are perfectly correlated and performance is identical. Hence, the other banks' performance contains no additional information about a given bank. This, in turn, allows banks to avoid adverse information spillovers and encourages them to invest in the same industry. In the context of investment in countries rather than industries, investors may invest in the same set of countries at a time, moving in and out of countries in a seemingly coordinated fashion in search for better returns, i.e., behaving in a herd-like manner.

In [Calvo and Mendoza's \(2000\)](#) model, international information cascades emerge due to fixed costs of gathering and processing country-specific information by investors: as the number of investible markets increases, benefits from paying for costly information about each market decline, making decisions based on rumours or following the market more likely. This also holds true in the presence of variable performance costs, if the structure of incentives is such that the marginal cost of underperforming compared to the market exceeds the marginal gain of beating the market. If investors worldwide follow the relevant global market portfolio, stock prices will be highly positively correlated, regardless of movements in fundamentals. [Cipriani and Guarino \(2008\)](#) show that information cascades, i.e., the disregarding of private information, can also lead to correlated trading against the market, i.e., behaviour opposite to herding, and that these cascades can spill over into other markets, resulting in financial contagion. Indeed, [Kaminsky et al. \(2004\)](#) analysed investment of mutual funds' managers and investors in Latin America and found positive trading behaviour in reaction to news from other emerging markets but negative reactions in trading to US news, this effect being stronger during crises abroad (Mexican, Russian, etc.). Hence, herding does happen globally but its direction and intensity seem to change across countries and over time.

3. Data and methodology

3.1. Data

We utilise DataStream's daily data on closing values of indices, denominated in national currencies, both on the national and sector levels (DataStream Global Indices Levels 1 and 2, respectively), as well as for the global stock market index.² The sectors covered are: basic materials, consumer goods, consumer services, financials, health, industrials, oil & gas, telecommunications, and utilities.³ There is a trade-off between the number of the countries to be analysed and the sample's length: we would prefer to have as many countries as possible but series for some countries are very short; therefore the longer the time period covered, the fewer the countries that can be included. In addition, we desire a fixed set of countries to be analysed over time, as adding more countries as the data was

² According to DataStream, all indices are value-weighted and calculated on a "representative list" of stocks for each market, with the number of stocks for each market being determined by the size of the market and the sample covering a minimum of 75–80% of total market capitalisation. Stocks with the highest market value for each market are included. Index constituents for each market are reviewed quarterly, with delisted stocks being removed from an index when notification of delisting is received. Excluded securities are: fixed interest stocks, temporary issues, warrants, unit trusts, mutual funds, investment funds, foreign listings, including ADRs.

³ Technology is omitted due to insufficient length of the time series provided for most countries.

Table 1
Composition of the data sets.

Argentina [†]
Australia
Austria
Brazil
Canada
Chile
China
Colombia
Czech republic
France
Greece
Hong Kong
India
Ireland [†]
Israel
Italy
Japan
Korea
Luxemburg [†]
Malaysia
Netherlands [†]
New Zealand
Norway
Pakistan
Philippine
Singapore
South Africa [†]
Spain
Thailand
Turkey
UK
US

Note: The long sample (06 January 1998 to 02 January 2012) contains data on all 32 countries, on both national and sector level, for the following sectors: basic materials, consumer goods, financials, industrials, oil & gas. The short sample (from 01 November 2007 to 02 January 2012) covers 27 countries (those marked with † are excluded due to data availability issues for some sectors) across all nine sectors analysed.

becoming available could result in time-series behaviour of the international herding measure driven by additions of new countries rather than changes in herding itself. Therefore, we decided to work with two sets of data. To analyse changes in herding over time, we restricted the number of countries to 32 and of sectors to five (basic materials, consumer goods, financials, industrials, oil & gas), which results in a sample for the period from 06 January 1998 to 02 January 2012. To analyse the differences in herding across sectors, data on more (all nine) sectors was gathered, which caused the sample to shrink in the time and cross-country dimension: the short sample covers 27 countries across all nine sectors in the period from 01 November 2007 to 02 January 2012. [Table 1](#) shows the list of countries included in each sample. The 32 countries included in the long sample capture in the entire sample period on average almost 87% of the market capitalisation of the DataStream's world market index, hence our sample, even though somewhat restricted by data availability issues, can be seen as fairly representative for the global stock market.

3.2. Methodology

3.2.1. Herding and the cross-sectional dispersion in returns

This study employs cross-country deviations in index returns to identify herding behaviour, an approach proposed by [Christie and Huang \(1995\)](#) and [Chang et al. \(2000\)](#). [Christie and Huang \(1995\)](#) hypothesised that herding in financial markets manifests itself in suppression of individual beliefs and their replacement by the market-wide consensus, especially during periods of extreme market

movements. This behaviour results in an increased similarity of returns across financial assets, hence a lower cross-sectional variability in returns. These authors proposed the use of cross-sectional return dispersion of stock returns, S_t , to infer about the existence of herding:

$$S_t = \sqrt{\frac{\sum_{i=1}^n (r_{it} - \bar{r}_t)^2}{n-1}}, \quad (1)$$

where r_{it} is the return on stock i at time t and \bar{r}_t is the cross-sectional average of n assets' returns at time t . Christie and Huang (1995) hypothesised that herding is more pronounced during periods of market distress, i.e., high absolute market returns, which leads to more synchronised movements in asset prices and to lower values of return dispersion, S_t . Therefore, in the model:

$$S_t = \alpha + \beta_1 D_t^L + \beta_2 D_t^U + \varepsilon_t, \quad (2)$$

where $D_t^L = 1(D_t^U = 1)$ for the lower (upper) tail of market return distribution, herding would manifest itself in negative values of β_1 and β_2 , i.e., a too low return dispersion due to suppression of individual, heterogeneous views and to investors simply following the market.

Christie and Huang (1995) further note that even high positive values of S_t in extreme market situations, i.e., positive values of β_1 and β_2 , could be indicative of herding, provided these values are lower than what a rational asset pricing model would predict. Hence, these authors advocate comparing the cross-sectional return dispersion of predicted returns with those observed: no significant difference between these two quantities would imply rational pricing and no herding, whereas the dispersion of observed returns being lower than that of predicted returns would indicate the suppression of individual views and following the market by investors, i.e., market-wide herding.

The idea of testing for the existence of herding by comparing the dispersion of observed with predicted returns is further developed by Chang et al. (2000). They demonstrate that the cross-sectional absolute deviation of stock returns, measured as:

$$S_t^* = CSAD_t = \frac{\sum_{i=1}^n |r_{i,t} - r_{M,t}|}{n}, \quad (3)$$

is a linear function of market return, $r_{M,t}$, assuming the stock returns are generated by a model such as the CAPM. This relationship is shown in Fig. 1A. These authors further propose that if market participants are more likely to herd (follow the market) in periods of financial distress, i.e., when absolute market returns are high, herding will dampen the dispersion of returns, resulting in downward deviations of S_t^* from its linear relationship with $r_{m,t}$. Therefore, in the model:

$$S_t^* = CSAD_t = \alpha + \gamma_1 |r_{M,t}| + \gamma_2 r_{M,t}^2 + \varepsilon_t, \quad (4)$$

γ_2 should be negative if investors suppress their private views and follow the market, and not significantly different from zero if return behaviour is in line with an equilibrium pricing model. This case is shown in Fig. 1B. A model differentiating between positive and negative market returns would be:

$$CSAD_t = (\alpha^D + \gamma_1^D |r_{M,t}| + \gamma_2^D r_{M,t}^2)(1 - UP_t) + (\alpha^U + \gamma_1^U |r_{M,t}| + \gamma_2^U r_{M,t}^2)UP_t + \varepsilon_t, \quad (5)$$

where $UP_t = 1$ if $r_{M,t} > 0$ and zero otherwise. Given the existence of herding, understood as an information cascade leading to market-wide suppression of private beliefs and excessive reliance on market movements as indicative of assets value, the parameters γ_2^D and γ_2^U should be significantly negative.

As our aim is to investigate the existence and nature of herding on a global scale, models (4) and (5) were estimated using index values from different countries rather than prices of individual securities from one market. We estimate these two models for each economic sector separately ($r_{i,t}$ being the return on an sector-specific index from country i , the analysis repeated for each sector) and for national markets as well ($r_{i,t}$ being the return on the national market-wide index from country i), for both short and long sample, each using two alternative proxies of market returns $r_{M,t}$: the average value of the sector return, computed over all countries included in the analysis (27 in the short sample and 32 in the long sample) and repeated for each sector, and the return on the global index for each relevant sector. The results are reported under 'Average return' and 'World sector index', respectively. To investigate international herding across national markets, without differentiating among sectors,

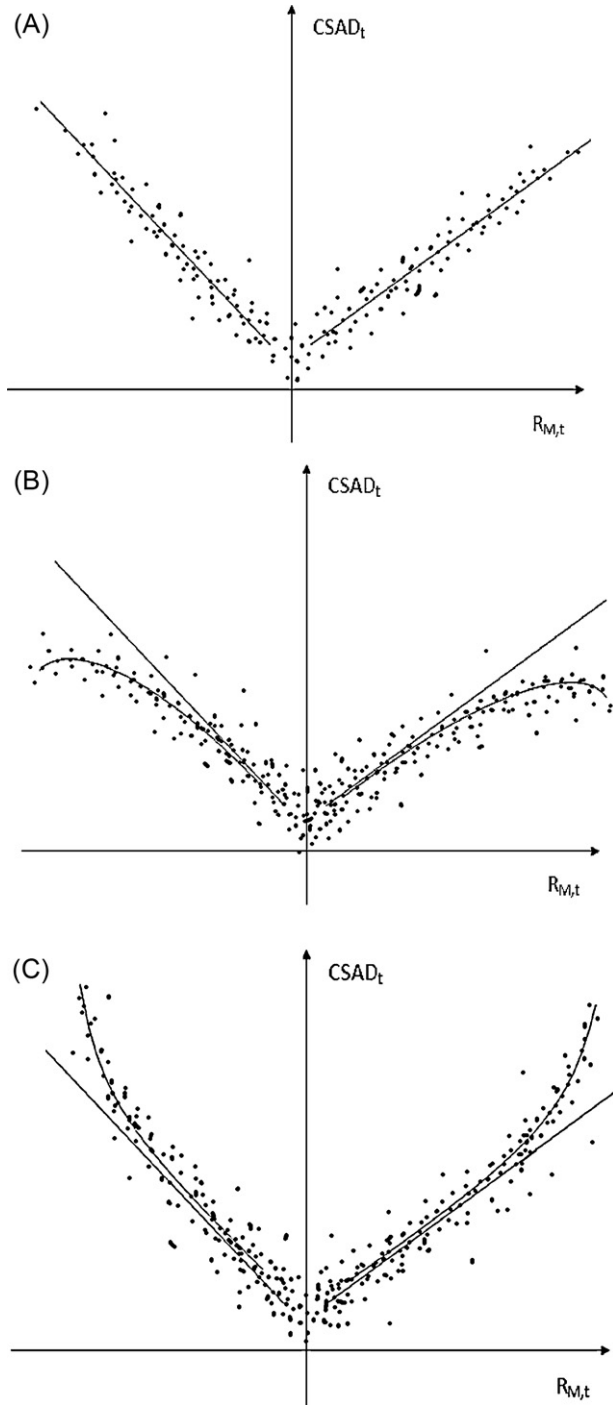


Fig. 1. The relationship between cross-sectional absolute return dispersion, $CSAD_t$, and the market return, $R_{M,t}$, implied by (A) the rational pricing models, (B) the existence of market-wide herding and (C) the existence of localised herding.

we used DataStream's national market indices. The relevant proxies for the 'market' are analogous to those for sectors, i.e., either the average over the national indices from all countries considered, or the DataStream's global market index.

