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Herding in financial markets: a review of the literature
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Abstract

Purpose – The purpose of this paper is to provide a review of theory and empirical evidence on herding behavior in financial markets.
Design/methodology/approach – Review and discussion of the literature.
Findings – More than two decades of empirical and theoretical research have provided a significant insight on investor herding behavior.
Research limitations/implications – The discussion indicates that there are still open issues and areas with inconclusive evidence, e.g. the author knows relatively little for markets other than equity markets.
Practical implications – The paper may need empirical methodologies to evaluate herding that address current limitations.
Originality/value – The paper reviews recent empirical evidence and identifies open issues for future research.

Keywords Herding, Analyst recommendations, Institutional investors
Paper type Literature review

> There's plenty of herd behavior in the market (Olli Rehn, European Union Economic and Monetary Affairs Commissioner, commenting on the Irish aid-package during the European debt crisis[1]).

1. Introduction

The notion of herding is met in very different settings from neurology and zoology, to sociology, psychology, economics and finance. Generally speaking, in economics and finance with the term herding or herd behavior we mean the process where economic agents are imitating each other actions and/or base their decisions upon the actions of others. For example, it may be a group of market participants who trade in the same direction during the same time (Nofsinger and Sias, 1999), investors who ignore their initial assessment and trade by following the trend in the previous trade (Avery and Zemsky, 1998), mutual imitation (Welch, 2000), excessive agreement in analyst predictions (DeBondt and Forbes, 1999), a behavior converge to the average (Hirshleifer and Teoh, 2003), a form of correlated behavior (Hwang and Salmon, 2004), a group of investors following each other into (out of) the same securities (Sias, 2004), among other similar descriptions.

The reasons behind this behavior may be diverse. As the discussion below suggests, market participants may infer information from the actions of previous participants, investors may react to the arrival of fundamental information, analysts may herd in order to protect reputation, institutional investors may herd for reasons

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related to remuneration, investors may simply be irrational and herd behavior can arise as the consequence of psychological and/or social conventions. It has been argued that herding may result in efficient outcomes; however, some economists suggest that it may destabilize prices and lead to bubble-like episodes in financial markets.

It is usually assumed, predominantly by the press, that herd behavior is widespread among institutional and individual investors and is often cited as the main reason behind periods of extreme volatility and market instability. Consider, for instance, the period during November 2010 where a major sell-off of European bonds by international investors drove the Spanish ten-year yield spreads to 5.35 percent (the highest level since 2002), the Portuguese spreads to 7.23 percent, and the Irish spreads to 9.42 percent (the euro also experienced a significant decline). The quote mentioned above suggests that economic agents, such as the European Union Economic and Monetary Affairs Commissioner, consider herd behavior by investors as (partly) responsible for the market turmoil. Note, however, that despite popular beliefs that herding is a widespread behavior the available empirical evidence is not conclusive. As Welch (2000) points out: "Herding in financial markets, in particular, is often presumed to be pervasive, even though the extant empirical evidence is surprisingly sparse" (p. 370).

The aim of this paper is to provide a brief review of theory and empirical evidence on herding behavior in financial markets and identify open issues and limitations in the literature. Many issues emerge from the discussion. First, the theoretical models proposed to explain herding behavior in financial markets may be divided in two main classes: models that assume rational or near rational agents and models that assume non-rational behavior. There is a relative gap in the literature for theoretical models that allow for an interplay between sources of herding. At the same time many models yield implications that are difficult to evaluate empirically with existing databases. Second, the empirical evidence is inconclusive. For example, while many important studies find limited evidence of institutional investor herding other studies come to opposite conclusions; or in contrast to a number of studies that report evidence consistent with analyst herding for various reasons, the findings of more recent studies indicate that analysts "anti-herd." Third, the main empirical methodologies to measure herding have limitations that may not allow economists to fully understand the process of herding.

Some of the issues that need to be addressed by future empirical studies have to do with measuring the intensity of herd behavior (e.g. existing studies often neglect the volume of trading), with the "identity" of institutional herders (is it the same funds that herd over time?), with the stability of the sources of herding over time (do the same people herd for the same reason over time?), and with the building of suitable databases or with designing methodologies that do not require access to information that may not be readily available. Also, an important issue that needs to be more adequately addressed is what drives herd behavior. Bikhchandani and Sharma (2000) distinguish between "spurious herding" where investors take similar decisions because they face similar information sets and react to the same changes in fundamental factors, and "intentional herding" where investors copy each others actions whith intent; e.g. in informational cascades or in order to preserve reputation and protect renumeration. Finally, we know (comparatively) little about investor herding behavior in markets other than the major equity markets (e.g. emerging equity markets, energy markets, commodity markets, etc.).