3.2.2. Positive versus negative values of the herding coefficient

A number of studies report instances of excessively high cross-sectional return dispersion, which we term 'negative herding', i.e., positive, rather than negative, values of γ_2 (Christie and Huang, 1995; Gleason et al., 2004; Henker et al., 2006; Goodfellow et al., 2009, for Polish individual investors; Chiang et al., 2010; Economou et al., 2011, for herding with an external market).⁴ This implies return dispersion during market stress which is higher, not lower, than what a rational pricing model would predict (Fig. 1C). Hence, market participants as a group do not suppress their individual views in favour of the market wide consensus. Rather, they seem to do the opposite: to largely ignore information conveyed by the market-wide price movements and focus on views dominant among a subset of actors, in a way which is excessive and exaggerated. This relevant subset of actors may be a herd jointly moving in and out of positions, or, in an extreme case, each individual investor. This behaviour is in line with three phenomena: localised herding, excessive "flight to quality" during market stress, and overconfidence. Firstly, as explained in the introduction, by localised herding we understand a synchronous movement of a subset of investors into a subset of assets/markets, resulting in price rises (decreases) in positions they move into (out of) and an increased dispersion in returns across assets/countries.⁵

As for the excessive flight to quality, periods of high volatility and uncertainty are known to induce portfolio rebalancing, whereby investors shift their capital from the more risky/uncertain positions/markets into the more secure ones. Conducted on a global scale, this would result in opposite price movements for risky versus safe markets, and, hence, a higher cross-country dispersion of returns. This process might be reinforced by the more pronounced home bias in investment in times of market stress, with investors based mostly in developed countries selling foreign stocks and purchasing domestic assets instead. In addition, to the extent that this process is driven by irrational fears, its magnitude and impact on prices can be excessive, resulting in values of $CSAD_t$ above their rational levels implied by the equilibrium pricing models.⁶

Another explanation of excessive return dispersion in times of high market returns can be sought in overconfidence of investors (Goodfellow et al., 2009).⁷ Especially following periods of high positive

⁴ Hwang and Salmon (2004) analyse the cross-sectional dispersion of betas rather than returns and term the instances of excessive dispersion "adverse herding".

⁵ Studies reviewed in Section 2.3., which utilise funds flows or transaction data, deal with the localised version of herding.

⁶ Several theoretical models demonstrate that during market stress, the resulting increase in investors' risk-aversion will generate flight-to-quality, i.e., selling of more risky and buying of less risky stocks, or demanding a higher premium for the former, resulting in capital flows across assets and markets and opposite price movements between more and less risky securities (Vayanos, 2004; Caballero and Krishnamurthy, 2005; Broner et al., 2006). Kaminsky et al. (2003) show capital outflows from troubled markets around several major crisis events, a phenomenon which would have caused an increase in return dispersion across countries (as found in this paper), and Favero and Giavazzi (2002) argue that herd-like flight to quality in response to crises could have raised the dispersion of interest rates in Europe. Negative correlation has been observed between stock and bond returns, being interpreted as a result of flight to quality, e.g., from risky stocks to safer bonds (Baur and Lucey, 2009), and even across stocks in the US market (e.g., from small to large stocks, as in Berger and Turtle, 2011, in response to emerging market crises) and associated with herd-like behaviour (Davis and Madura, 2012). The latter two studies demonstrate that this flight to quality was excessive, as compared to rational reactions to changes in the relevant risk factors.

⁷ The link between overconfidence and herding finds support in various branches of the literature. Nöth and Weber (2003) show in an experimental study that informational cascades (i.e., market-wide, as opposed to localised, herding resulting in negative values of γ_2) collapse if there is sufficient overconfidence in, or quality of, private information received by the agents. Hence, overconfidence causes an increase in heterogeneity of beliefs, trading, and, consequently, of price movements. Furthermore, based on their theoretical model, Sornette and Zhou (2006) demonstrate that overconfident agents tend to imitate other's decisions, but his behaviour is not necessarily a market-wide phenomenon; rather, different groups will coordinate around different beliefs, resulting in heterogeneous trading and returns. Menkhoff et al. (2006) review the relevant literature and argue that herding and overconfidence should be negatively related. In the model of Daniel et al. (1998), overconfidence leads to overreactions to private and underreactions to public news, a phenomenon found in the US data by Chuang and Lee (2006). As private information tends to be mostly available to local agents whereas public news should reach all investors, regardless of their location, the resulting overreactions to private, location-specific information will produce heterogeneous price movements across countries.

returns, traders may tend to attribute high returns on their portfolios to their own stock-picking and timing skills and other abilities rather than to the overall market conditions. This could result in traders overemphasising their own views and downplaying the importance of market signals when making subsequent valuation and investment decisions. If this process takes place internationally, and to the extent to which these traders turning their backs to the market are heterogeneous, a greater dispersion in opinions and asset prices will result. Once again, under these conditions, the values of $CSAD_t$ above the rational level would be observed.

4. Results

4.1. Evidence on international herding

Estimation results for each of the nine sectors and the national indices over the shorter sample period are reported in Table 2. Firstly, the analysis of national indices shows no evidence of international herding when all observations (positive and negative) are considered (model 4), and a positive value of γ_2 only in up markets for the world index used as a proxy for the market. For both proxies of the market the results indicate that deviations from the rational pricing pattern differ between up and down markets (last column of Table 2).

When sector indices are considered separately, some instances of irrational pricing become visible. When the average return is used as the market proxy, basic materials, customer services and oil and gas show evidence of a significant excess return dispersion for high absolute values of market returns (compared to what, e.g., the market model would predict), i.e., positive and significant γ_2 . For the up markets, significant and positive γ_2 is reported for all but two sectors (financials and industrials), whereas when the market is down, none of the sectors shows evidence of significant deviations from the market-model implied cross-country return pattern.

Using the world sector as the market proxy in model (4) combining up and down markets, evidence of ‘negative herding’ (positive γ_2) seems to be stronger than for the other proxy: only financials, telecommunications and utilities seem to follow the pricing pattern implied by the CAPM, with the remaining six sectors showing evidence of a positive and significant excess cross-country dispersion of returns. Exactly the same pattern emerges when only the cases of positive world market returns are considered (up market). In down markets, however, financials display a positive and significant value of γ_2 whereas the values of this parameter for consumer goods and health become insignificant. The herding parameter γ_2 is significantly higher in up than down markets for basic materials and consumer goods and significantly lower for the global financial sector.

Estimation results for each of the five sectors and the national indices observed over the longer sample period are reported in Table 3. As for the national stock indices world-wide, there is no significant evidence of deviations from the rational price behaviour (as dictated by, e.g., the market model), the parameter γ_2 being insignificant in all cases considered. This holds true for the whole sample and when we distinguish between up and down markets, and for both proxies of market return, i.e., the average return of national indices and the world market index return. The difference in the deviations from rational pricing between up and down markets is insignificant when the former is used, but significant for the latter.

When we consider the sector-specific indices separately, again some instances of irrational pricing emerge. When the average return is used as the market proxy, two out of five sectors (basic materials and oil and gas) show significant and positive values of γ_2 , indicating the cross country return dispersion as being higher compared to its rational levels. When looking onto up and down markets separately, these deviations seem to be more pronounced in up markets: γ_2 is significant and positive for basic materials, consumer goods, and oil and gas in up markets, but only remains significant and positive in the down markets for oil and gas. The differences in deviations from the rational pricing pattern between up and down markets are significant for consumer goods and the oil and gas sectors, with γ_2 being higher in up than down markets.

When the world sector-specific index is used as the market proxy, the consumer goods sector in addition to basic materials and oil and gas shows significant and positive values of γ_2 . The results on deviations from rational pricing differ between up and down markets. When the market return

Table 2

International herding in sectors, short sample (01/11/2007–02/01/2012).

Sector/market proxy	Whole sample			Down market			Up market			χ^2 on H_0 :	
	α	γ_1	γ_2	α^D	γ_1^D	γ_2^D	α^U	γ_1^U	γ_2^U	$\gamma_1^D = \gamma_1^U$	$\gamma_2^D = \gamma_2^U$
Basic materials											
Average return	.009484*** (25.0542)	.389457*** (6.83072)	2.08811* (1.67692)	.010215*** (20.8491)	.355581*** (4.51259)	2.04204 (1.18845)	.008909** (20.6852)	.402488*** (6.07808)	2.95848* (1.88622)	.238543	.170410
World sector index	.010211*** (25.5566)	.279201*** (8.23044)	2.26814*** (4.85511)	.010963*** (20.4781)	.266930*** (6.24870)	1.92188*** (3.66999)	.009824*** (24.2418)	.247383*** (6.38613)	3.62723*** (5.12307)	.141796	1.70534**
Consumer services											
Average return	.008297*** (34.7227)	.393509*** (9.73672)	1.69543* (1.72537)	.008606*** (29.2183)	.346722*** (7.52548)	1.55322 (1.61592)	.008321*** (25.5614)	.339247*** (5.49567)	6.69810*** (4.03305)	.009863	6.89363***
World sector index	.009102*** (37.4255)	.315059*** (8.15353)	4.08750*** (3.68707)	.009607*** (28.3789)	.255392*** (5.24687)	4.43491*** (3.73516)	.008592*** (26.8960)	.379981*** (6.10246)	3.88441** (2.14901)	2.20009	.053605
Consumer goods											
Average return	.007654*** (35.3563)	.367827*** (8.10452)	1.56381 (1.17325)	.007782*** (28.4315)	.417945*** (7.92437)	−.841256 (−.668769)	.007827*** (30.9581)	.223581*** (4.34388)	8.89332*** (4.80712)	7.92473***	19.8617***
World sector index	.008218*** (36.8986)	.280429*** (12.0049)	3.47293*** (9.07547)	.008443*** (27.4130)	.337045*** (6.44674)	1.11160 (.824113)	.007766*** (26.2207)	.294988*** (7.36683)	3.63025*** (9.59580)	.415495	3.30329*
Financials											
Average return	.007997*** (30.4039)	.402004*** (10.9527)	.166637 (.258593)	.007933*** (24.2582)	.406215*** (8.86446)	−.558179 (−.598409)	.007965*** (22.4736)	.416710*** (7.35178)	.611868 (.547659)	.022480	.600963
World sector index	.008062*** (24.8770)	.366707*** (9.25054)	.887105 (1.23874)	.008788*** (21.8593)	.268138*** (6.32528)	2.31161*** (2.96645)	.007455*** (18.7299)	.453513*** (8.65532)	−.217565 (−.259509)	7.94823***	5.30165**
Health											
Average return	.008322*** (32.3594)	.632510*** (8.70079)	−.694308 (−.287413)	.008754*** (27.8066)	.604831*** (6.99937)	−1.69966 (−.629872)	.008324*** (29.4005)	.475633*** (6.19242)	12.0947*** (4.12152)	1.52927	13.7985***
World sector index	.009182*** (43.5165)	.46330*** (13.7751)	1.89421*** (3.64315)	.009472*** (32.5847)	.443059*** (7.75884)	1.66281 (1.25890)	.008852*** (29.1537)	.502616*** (10.0551)	1.81782*** (2.60085)	.718336	.011939
Industrials											
Average return	.007110*** (31.0261)	.369146*** (8.88589)	1.21407 (.926592)	.007519*** (24.4848)	.330483*** (6.28276)	1.02286 (.672652)	.006854*** (22.4400)	.368458*** (5.67138)	3.64416 (1.39184)	.254566	.917280
World sector index	.007372*** (26.9998)	.328751*** (8.72514)	1.73934** (2.07397)	.007810*** (22.5449)	.318790*** (7.60645)	1.34859 (1.82336)	.007085*** (21.6929)	.319355*** (5.98758)	2.74592* (1.82402)	.000110	.970295
Oil & gas											
Average return	.009278*** (32.3953)	.347994*** (6.68479)	2.39490* (1.78923)	.009405*** (22.9251)	.375519*** (5.47711)	.795387 (.500512)	.009376*** (23.1061)	.265164*** (3.04092)	6.26172** (2.10362)	1.06349	2.77715*

Table 2 (Continued)

Sector/market proxy	Whole sample			Down market			Up market			χ^2 on H_0 :	
	α	γ_1	γ_2	α^D	γ_1^D	γ_2^D	α^U	γ_1^U	γ_2^U	$\gamma_1^D = \gamma_1^U$	$\gamma_2^D = \gamma_2^U$
World sector index	.009402*** (32.8570)	.341743*** (10.5182)	1.38754*** (3.02965)	.009739*** (25.6370)	.317236*** (8.31414)	1.38864** (2.50255)	.009173*** (23.9818)	.354712*** (6.98502)	1.71582** (2.01837)	.391925	.110742
Telecommunications											
Average return	.009129*** (33.5380)	.424781*** (7.29840)	1.28628 (1.04834)	.009191*** (30.5501)	.427480*** (7.55810)	−.365581 (−.257432)	.009056*** (20.6626)	.415645*** (4.14248)	4.17852** (2.42115)	.012363	5.32841**
World sector index	.009076*** (35.8286)	.383045** (10.2386)	1.20822 (1.46659)	.009273*** (29.3379)	.384248** (8.93301)	−.207351 (−.226491)	.008736*** (21.5041)	.417838*** (6.17586)	1.95452 (1.28116)	.248230	2.11668
Utilities											
Average return	.007765*** (31.8396)	.471580*** (9.00316)	1.32788 (.902725)	.007764*** (22.7503)	.507892*** (7.24548)	−1.03939 (−.607568)	.007882*** (26.0630)	.391245*** (6.91731)	6.34914*** (5.45637)	2.54675	22.4946***
World sector index	.008230*** (29.1656)	.400768** (10.6184)	.833379 (1.54847)	.008445*** (22.2716)	.397218** (6.94460)	.307130 (.284852)	.007875*** (24.1388)	.434710*** (8.27327)	.858059 (1.35558)	.37784	.369055
National markets											
Average return	.005966*** (27.8902)	.367875*** (9.23899)	.272051 (.257865)	.006297*** (23.9972)	.383881*** (8.28862)	−1.23969 (−1.00726)	.005791*** (19.3085)	.315361*** (4.72864)	3.47277 (1.50723)	.694026	3.15643*
World index	.006262*** (28.7315)	.334322** (10.4587)	1.05571 (1.31995)	.006507*** (22.8504)	.358857** (8.21128)	−.070956 (−.077756)	.006065*** (21.6119)	.309292*** (6.75328)	2.33836* (1.87388)	.725170	2.79471*

Note: The table presents results for models (4) and (5) estimated over the short sample (01/11/2007–02/01/2012). We employ DataStream's daily closing values of indices, denominated in national currencies, for each sector and each the total stock market, at the national and global level (DataStream Global Indices Levels 1 and 2, respectively). Model (4) is: $CSAD_t = \alpha + \gamma_1 |r_{M,t}| + \gamma_2 r_{M,t}^2 + \varepsilon_t$ and model (5) is: $CSAD_t = (\alpha^D + \gamma_1^D |r_{M,t}| + \gamma_2^D r_{M,t}^2)(1 - UP_t) + (\alpha^U + \gamma_1^U |r_{M,t}| + \gamma_2^U r_{M,t}^2)UP_t + \varepsilon_t$, where $CSAD_t = \left(\sum_{i=1}^n |r_{i,t} - r_{M,t}| \right) / n$ measures the cross-sectional absolute dispersion of index returns on day t , with $r_{i,t}$ being the return on stock index from country i at time t and \bar{r}_t the cross-sectional average of n index returns at time t , $r_{M,t}$ stands for a proxy of returns on the relevant market, and $UP_t = 1$ if $r_{M,t} > 0$ and zero otherwise (up and down market, respectively). Two alternative proxies of market returns $r_{M,t}$ are: the average value of index return in each sector, computed over all countries included in the analysis, and the return on the sector-specific global index for each sector. The results obtained using these proxies are reported under 'Average return' and 'World sector index', respectively. Standard errors are heteroskedasticity- and autocorrelation-robust, with t -ratios in parentheses. χ^2 is the Wald test statistic for the Null hypothesis of either $\gamma_1^D = \gamma_1^U$ or $\gamma_2^D = \gamma_2^U$, these parameters being from model (5).

* Significance at 10% level.

** Significance at 5% level.

*** Significance at 1% level.

Table 3

International herding in sectors, long sample (06/01/1998–02/01/2012).

Sector/market proxy	Whole sample			Down market			Up market			χ^2 on H_0 :	
	α	γ_1	γ_2	α^D	γ_1^D	γ_2^D	α^U	γ_1^U	γ_2^U	$\gamma_1^D = \gamma_1^U$	$\gamma_2^D = \gamma_2^U$
Basic materials											
Average return	.009036*** (56.2446)	.417893*** (12.8883)	2.14679** (2.37602)	.009459*** (48.9232)	.400000*** (9.79533)	1.65353 (1.52170)	.008785*** (45.2659)	.404061*** (9.64964)	4.26869*** (3.02202)	.005678	2.32882
World sector index	.009780*** (55.4832)	.314453*** (14.5694)	2.06889*** (5.24645)	.010153*** (47.9202)	.311569*** (12.3292)	1.58184*** (4.34013)	.009575*** (47.9777)	.289174*** (11.1329)	3.47357*** (5.05470)	.471042	6.13198**
Consumer goods											
Average return	.008820*** (47.9828)	.467637*** (10.9149)	.299098 (.141845)	.009069*** (38.6028)	.477779*** (8.77017)	−.963042 (−.433330)	.008770*** (44.1806)	.396708*** (7.46414)	5.71486** (1.97595)	1.40157	5.02353**
World sector index	.009214*** (47.8445)	.384378*** (19.1095)	2.68468*** (5.71585)	.009564*** (39.8109)	.400938*** (10.1789)	.780953 (.539630)	.008728*** (39.2593)	.427185*** (15.5388)	2.85374*** (5.65858)	.156137	2.53927
Financials											
Average return	.007699*** (49.4963)	.435264*** (14.5421)	.590250 (.829375)	.008151*** (45.0683)	.380950*** (9.89060)	.951177 (.849789)	.007281*** (38.8766)	.493149*** (12.3981)	.382464 (.324093)	4.87237**	.113803
World sector index	.007834*** (47.8824)	.424043*** (16.8317)	.487381 (.959897)	.008292*** (45.0272)	.360500*** (13.2290)	1.31028** (2.39538)	.007408*** (36.5927)	.485111*** (14.5875)	−.196843 (−.297528)	10.9091***	3.71217*
Industrials											
Average return	.008673*** (25.2282)	.339589*** (3.08004)	6.02817 (1.05450)	.009208*** (22.1220)	.289039** (2.31291)	5.9935 (1.00288)	.008380*** (21.5589)	.322648** (2.34585)	10.6213 (1.28436)	.148448	1.06069
World sector index	.008900*** (39.3850)	.386032*** (13.1028)	.885946 (1.26420)	.009278*** (37.2715)	.385365*** (11.4632)	.116304 (.174655)	.008655*** (33.9995)	.368319*** (9.38136)	2.37138* (1.89016)	.180373	3.29340*
Oil & gas											
Average return	.010217*** (56.9294)	.361459*** (10.8894)	2.97076*** (3.30508)	.010601*** (46.8929)	.351505*** (8.68674)	1.85374* (1.85539)	.010005*** (45.9836)	.332777*** (6.64239)	6.21205*** (3.17245)	.10325337	4.18467**
World sector index	.010364*** (58.4063)	.367589*** (18.3798)	1.20165*** (3.63242)	.010778*** (49.1545)	.347694*** (14.7480)	1.12383*** (3.02372)	.010060*** (45.4284)	.376306*** (12.2373)	1.62419** (2.48874)	.626971	.487671

Table 3 (Continued)

Sector/market proxy	Whole sample			Down market			Up market			χ^2 on H_0 :	
	α	γ_1	γ_2	α^D	γ_1^D	γ_2^D	α^U	γ_1^U	γ_2^U	$\gamma_1^D = \gamma_1^U$	$\gamma_2^D = \gamma_2^U$
National markets											
Average return	.006246*** (49.5974)	.376476*** (13.6089)	.288799 (.317891)	.006555*** (44.0075)	.381520*** (11.8701)	−.986832 (−1.06388)	.006072*** (31.3946)	.343579*** (6.43147)	3.33246 (1.31728)	.415141	2.57402
World index	.006671*** (42.7380)	.356011*** (14.5854)	.609510 (.991274)	.006986*** (38.1980)	.358595*** (12.9820)	−.257690 (−.454704)	.006430*** (34.4061)	.348001*** (9.89224)	1.77213 (1.60117)	.086364	3.33660*

Note: The table presents results for models (4) and (5) estimated over the long sample (06/01/1998–02/01/2012). We employ DataStream's daily closing values of indices, denominated in national currencies, for each sector and each the total stock market, at the national and global level (DataStream Global Indices Levels 1 and 2, respectively). Model (4) is: $CSAD_t = \alpha + \gamma_1|r_{M,t}| + \gamma_2\bar{r}_{M,t}^2 + \varepsilon_t$ and model (5) is: $CSAD_t = (\alpha^D + \gamma_1^D|r_{M,t}| + \gamma_2^D\bar{r}_{M,t}^2)(1 - UP_t) + (\alpha^U + \gamma_1^U|r_{M,t}| + \gamma_2^U\bar{r}_{M,t}^2)UP_t + \varepsilon_t$, where $CSAD_t = \left(\sum_{i=1}^n |r_{i,t} - \bar{r}_t|\right) / n$ measures the cross-sectional absolute dispersion of index returns on day t , with $r_{i,t}$ being the return on stock index from country i at time t and \bar{r}_t the cross-sectional average of n index returns at time t , $r_{M,t}$ stands for a proxy of returns on the relevant market, and $UP_t = 1$ if $r_{M,t} > 0$ and zero otherwise (up and down market, respectively). Two alternative proxies of market returns $r_{M,t}$ are: the average value of index return in each sector, computed over all countries included in the analysis, and the return on the sector-specific global index for each sector. The results obtained using these proxies are reported under 'Average return' and 'World sector index', respectively. Standard errors are heteroskedasticity- and autocorrelation-robust, with t -ratios in parentheses. χ^2 is the Wald test statistic for the Null hypothesis of either $\gamma_1^D = \gamma_1^U$ or $\gamma_2^D = \gamma_2^U$, these parameters being from model (5).

* Significance at 10% level.

** Significance at 5% level.

*** Significance at 1% level.

is positive, all sectors apart from finance show positive and significant deviations from the rational equilibrium, i.e., ‘negative herding’. When the world market is down, only basic materials and finance show significant evidence of positive γ_2 . Herding measurements differ significantly between up and down markets for basic materials and industrials (higher in up markets), as well as for financials (higher in down markets).

The overall evidence of cross-country return behaviour can be summarised as follows. Firstly, there is effectively no evidence of herding, positive or negative, when national indices comprising of all sectors are considered. However, the results indicate that γ_2 differs between up and down markets. Secondly, even with no herding recorded for the overall indices, some sectors (most notably basic materials, consumer services and oil and gas) tend to show significant deviations from the return behaviour implied by rational pricing. In contrast, financials, telecoms and utilities show hardly any signs of herding, positive or negative. Thirdly, herding in sectors also changes between up and down markets, but there is no pattern across all sectors: γ_2 is positive and significant for basic materials, consumer goods, and oil and gas for different specifications and samples, whereas in down markets, financials tends to show evidence of ‘negative herding’ (positive and significant γ_2). The difference in herding parameter values between up and down markets is significant for several sectors, the most robust evidence being for basic materials (γ_2 significantly higher in up markets) and financials (γ_2 significantly lower in up markets). In summary, deviations from rational pricing differ across sectors and up and down markets, as well as for different sample periods and market proxies. Therefore, we continue our analysis by investigating the time-varying, sector-specific behaviour of the herding parameters in up and down markets.

Plots of the return dispersion measures on returns of their respective market proxies are presented in Fig. 2 (for short samples only, plots for long samples are virtually identical). It can be seen that there is no sign of ‘positive herding’ (negative value of γ_2) in any of these cases (as presented in Fig. 1B), as no downward deviations of $CSAD_t$ for high absolute values of the market return are observable. Rather, all sectors demonstrate excessive dispersion for extreme market returns, as shown in Fig. 1C. Therefore, our results of ‘negative herding’ are not driven by statistical issues with the data such as influential outliers.

As for the market proxy, we continue to use both the average cross-country returns and the global indices, for several reasons. Firstly, as the results differ for these two proxies, they may be capturing different aspects of herding: towards (or away from) the information conveyed by the markets included in our sample versus towards (or away from) the information captured by the more comprehensive worldwide market indices. However, on theoretical grounds, the average return (rather than the world market return) is a preferred market proxy as an unbiased estimator of the expected return (Chang et al., 2000).

4.2. Quantile regressions results

Our results of almost uniformly positive values of the herding parameter γ_2 in the international context (‘negative herding’) sharply contrast with other studies using the methodology by Chang et al. (2000) which mostly report, or emphasise the most, negative values of γ_2 interpreted as evidence of market-wide herding within national boundaries (‘positive herding’). Of course, it may be that herding on a global scale, as analysed here, differs from herding on a national level, which would explain why our results are at odds with those reported elsewhere. In this subsection, we investigate an alternative explanation, i.e., that ‘positive herding’ does take place in the international context but is ‘hidden away’ in the data, which is also driven (or ‘contaminated’, for our purposes) by noise and other effects jointly shifting the evidence towards positive values of γ_2 .

To this end, we follow Chiang et al. (2010) and employ the method of quantile regression. Specifically, we search for ‘positive herding’ where it would most likely be observed, i.e., in the lower quantiles of the distribution of $CSAD_t$, as this type of herding has been hypothesised to cause a downward shift in the return dispersion for high absolute values of market return (Fig. 1B). Quantile regression differs from the OLS approach as, rather than giving the expected value of the dependent variable for any fixed value of the independent variable, it instead reports a preselected quantile of the distribution

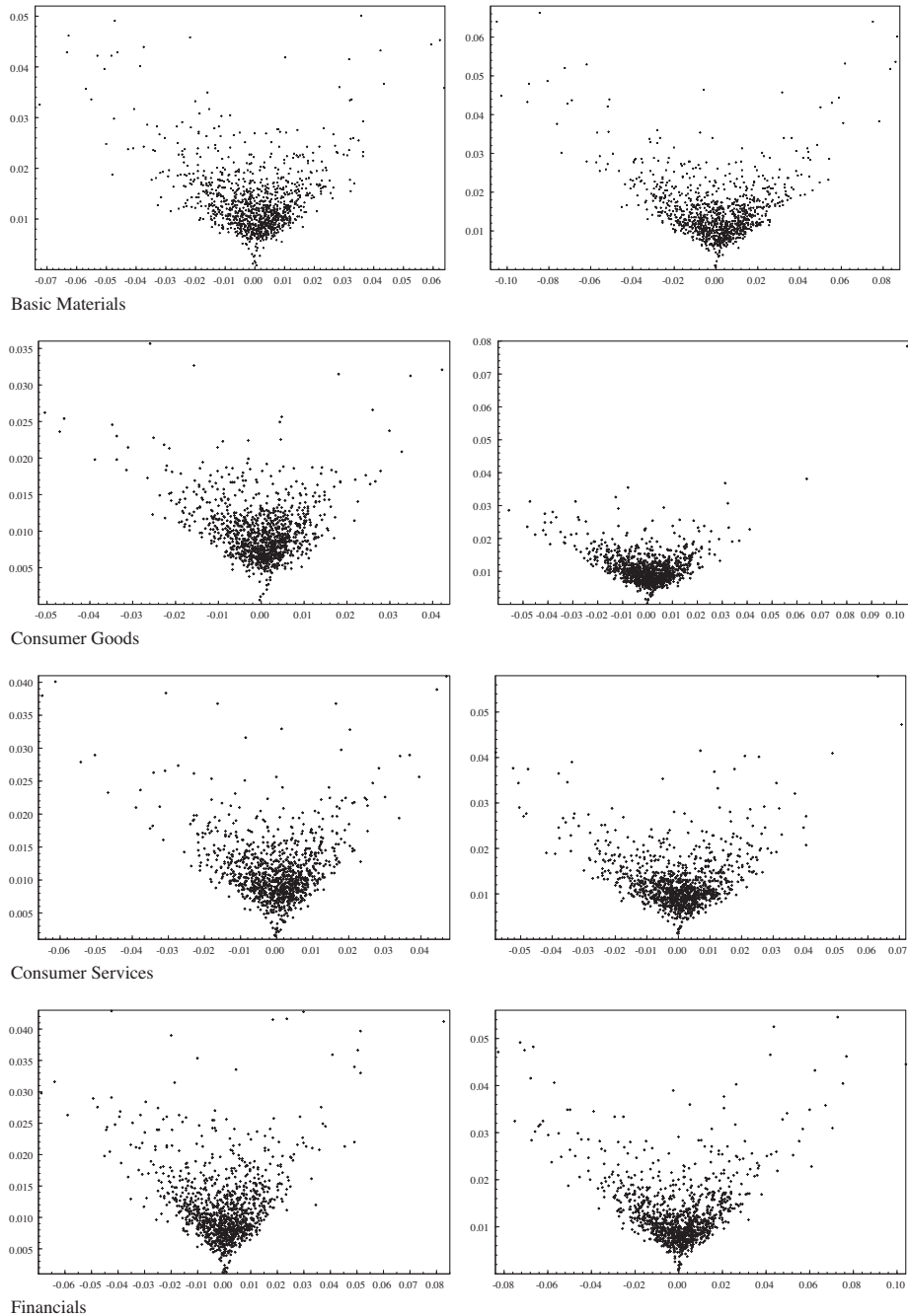


Fig. 2. Plots of cross-sectional return dispersions on returns of the market proxies. *Note:* Plots on the left hand side are generated using as a market return proxy the mean index return computed across all countries included in the analysis, whereas those on the right hand side use as a proxy for market return the return on the world-wide index for the relevant sector, as reported by the DataStream.

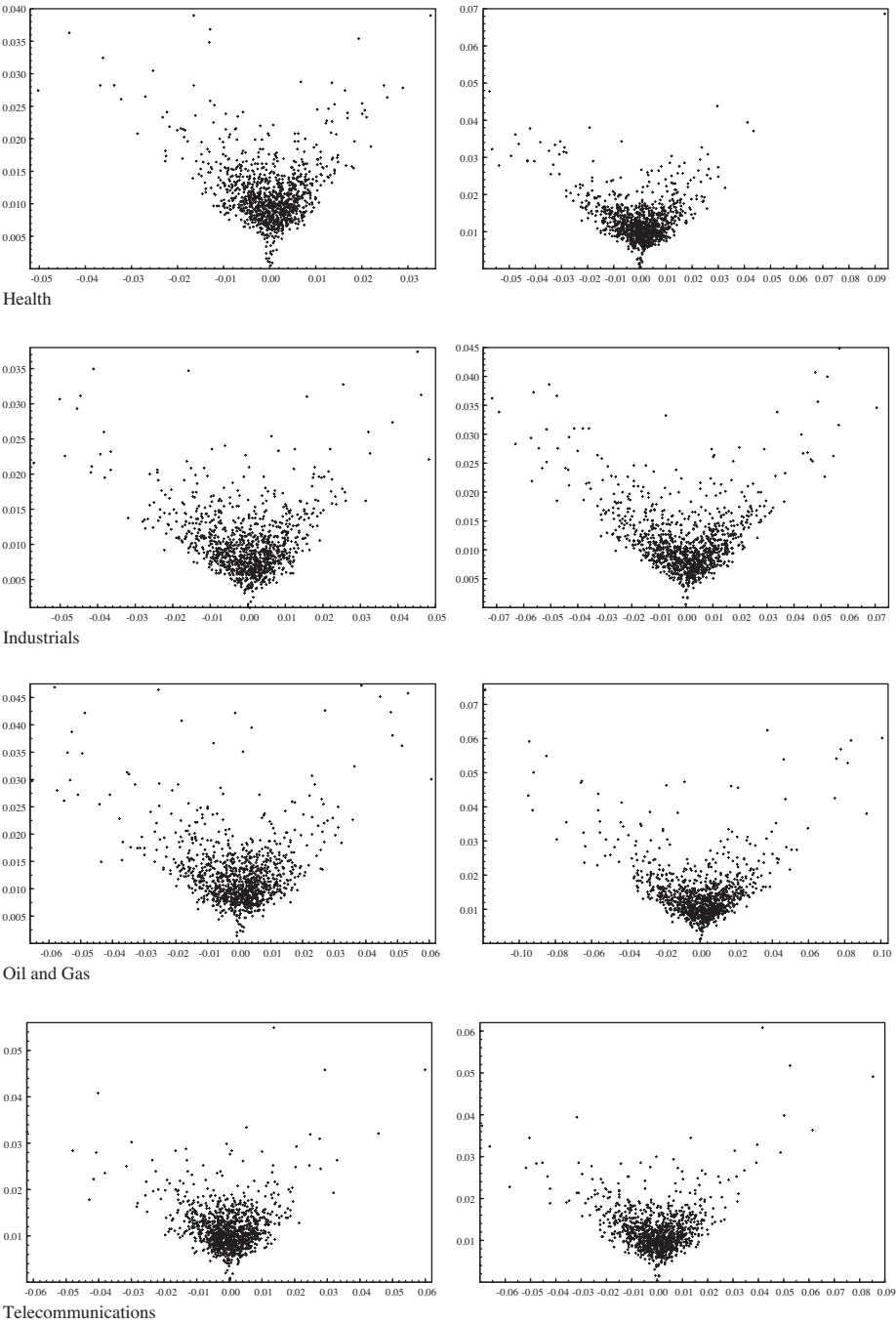


Fig. 2. (Continued)

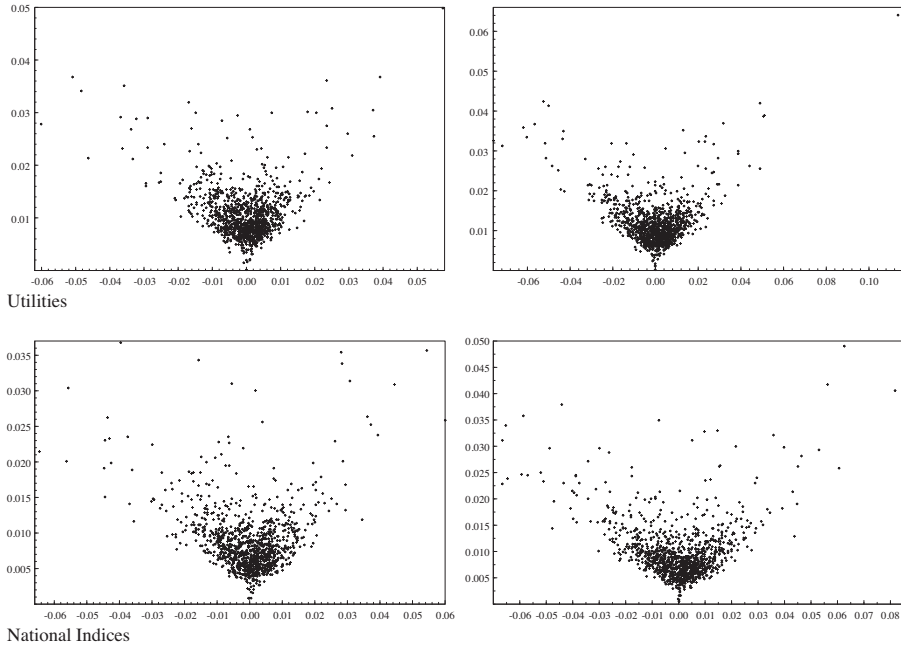


Fig. 2. (Continued).

of the dependent variable (for any fixed value of the independent variable). Hence, for the model (4), whereas the OLS estimates give:

$$E[CSAD_t|r_{M,t}] = \hat{\alpha} + \hat{\gamma}_1|r_{M,t}| + \hat{\gamma}_2 r_{M,t}^2, \quad (6)$$

the quantile regression allows us to predict the τ th quantile of $CSAD_t$ for a given value of $r_{M,t}$:

$$Q[\tau|r_{M,t}] = \hat{\alpha} + \hat{\gamma}_1|r_{M,t}| + \hat{\gamma}_2 r_{M,t}^2. \quad (7)$$

The same logic applies to model (5). We use the 10th quantile ($\tau=0.10$) in our analysis.

To obtain a good cross-sectional picture of the ‘positive herding’ potentially buried in the data, short samples of nine economic sectors have been utilised. The results from quantile regressions are reported in Table 4. There is not a single case where the herding coefficient γ_2 is negative and significant, but many cases where it is positive and highly significant, even though the pattern of occurrence of herding in sectors differs from the one revealed by the OLS regressions. Hence, there is no evidence of ‘positive herding’ (negative values of γ_2) on an international level, even where it is most likely to be observed (low quantiles of dispersion distribution). For the national market indices, once again no deviations from the rational level are observed.

4.3. Herding within sectors versus herding towards the US and the global markets

Chiang and Zheng (2010) suggest that herding on a given stock exchange might take place towards the ‘national’ market portfolio, but in today’s globalised world it is also likely that investors (partially) herd with an influential foreign market, e.g., with the US (also Economou et al., 2011). To investigate the possibility that herding in each sector can occur towards (or away from) the US or the global stock

Table 4

International herding in sectors, quantile regression results for the short sample.

Sector/market proxy	Whole sample			Down market			Up market			χ^2 on H_0 :	
	α	γ_1	γ_2	α^D	γ_1^D	γ_2^D	α^U	γ_1^U	γ_2^U	$\gamma_1^D = \gamma_1^U$	$\gamma_2^D = \gamma_2^U$
Basic materials											
Average return	.005833*** (26.8576)	.300441*** (7.35925)	.963084 (.709591)	.006006*** (15.9686)	.265791*** (3.92194)	1.40891 (.714170)	.005744*** (14.5594)	.292618*** (4.49455)	2.82790 (1.27657)	.086476	.245881
World sector index	.005822*** (28.6075)	.274934*** (10.3729)	1.00363** (1.97829)	.005903*** (16.6117)	.265248*** (6.21713)	1.09004* (1.71494)	.006064** (21.4946)	.228328*** (6.27592)	2.34363** (2.34408)	.431684	1.05479
Consumer services											
Average return	.005010*** (23.4324)	.356101*** (9.48068)	.755922 (.731618)	.005168*** (15.2699)	.312168*** (6.09981)	1.62449 (1.29974)	.004932*** (9.63282)	.350690*** (3.63508)	4.44196 (1.09898)	.124822	.447726
World sector index	.005504*** (16.7875)	.290209*** (5.96487)	2.20927 (1.40064)	.005808*** (15.9023)	.287837*** (4.60483)	1.19827 (.575234)	.005099** (12.3897)	.301987*** (4.53234)	4.17250* (1.79156)	.024742	.945120
Consumer goods											
Average return	.004951*** (30.6164)	.271995*** (9.37902)	2.64992*** (2.72595)	.005201*** (29.0315)	.262677*** (7.52065)	2.73499** (2.44634)	.004976*** (20.0135)	.181954*** (2.99338)	9.15774*** (3.12655)	1.30542	4.11875**
World sector index	.005273*** (32.0324)	.220422*** (7.25361)	3.36530*** (3.81909)	.005559*** (30.9302)	.247434*** (6.52466)	2.68080** (2.54027)	.004963*** (19.1188)	.201826*** (5.00638)	4.80217*** (3.73935)	.713950	1.68354
Financials											
Average return	.004495*** (17.1093)	.348756*** (9.55915)	.134017 (.181672)	.004566*** (12.3114)	.325216*** (5.52083)	.261479 (.170167)	.004497*** (12.8739)	.369641*** (7.02193)	−.291246 (−.168070)	.316402	.057577
World sector index	.004610*** (24.8039)	.309179*** (13.6246)	.717336* (1.67120)	.004725*** (14.7630)	.298227*** (8.28023)	.758993 (1.06427)	.004330*** (14.7361)	.348661*** (8.75280)	.363590 (.392317)	.895508	.111735
Health											
Average return	.005173*** (17.7376)	.518087*** (6.38616)	−1.52423 (−.380107)	.005747*** (15.8367)	.443511*** (5.07485)	−.268964 (−.067185)	.005182*** (11.7761)	.392884*** (3.19180)	10.8998* (1.89735)	.119437	2.73076*
World sector index	.005687*** (20.1911)	.365144*** (7.72164)	1.86241 (1.22111)	.006257*** (13.0522)	.341129*** (3.87727)	2.10892 (.922173)	.005556*** (16.8703)	.338778*** (4.56707)	3.56897 (1.16543)	.000420	.148559
Industrials											
Average return	.004127*** (21.5527)	.364630*** (10.5829)	−1.01503 (−.851041)	.004549*** (13.9664)	.330820*** (6.74283)	−.551979 (−.350338)	.003908*** (13.7454)	.357786*** (4.88775)	.422834 (.114882)	.094374	.059605
World sector index	.004482*** (19.0284)	.266630*** (8.04420)	1.77255** (2.09574)	.004620*** (14.2385)	.292379*** (7.28936)	.200888 (.178797)	.004166*** (13.2244)	.284050*** (6.35878)	2.09890* (1.90672)	.019232	1.39514
Oil & gas											
Average return	.005660*** (22.7893)	.288366*** (8.19756)	1.21819 (1.32687)	.005781*** (14.8553)	.293184*** (4.72692)	1.11585 (.646915)	.005735*** (16.4827)	.252363*** (3.06048)	2.42195 (.684370)	.134844	.110198

Table 4 (Continued)

Sector/market proxy	Whole sample			Down market			Up market			χ^2 on H_0 :	
	α	γ_1	γ_2	α^D	γ_1^D	γ_2^D	α^U	γ_1^U	γ_2^U	$\gamma_1^D = \gamma_1^U$	$\gamma_2^D = \gamma_2^U$
World sector index	.005654*** (24.0209)	.281910*** (12.3470)	.743714 (1.54260)	.006165*** (13.0490)	.253623*** (5.87491)	.690381 (.828710)	.005563*** (19.7814)	.285966*** (7.14433)	.710508 (.610638)	.305331	.000207
Telecommunications											
Average return	.005777*** (27.7928)	.311307*** (5.74765)	1.90959 (.855390)	.005675*** (19.9977)	.360466*** (5.71899)	−1.81775 (−.751875)	.005920*** (18.6979)	.248815*** (2.97653)	6.93098** (2.49579)	1.11790	5.51330**
World sector index	.005744*** (28.8139)	.290992*** (8.15777)	1.73812 (1.28832)	.005711*** (18.9973)	.332626*** (6.82715)	−.672094 (−.466450)	.005710*** (21.0983)	.278398*** (5.75904)	2.68886 (1.61056)	.619704	2.32757
Utilities											
Average return	.004725*** (21.9171)	.387125*** (7.33525)	−.033127 (−.013988)	.004830*** (18.0303)	.367086*** (6.24235)	.271004 (.118598)	.004667*** (15.3084)	.343793*** (4.61628)	5.77781** (2.20110)	.058006	2.45970
World sector index	.004963*** (24.1812)	.332540*** (10.3532)	.410417 (.470448)	.004963*** (15.8997)	.332540*** (8.20764)	.410417 (.413110)	.004883*** (15.9676)	.335330*** (6.21344)	1.64091 (1.10660)	.001687	.466726
National markets											
Average return	.003541*** (20.6977)	.263166*** (8.26356)	.209498 (.232046)	.003764*** (18.8260)	.284789*** (8.13760)	−.687236 (−.579514)	.003346*** (11.8121)	.246439*** (3.76822)	2.14441 (.685838)	.270585	.716914
World index	.003592*** (18.2421)	.259328*** (8.46764)	.841808 (.943780)	.003822*** (12.4343)	.283351*** (6.47567)	.062255 (.061563)	.003520*** (11.5385)	.223192*** (4.57219)	2.37378 (1.34391)	.886313	1.33928

Note: The table presents results for quantile regression equivalents of models (4) and (5) estimated over the short sample (01/11/2007–02/01/2012). We employ DataStream's daily closing values of indices, denominated in national currencies, for each sector and each the total stock market, at the national and global level (DataStream Global Indices Levels 1 and 2, respectively). Quantile regression equivalent of model (4) is: $Q[\tau|r_{M,t}] = \alpha + \gamma_1|r_{M,t}| + \gamma_2r_{M,t}^2 + \varepsilon_t$ and that of model (5) is: $Q[\tau|r_{M,t}] = (\alpha^D + \gamma_1^D|r_{M,t}| + \gamma_2^D r_{M,t}^2)(1 - UP_t) + (\alpha^U + \gamma_1^U|r_{M,t}| + \gamma_2^U r_{M,t}^2)UP_t + \varepsilon_t$.

The 10th quantile is used ($\tau = .10$). $CSAD_t = (\sum_{i=1}^n |(r_{i,t} - r_{M,t})|) / n$ measures the cross-sectional absolute dispersion of index returns on day t , with r_{it} being the return on stock index from country i at time t and \bar{r}_t the cross-sectional average of n index returns at time t , $r_{M,t}$ stands for a proxy of returns on the relevant market, and $UP_t = 1$ if $r_{M,t} > 0$ and zero otherwise (up and down market, respectively). Two alternative proxies of market returns $r_{M,t}$ are: the average value of index return in each sector, computed over all countries included in the analysis, and the return on the sector-specific global index for each sector. The results obtained using these proxies are reported under 'Average return' and 'World sector index', respectively. Standard errors are heteroskedasticity- and autocorrelation-robust, with t -ratios in parentheses. χ^2 is the Wald test statistic for the Null hypothesis of either $\gamma_1^D = \gamma_1^U$ or $\gamma_2^D = \gamma_2^U$, these parameters being from model (5).

* Significance at 10% level.

** Significance at 5% level.

*** Significance at 1% level.

market, in addition to herding away from the global sector-specific market, we add the returns on the US and the global stock market indices to our regressions.⁸ For instance, model (4) becomes:

$$CSAD_t = \alpha + \gamma_1 |r_{M,t}| + \gamma_2 r_{M,t}^2 + \gamma_1^G |r_{G,t}| + \gamma_2^G r_{G,t}^2 + \gamma_1^{US} |r_{US,t}| + \gamma_2^{US} r_{US,t}^2 + \varepsilon_t, \quad (8)$$

and model (5) is adjusted in an analogous way. Two proxies of the US market are used: the sector specific US index and the total US stock market index. Empirically, due to high correlations between each proxy of the sector-specific market portfolio's return, $r_{M,t}$, the return on the global stock market portfolio, $r_{G,t}$, and the return on the US market proxy, $r_{US,t}$, the two latter variables are orthogonalised. The orthogonalisation of $r_{US,t}$ is conducted by regressing it on the sector-specific market portfolio's return and on the return of the global stock market portfolio, with the resulting residuals representing orthogonalised US returns and being utilised in estimations of model (8). The orthogonalisation of $r_{G,t}$ is conducted by regressing it on the sector-specific market portfolio's return. This is done for each sector and each proxy of the sector-specific market portfolio's returns, and for both the relevant US sector specific and the total US stock market indices.

The results (not reported to conserve space) show that the addition of the global and US market variables does not change our main conclusions regarding the existence and character of herding in sectors. The observed pattern of herding is almost identical to the one presented in Table 2. Specifically, across all sectors, market proxies and model specifications, the herding coefficient γ_2 is never negative and significant; most values are positive and significant instead. Herding towards (or away from) the global or the US stock market rather than the sector world-wide is insignificant in most cases. For those instances where it is significant, the parameter's value is positive in the overwhelming majority of cases. Hence, we conclude that our initial results of 'negative herding' on the sector level were not biased by omission of possible herding to, or away from, the US or the global stock market.

4.4. Changes in herding over time

Any type of investor behaviour, including herding, could be expected to change over time.⁹ To investigate the time-varying nature of herding, we start by obtaining the moving-window estimates of parameters γ_2 in models (4) and (5) over the longer sample and present the results for model (4) in Fig. 3 (results for model (5) omitted to preserve space). It can be seen that herding seems to vary over time for all sectors analysed, as well as for the national indices. To formally investigate these time variations, we repeat our analysis for three equal subperiods of the longer period. Subperiod 1 (06 January, 1998 to 03 September, 2002) corresponds to the last phase of the IT bubble as well as the bearish phase which followed its burst, subperiod 2 (04 September, 2002 to 10 August, 2006) covers the subsequent bullish phase before bad news related to the US subprime market started to arrive, and subperiod 3 (10 August, 2006, to 02 January, 2012) roughly captures the era of the recent financial debacles and sluggish recovery.

Results from estimations of models (4) and (5) are reported in Table 5. In general, they confirm our previous findings: herding parameters γ_2 are never negative and significant; most of the values are significant and those significant ones are always positive. Hence, excessive return dispersion appears to be a feature which is persistent in time and robust across different economic sectors. It is interesting to note that there appears to be a common pattern in the time-series behaviour of the herding parameter: most values decline over time. To formally test this observation, *t*-tests are conducted on the relevant pairs of herding coefficients γ_2 , with the results reported in Table 6. As for a decline in the herding parameter between subperiods 1 and 2, all sectors except for basic materials show some evidence of significantly lowered values, either in coefficients from model (4) or (5). This movement continues between subperiods 2 and 3: only basic materials shows no significant change in herding, and for the oil and gas sector the parameter γ_2 is actually higher. Lastly, when comparing the values of γ_2 between

⁸ We thank the reviewer for suggesting to use the US in addition to the global market proxy.

⁹ For instance, Christoffersen and Tang (2010) show herding to be more pronounced in periods of poor market information, i.e., of low turnover and returns, and Chiang and Zheng (2010) and Kremer and Nautz (forthcoming) report herding to be higher in times of market stress.

Table 5
Changes in international herding over time.

Sector/market proxy	Whole sample			Down market			Up market			χ^2 on H_0 :	
	α	γ_1	γ_2	α^D	γ_1^D	γ_2^D	α^U	γ_1^U	γ_2^U	$\gamma_1^D = \gamma_1^U$	$\gamma_2^D = \gamma_2^U$
Basic materials											
<i>Average return</i>											
Period 1	.010453** (46.9335)	.331948** (5.68206)	6.22934** (2.11430)	.010766** (41.1379)	.285047** (4.09134)	4.17022 (1.41145)	.010484** (34.8634)	.228918** (2.82677)	18.0284** (4.03028)	.292679	6.670859**
Period 2	.007860** (52.1818)	.283602** (8.10153)	4.9261** (4.73464)	.008140** (39.4619)	.317957** (6.4728)	3.23271** (2.42356)	.007800** (37.4354)	.207119** (3.62998)	10.4355** (3.12951)	2.518254	4.659723**
Period 3	.009828** (32.7053)	.387774** (7.40387)	2.305690* (1.72109)	.010108** (26.2591)	.395960** (5.76315)	1.553510 (.950501)	.009747** (27.0633)	.343033** (5.66282)	4.472710** (2.85791)	.350489	1.772493
<i>World sector index</i>											
Period 1	.011548** (48.3762)	.233212** (5.10957)	5.43494** (3.16594)	.011735** (39.6059)	.186999** (3.19787)	4.73902** (2.29492)	.011532** (31.3544)	.210788** (2.62492)	9.99466** (2.94387)	.057438	1.749147
Period 2	.008086** (51.8166)	.275600** (7.62089)	4.096300** (2.68631)	.008157** (41.5163)	.336997** (7.08821)	1.881720 (.998700)	.008077** (36.7361)	.216782** (4.81820)	6.715700** (3.72448)	3.710119*	4.129127**
Period 3	.010387** (33.8538)	.287900** (8.78390)	2.276300** (3.80983)	.011148** (25.3875)	.274705** (6.48157)	1.865640** (2.83738)	.010038** (31.1517)	.251867** (7.21613)	3.853130** (5.04264)	.182259	3.932615**
Consumer goods											
<i>Average return</i>											
Period 1	.011884** (53.7982)	.380215** (6.71981)	6.80307** (2.39674)	.012288** (42.4706)	.273967** (3.91579)	9.12023** (3.06934)	.011707** (36.5158)	.380034** (3.91514)	12.1606** (2.02562)	.859065	.230315
Period 2	.007719** (42.9887)	.407167** (5.42372)	5.700660 (.908575)	.007621** (28.8993)	.538518** (5.43536)	.274780 (.039463)	.007821** (37.9006)	.310755** (3.48325)	9.744470 (1.35168)	2.982800*	.904161
Period 3	.007563** (39.5796)	.361738** (8.75213)	1.870560 (1.38662)	.007711** (30.8537)	.411189** (8.23550)	−.641770 (−.497273)	.007758** (33.1532)	.196496** (3.93182)	11.041400** (4.84764)	9.283153**	20.85709**
<i>World sector index</i>											
Period 1	.012813** (58.8687)	.270651** (6.51752)	6.10876** (4.12439)	.013207** (47.4553)	.228462** (4.75045)	6.10600** (4.24010)	.012408** (39.1438)	.316007** (5.09337)	5.98700** (2.59513)	1.231177	.001918
Period 2	.007870** (42.2031)	.372430** (8.25785)	5.720640** (2.72637)	.008049** (28.1615)	.378813** (4.90151)	5.180380 (1.41979)	.007714** (33.6108)	.373612** (7.05553)	5.829230** (2.28494)	.003229	.021451
Period 3	.008053** (40.2680)	.277225** (12.4345)	3.666430** (9.91808)	.008177** (30.1354)	.342729** (7.39063)	1.006950 (.870579)	.007673** (28.3718)	.290676** (7.54764)	3.869130** (10.55130)	.806147	6.008630**
Financials											
<i>Average return</i>											
Period 1	.009561** (44.7008)	.360715** (6.85107)	4.489560** (2.07173)	.009833** (39.0530)	.315939** (5.02626)	3.698130* (1.75697)	.009604** (34.7799)	.275408** (4.49825)	13.3379** (4.90979)	.266164	8.519548**

Period 2	.006189*** (44.9512)	.389296*** (8.13470)	−.031910 (−.011680)	.006563*** (34.7328)	.422599*** (7.81630)	−4.664570** (−1.99913)	.006065*** (39.5332)	.288788*** (5.55213)	11.1034*** (3.58072)	3.465797*	15.7838***
Period 3	.008109*** (30.9643)	.386314*** (9.74801)	1.144470 (1.33056)	.008250*** (23.5163)	.354929*** (6.65234)	1.336160 (.98232)	.007928*** (22.8491)	.427114*** (7.43648)	.911403 (.713405)	.952111	.050148
<i>World sector index</i>											
Period 1	.010191*** (43.0898)	.285575*** (6.88035)	5.096870*** (4.04766)	.010245*** (36.2379)	.279946*** (5.02963)	4.141150** (2.34243)	.010126*** (30.3339)	.291336*** (5.29676)	6.238270*** (3.96100)	.024367	.835731
Period 2	.006447*** (48.1519)	.343226*** (10.0875)	4.288600*** (2.93842)	.006429*** (31.3892)	.440189*** (6.61458)	−1.834130 (−.494302)	.006264*** (32.4397)	.346454*** (6.67086)	4.931390** (2.30601)	1.308132	2.539292
Period 3	.008071*** (27.5879)	.378503*** (9.82467)	.984841 (1.44906)	.008702*** (24.0262)	.285393*** (6.99369)	2.360990*** (3.32082)	.007554*** (20.9708)	.460646*** (9.16906)	−.087949 (−.111788)	8.045165***	5.912364**
Industrials											
<i>Average return</i>											
Period 1	.012628*** (29.8908)	−.032166 (−.212735)	25.561*** (3.06960)	.012711*** (24.4662)	−.053309 (−.326402)	23.1774*** (2.96712)	.013034*** (19.5742)	−.216291 (−.849293)	40.3017*** (2.70183)	.495388	1.670076
Period 2	.007284*** (48.2390)	.368975*** (8.08832)	3.254890 (1.43772)	.007418*** (35.6500)	.491050*** (7.90322)	−4.046950 (−1.62804)	.007421*** (36.2291)	.173613** (2.39714)	19.1598*** (3.52634)	11.055931***	15.3362***
Period 3	.007007*** (36.7188)	.411486*** (11.8306)	.698726 (.640333)	.007420*** (29.7929)	.374448*** (8.67556)	.506320 (.398961)	.006771*** (25.3135)	.403971*** (6.34716)	3.370090 (1.26112)	.151694	.949444
<i>World sector index</i>											
Period 1	.012360*** (50.4661)	.333650*** (7.54051)	2.943450*** (2.67162)	.012470*** (34.0197)	.324355*** (4.60188)	2.726030 (1.62672)	.012280*** (40.9427)	.334614*** (6.94561)	3.579480*** (2.72650)	.014661	.161383
Period 2	.007410*** (45.2447)	.337788*** (8.32083)	6.062290*** (3.34249)	.007429*** (31.9896)	.458857*** (7.85683)	−.056131 (−.021121)	.007287*** (33.3275)	.294205*** (5.15202)	8.080610*** (2.96439)	4.5803**	5.013769**
Period 3	.007574*** (30.3646)	.309983*** (8.37946)	2.333490** (2.46065)	.007929*** (24.9552)	.310834*** (8.26520)	1.597080** (2.31956)	.007385*** (22.2860)	.285497*** (4.85174)	3.889680** (2.08143)	.196770	1.7864
Oil & gas											
<i>Average return</i>											
Period 1	.012583*** (50.2070)	.244155*** (3.80426)	12.9621*** (3.93512)	.012881*** (39.8459)	.168589* (1.92055)	12.7191*** (2.92510)	.012330*** (34.7072)	.287666*** (3.04367)	15.9996*** (3.25180)	.842005	.239097
Period 2	.009051*** (50.0744)	.331253*** (7.8977)	−.195434 (−.096732)	.009204*** (38.1228)	.379804*** (6.51358)	−2.599120 (−1.04692)	.009032*** (35.8129)	.255144*** (3.55569)	5.411510 (1.17166)	1.987476	2.673519

Table 5 (Continued)

Sector/market proxy	Whole sample			Down market			Up market			χ^2 on H_0 :	
	α	γ_1	γ_2	α^D	γ_1^D	γ_2^D	α^U	γ_1^U	γ_2^U	$\gamma_1^D = \gamma_1^U$	$\gamma_2^D = \gamma_2^U$
Period 3	.009370*** (36.7300)	.363063*** (8.22307)	2.881050*** (2.67836)	.009762*** (26.3892)	.367331*** (6.17939)	1.620640 (1.24236)	.009246*** (27.5136)	.302570*** (4.56454)	6.448570*** (3.00628)	.554995	3.772790*
<i>World sector index</i>											
Period 1	.012820*** (46.6236)	.330149*** (7.49916)	3.45836** (2.34065)	.012977*** (37.7963)	.324706*** (6.14197)	2.84924* (1.83094)	.012813*** (32.3714)	.295993*** (4.65881)	5.66847** (2.54215)	.120689	1.075673
Period 2	.009293*** (45.5419)	.297843*** (7.02459)	2.752870 (1.49542)	.009211*** (30.0960)	.397771*** (6.63369)	−1.323340 (−.561733)	.009421*** (37.6733)	.205095*** (3.85963)	7.025350*** (2.94287)	5.869993**	6.336499**
Period 3	.009417*** (37.7384)	.360152*** (12.6856)	1.369250*** (3.40521)	.009714*** (27.3184)	.339624*** (10.1764)	1.342670*** (2.97253)	.009220*** (24.3349)	.369890*** (7.22008)	1.707870** (2.23254)	.311876	.187913
National markets											
<i>Average return</i>											
Period 1	.008273*** (43.7620)	.230790*** (4.91098)	8.208200*** (3.58452)	.008468*** (36.4618)	.179043*** (2.92490)	8.574460*** (3.10954)	.008299*** (29.6816)	.179379** (2.40245)	14.871400*** (3.46098)	.000012	1.448362
Period 2	.005406*** (48.4264)	.250645*** (6.71256)	4.381310* (2.03417)	.005629*** (37.9109)	.338045*** (7.83564)	−1.392250 (−.737588)	.005474*** (37.2937)	.080895* (1.65162)	18.956800*** (5.61801)	15.458497***	27.25244***
Period 3	.005986*** (31.5703)	.350778*** (10.0741)	.395813 (.421646)	.006157*** (27.9468)	.382165*** (10.0375)	−1.346090 (−1.43655)	.005973*** (19.6933)	.279931*** (3.94654)	4.043230 (1.46284)	1.652146	3.406668*
<i>World sector index</i>											
Period 1	.009041*** (42.5012)	.235198*** (5.27961)	4.946220*** (3.00701)	.009399*** (32.4241)	.182203*** (3.23649)	5.469740** (2.60166)	.008728*** (30.0601)	.277159*** (4.36091)	5.117220** (2.11919)	1.334041	.012652
Period 2	.005504*** (46.5517)	.293853*** (8.30815)	5.631340*** (2.88695)	.005482*** (32.6956)	.430265*** (8.51711)	−2.767150 (−1.02038)	.005401*** (32.3217)	.250427*** (4.47190)	8.232910** (2.51322)	6.169474**	6.791271***
Period 3	.006327*** (32.1519)	.311050*** (9.97017)	1.342470 (1.64108)	.006484*** (25.3038)	.344762*** (8.47505)	.049568 (.058208)	.006213*** (24.0424)	.277294*** (6.13720)	2.783030** (2.10938)	1.504141	3.592274*

Note: The table presents results for models (4) and (5) estimated over three subsamples of the long sample (06/01/1998–02/01/2012). These subsamples are: subperiod 1 (06 January, 1998 to 03 September, 2002), subperiod 2 (04 September, 2002 to 10 August, 2006), and subperiod 3 (10 August, 2006, to 02 January, 2012). We employ DataStream's daily closing values of indices, denominated in national currencies, for each sector and each the total stock market, at the national and global level (DataStream Global Indices Levels 1 and 2, respectively). Model (4) is: $CSAD_t = \alpha + \gamma_1 |r_{M,t}| + \gamma_2 r_{M,t}^2 + \varepsilon_t$ and model (5) is: $CSAD_t = (\alpha^D + \gamma_1^D |r_{M,t}| + \gamma_2^D r_{M,t}^2)(1 - UP_t) + (\alpha^U + \gamma_1^U |r_{M,t}| + \gamma_2^U r_{M,t}^2)UP_t + \varepsilon_t$, where $CSAD_t = (\sum_{i=1}^n |(r_{i,t} - r_{M,t})|) / n$ measures the cross-sectional absolute dispersion of index returns on day t , with $r_{i,t}$ being the return on stock index from country i at time t and \bar{r}_t the cross-sectional average of n index returns at time t , $r_{M,t}$ stands for a proxy of returns on the relevant market, and $UP_t = 1$ if $r_{M,t} > 0$ and zero otherwise (up and down market, respectively). Two alternative proxies of market returns $r_{M,t}$ are: the average value of index return in each sector, computed over all countries included in the analysis, and the return on the sector-specific global index for each sector. The results obtained using these proxies are reported under 'Average return' and 'World sector index', respectively. Standard errors are heteroskedasticity- and autocorrelation-robust, with t -ratios in parentheses. χ^2 is the Wald test statistic for the Null hypothesis of either $\gamma_1^D = \gamma_1^U$ or $\gamma_2^D = \gamma_2^U$, these parameters being from model (5).

* Significance at 10% level.

** Significance at 5% level.

*** Significance at 1% level.

Table 6
Intertemporal changes in international herding.

		Basic materials			Consumer goods			Financials		
Test for the difference in:		γ_2	γ_2^D	γ_2^U	γ_2	γ_2^D	γ_2^U	γ_2	γ_2^D	γ_2^U
<i>Average return</i>										
Period 2 to 1	t-Value	−0.25133	−0.33427	−1.48803	−0.4301	−2.88164	−0.99217	−2.18243	−3.14213	−0.36771
	p-Value	0.801598	0.73823	0.137002	0.667203	0.004026	0.321312	0.029269	0.001718	0.713154
Period 3 to 2	t-Value	−0.52015	−0.64503	−1.40695	−2.31038	−1.83738	0.257708	0.88409	2.694007	−2.79149
	p-Value	0.603051	0.519029	0.159698	0.021034	0.066399	0.796676	0.376823	0.007157	0.005329
Period 3 to 1	t-Value	−1.43921	−1.53774	−2.74366	−1.78137	−3.13955	−0.21303	−1.35857	−1.1734	−2.50466
	p-Value	0.150348	0.124372	0.006165	0.075102	0.001733	0.831343	0.174534	0.240866	0.012387
<i>World sector index</i>										
Period 2 to 1	t-Value	−0.32241	−1.14164	−0.69068	−0.0785	−0.207	−0.04563	−0.1616	−2.49592	−0.28514
	p-Value	0.747201	0.25383	0.489898	0.937441	0.836041	0.963614	0.871651	0.012695	0.775589
Period 3 to 2	t-Value	−0.39042	−0.00535	−0.45663	−0.19971	−2.50589	−0.18156	−1.00838	1.249512	−2.17408
	p-Value	0.696295	0.995736	0.648022	0.841741	0.012344	0.855958	0.313471	0.211719	0.029892
Period 3 to 1	t-Value	−0.63765	−0.78738	−1.0518	−0.22737	−1.178	−0.19491	−0.95646	−0.43805	−1.59649
	p-Value	0.523823	0.431214	0.2931	0.820171	0.239026	0.845494	0.339031	0.661429	0.110639
Test for the difference in:		Industrials			Oil & gas			National indices		
		γ_2	γ_2^D	γ_2^U	γ_2	γ_2^D	γ_2^U	γ_2	γ_2^D	γ_2^U
<i>Average return</i>										
Period 2 to 1	t-Value	−6.58072	−8.04402	−4.75911	−3.34261	−4.93053	−3.06329	−0.92852	−3.11867	0.619139
	p-Value	<0.0001	<0.0001	<0.0001	0.000855	<0.0001	0.002237	0.353321	0.001859	0.535941
Period 3 to 2	t-Value	−1.62413	2.716406	−4.21614	1.147896	2.597329	0.321416	−1.91849	0.028585	−2.56894
	p-Value	0.104608	0.006693	<0.0001	0.251237	0.009509	0.74795	0.055283	0.9772	0.010319
Period 3 to 1	t-Value	−7.92884	−7.57262	−12.3862	−2.11781	−3.49228	−2.1567	−2.16456	−2.89623	−2.8818
	p-Value	<0.0001	<0.0001	<0.0001	0.034394	0.000496	0.031225	0.030616	0.003844	0.004024
<i>World sector index</i>										
Period 2 to 1	t-Value	0.728872	−1.71014	1.117576	−0.25399	−2.1787	0.348917	0.164356	−2.94743	0.947757
	p-Value	0.46622	0.087494	0.263969	0.799542	0.029546	0.727212	0.869479	0.003265	0.343442
Period 3 to 2	t-Value	−0.89839	0.712697	−1.15703	−0.37203	0.881285	−1.43954	−1.29152	2.755979	−1.66098
	p-Value	0.369157	0.47617	0.247488	0.709935	0.378338	0.150255	0.196768	0.005939	0.096975
Period 3 to 1	t-Value	−0.16793	−0.39848	0.090433	−0.50558	−0.43154	−1.17063	−1.05198	−2.08283	−0.78065
	p-Value	0.866663	0.690344	0.927958	0.613241	0.666154	0.241977	0.293017	0.037475	0.43516

Note: This table presents results of *t*-tests on differences in herding parameters, as reported in Table 4, across three different subperiods. These subsamples are: subperiod 1 (06 January, 1998 to 03 September, 2002), subperiod 2 (04 September, 2002 to 10 August, 2006), and subperiod 3 (10 August, 2006, to 02 January, 2012). The herding parameters are: γ_2 in model (4) and γ_2^D and γ_2^U in model (5). Model (4) is: $CSAD_t = \alpha + \gamma_1 |r_{M,t}| + \gamma_2 r_{M,t}^2 + \varepsilon_t$ and model (5) is: $CSAD_t = (\alpha^D + \gamma_1^D |r_{M,t}| + \gamma_2^D r_{M,t}^2)(1 - UP_t) + (\alpha^U + \gamma_1^U |r_{M,t}| + \gamma_2^U r_{M,t}^2)UP_t + \varepsilon_t$, where $CSAD_t = \left(\sum_{i=1}^n |r_{i,t} - r_{M,t}| \right) / n$ measures the cross-sectional absolute dispersion of index returns on day *t*, with $r_{i,t}$ being the return on stock index from country *i* at time *t* and \bar{r}_t the cross-sectional average of *n* index returns at time *t*, $r_{M,t}$ stands for a proxy of returns on the relevant market, and $UP_t = 1$ if $r_{M,t} > 0$ and zero otherwise (up and down market, respectively). Two alternative proxies of market returns $r_{M,t}$ are: the average value of index return in each sector, computed over all countries included in the analysis, and the return on the sector-specific global index for each sector. The results obtained using these proxies are reported under 'Average return' and 'World sector index', respectively.

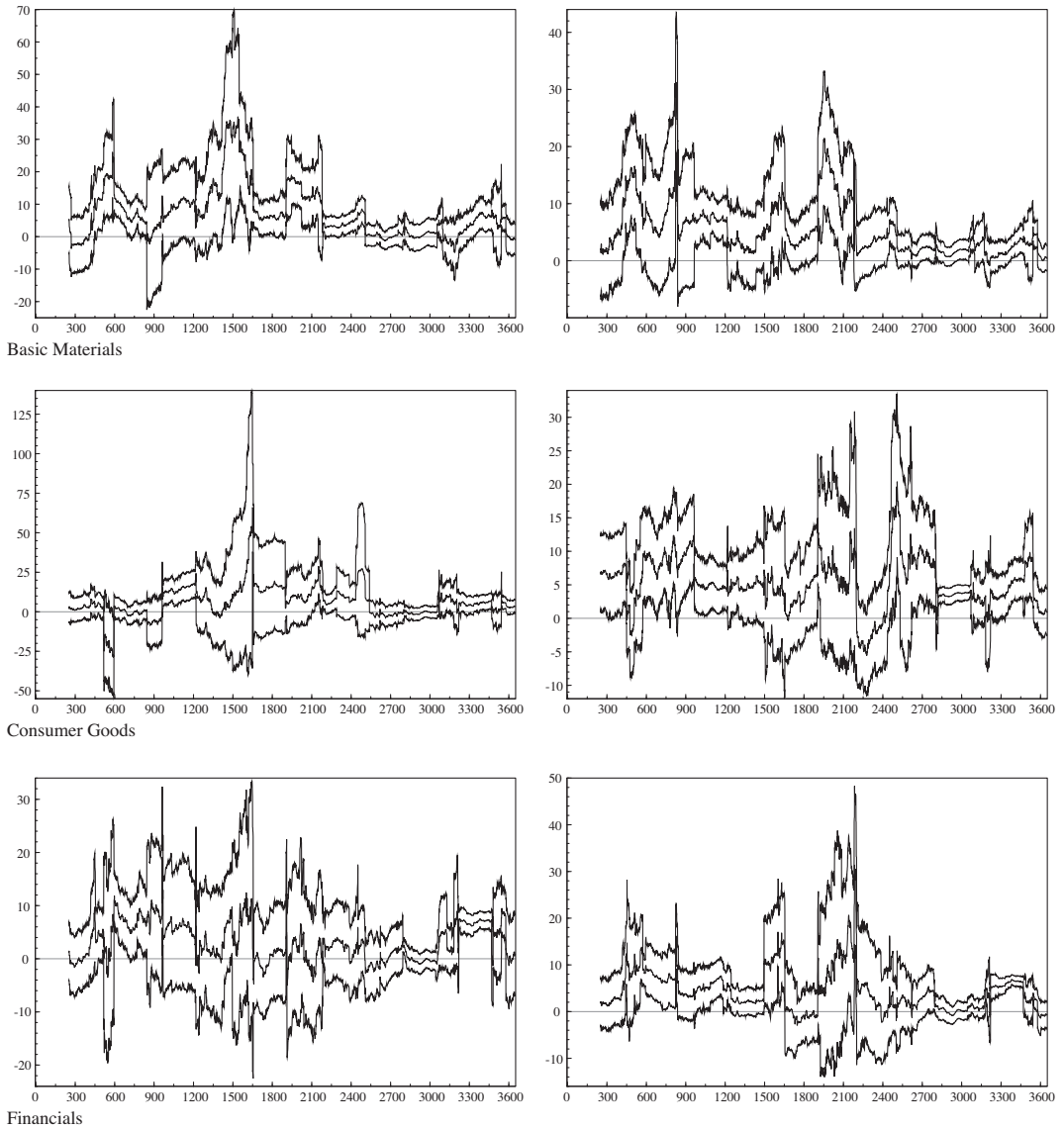


Fig. 3. Moving window estimates of the herding coefficient γ_2 . *Note:* Moving-window estimates of the herding parameter γ_2 from model (4) are represented by solid lines, with market proxy being the average return across all included countries for the relevant sector (left-hand side figures) or with the world-wide sector-specific index used as a proxy for the market (left-hand side figures). Dotted lines represent the upper and lower band of the 95% confidence interval for the estimated γ_2 , computed based on standard errors which are heteroscedasticity- and autocorrelation-consistent. Time varying estimates were obtained from moving-window estimations of model (4), with the window size of 250 days and step-size of one day.

the last and the first subperiod, all sectors and the national indices show a significant decline in the herding parameter over time. Given that, on average over the whole sample, the herding coefficient is positive, its decline means a movement towards the level of cross-sectional return dispersion implied by the rational asset pricing models, i.e., a decline in irrationality.

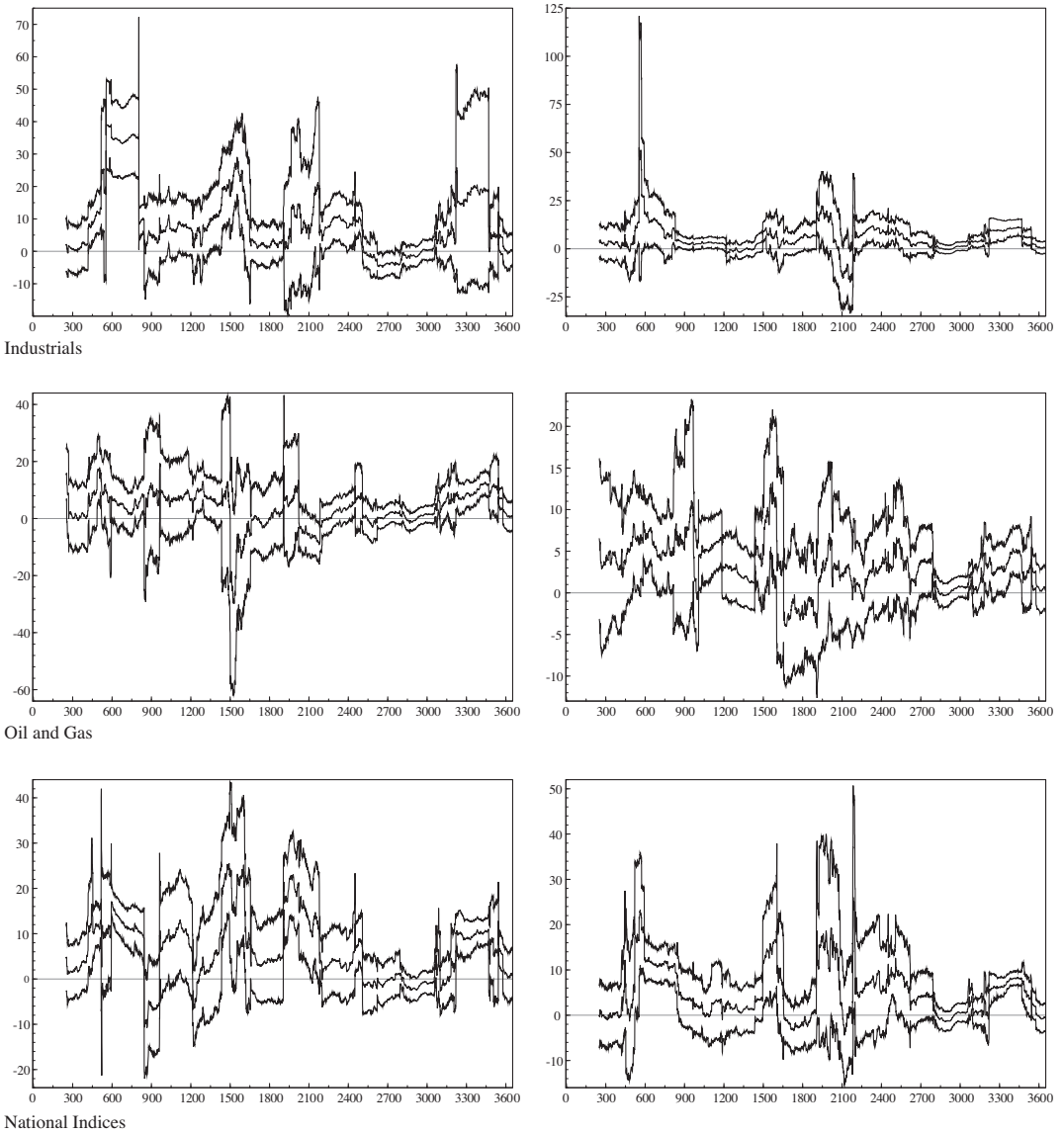


Fig. 3. (Continued).

5. Summary, discussion and conclusions

This paper is the first one to investigate the existence of international herding by utilising the information conveyed in the dispersion of index returns across countries, a method proposed by [Christie and Huang \(1995\)](#) and [Chang et al. \(2000\)](#). When we focus on the behaviour of national indices, there is virtually no evidence of deviations from the return dispersion levels dictated by the equilibrium pricing models such as the CAPM. That is to say, herding does not seem to take place internationally. However, when national indices are disaggregated and different economic sectors (industries) considered separately, some irrational price behaviour on a global scale appears to be

present, mostly for basic materials, consumer services and oil and gas stocks world-wide. These results are robust against changes in estimation methods and model specifications. The deviations from the rational level of cross-country return dispersion are more pronounced in up rather than down markets, and diminish over time.

In addition to unveiling cross-country irrationality in price behaviour on industry level, another interesting finding is the nature of this phenomenon. Previous studies on national markets mostly find, or exclusively emphasise, the existence of market-wide information cascades leading to herding during market distress: investors dismiss their private beliefs and follow the market in their asset valuation and trades, which leads to an excessive similarity of price movements and a reduction in cross-asset return dispersion. However, our study of index returns across countries reveals an opposite pattern: asset prices in different countries become excessively dissimilar to each other, despite sharing common fundamentals. This may be indicative of localised herding: as a herd of investors moves into (and out of) a set of countries, they bid the prices up on their target market, causing excessive dispersion in returns internationally. Other reasons include investor overconfidence and excessive flight to fundamentals at times of uncertainty.

Our findings contribute to the existing body of evidence on herding in a number of ways. Firstly, the national studies based on transaction data (reviewed in Section 2.1) gave indecisive picture of whether investors move into and out of positions in a herd-like manner. Our results of “negative herding” indicate that this indeed may be happening in international markets. Secondly, whereas most studies measuring the return dispersion on national markets (reviewed in Section 2.1) find it too low and interpret it as evidence of market-wide information cascades, our study unveils an opposite effect on international markets, at least for some sectors: returns are excessively different from each other, which is in line with localised, as oppose to market-wide, herding. Thirdly, the link between herding and contagion is not well established in the existing literature (Section 2.3). Some of our results (negative herding in some sectors) are in line with excessive flight to quality, a type of investor behaviour which could generate financial contagion. However, this would be observed only in some sectors, but not on the level of market indices.

The finding of irrational pricing patterns, potentially indicative of herding, apparent in some sectors but not on the level of market indices, could explain why the literature on financial crisis and herding is not conclusive. Namely, if the dataset utilised in any given paper over-represents industries more prone to herding, the latter will be more likely to be reported. Investment concentration on selected sectors rather than cross-sector diversification is in line the predictions of [Acharya and Yorulmazer \(2008\)](#), as investors may be trying to avoid information contagion. If our results were to be interpreted as evidence of herding away from the market, it would be in line with the theoretical model by [Cipriani and Guarino \(2008\)](#) and results in [Fazio et al. \(2003\)](#), as well as in [Kaminsky et al. \(2004\)](#) and [Economou et al. \(2011\)](#) who report herding away from the US market. Contrary to [Calvo and Mendoza's \(2000\)](#) prediction, an increasing number of investible markets over time did not result in greater herding, as we observe a movement of the cross-country return pattern towards its rational level, not away from it.

The fact that most herding is found in basic materials, consumer services and oil and gas is somehow surprising. After all, the literature maintains that herding is most severe when the quality and quantity of information is poor ([Hwang and Salmon, 2004](#); [Kremer and Nautz, forthcoming](#)). Therefore, one would expect herding to take place in new and rapidly growing industries featuring high levels of information asymmetry, volatility and uncertainty, such as ICT or financial stocks. On the other hand, empirical results reported in [Zhou and Lai \(2009\)](#) for transaction-level data on stocks traded in Hong Kong are in line with ours: herding is found to be least severe in IT, industrial goods and utilities. However, despite evidence that investor irrationality is most pronounced during financial crises (e.g., [Chiang and Zheng, 2010](#); [Kremer and Nautz, forthcoming](#)), our results show that deviations from the rational return patterns were lower, not higher, in the subperiod covering the recent financial turmoil.

What are the implications of the existence of herding in some industries for international investors? [Demirer et al. \(2010\)](#) point out that, because the cross-sectional return dispersion is related to idiosyncratic risk (see [Garcia et al., 2011](#), and the literature reviewed therein), evidence of herding within a given set of assets (especially of “negative herding”, i.e., excessive return dispersion) signals the existence of diversifiable risk and, for investors only holding these assets, insufficient diversification. For

instance, a portfolio comprising of stocks in the basic materials sector from around the globe would expose its holder to idiosyncratic risk, as our results show significant excessive deviations of index returns in this sector from the rational pattern implied by the CAPM. For the policy makers, the finding of no herding on the level of national indices world-wide implies that fears of financial contagions caused by irrational investors herding in and out of countries and destabilising local stock markets may be exaggerated. Herding does seem to exist in some sectors; however, devising a policy to tame irrationality-driven investment in only a subset of stocks may prove difficult. If there is no damage by herding on the level of national markets, the best policy may be to refrain from regulating herding in selected industries; this would help to avoid inevitable responses from the market participants (regulatory arbitrage) which would potentially lead to suboptimal asset allocation, increased transaction costs and could damage the market efficiency even further.

Lastly, the finding of no international herding on the level of national indices and in most sectors yields some support for the efficient market hypothesis. For those sectors where excessive return dispersion is observed, however, potential reasons include negative herding, excessive flight to quality, and investor overconfidence, and point towards market inefficiency, as stock prices seem to be systematically driven by factors other than the market risk. However, accounting for risk characteristics with a simple market model may be too simplistic and omitting relevant factors, hence the finding of excessive return dispersion could be due to model failure rather than irrationality of investors. This issue deserves to be investigated in future research.

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