Note that it is beyond the scope of this paper to discuss herding issues in contexts other than that related to financial markets (e.g. social herding or results from other human sciences) and that the review is not meant to be exhaustive but cover some of the most important breakthrough results and significant issues. The rest of the paper is organized as follows. Section 2 discusses theories of herding, Section 3 presents commonly used metrics for herding in the empirical literature; Sections 4 and 5 present empirical evidence on institutional investor herding and herding toward the market consensus, respectively; Section 6 reviews the evidence on analyst herding. Section 7 concludes the paper and discusses open issues and limitations in the empirical examination of herding behavior.

2. Why do people herd? Theories of herding

Is herd behavior rational? Some authors argue that under certain circumstances herding is a rational choice[2]. For instance, money managers may mimic the actions of other money managers in order to preserve reputation and/or compensation, younger analysts know that if they make bold forecasts and deviate from the consensus they are more likely to be fired, during a bank crisis depositors contribute to runs on banks because they see long lines of other depositors outside banks and know that if they do not join the line early there may be no funds left for them, etc. (on bank runs see Diamond and Dybvig, 1983). Bikhchandani and Sharma (2000) distinguish between "spurious" herding where investors face a similar fundamental-driven information set and thus make similar decisions and "intentional" herding where investors have an intention to copy the behavior of others. The former may lead to an efficient outcome while the latter may not (intentional herding may also lead to fragile markets, excess volatility and systemic risk).

Scharfstein and Stein (1990) argue that reputation concerns in labor markets with no perfect information and a need to share the blame when things go bad may lead managers to follow each other's actions[3]. Scharfstein and Stein present a learning model where the labor market is able to update its understanding of the manager's ability from the investment decisions a manager is making. Thus, manager concern for labor market reputation may lead to rational (but socially inefficient) herd behavior, i.e. managers may ignore significant private information and follow the decisions of other managers. In other words, herding may be viewed as insurance against manager underperformance (Rajan, 2006). In Trueman (1994) the perception of analyst abilities affects analyst compensation. Trueman's theoretical model indicates that the earnings forecasts of analysts do not necessarily reflect in an unbiased manner their private information, but rather there is a tendency to release forecasts closer to prior earnings expectations. Furthermore, analysts also tend to forecast earnings similar to those previously announced by other analysts in an effort to copy higher ability and obtain higher compensation, even when private analyst information does not justify this behavior. Graham (1999) develops a model where analysts are more likely to herd when they are characterized by high reputation or low ability (e.g. high reputation analysts have greater incentives to hide in the consensus in order to protect their reputation), when there is strong public information inconsistent with analyst private information, and when private information signals across analysts exhibit positive correlation.

In addittion, herd behavior can be a rational choice if investors do not have long horizons. For example, Froot *et al.* (1992) show that if speculators have short horizons they may herd on the same information trying to learn what other informed investors

know. Their model allows for some speculators to have short trading horizons, which implies that they may allocate research resources in a non-optimal way. This may violate informational efficiency (although at the pricing stage the market may be efficient) in the sense that investors may have the tendency to concentrate on one information source (that may be of poor quality or have no relation to fundamentals) rather than employ a diverse set of information sources. As a growing number of speculators acquire this information it will be disseminated in the market and thus it is profitable to acquire this information at an early stage (positive informational spillovers); in their model there may be multiple herding equilibria.

The implication of informational cascades models is similar. An informational cascade takes place when it is optimal for individuals to follow the observable actions of individuals before them, disregarding their own information (Bikhchandani *et al.*, 1992). For example, for investors that enter the market at a later stage it may be an optimal decision to ignore their own private information and mimic the trading behavior of previous investors since they may infer that previous investors possess private information. Informational cascades may have an influence over perfectly rational individuals and lead to the creation of bubbles. A decision model where it is rational for decision makers to look at the decisions made by previous decision makers since previous decision makers may possess related information that is important is analyzed by Banerjee (1992). The analysis also indicates that the decision rules chosen by optimizing individuals will lead them to do what other individuals are doing instead of employing their own information. A general sequential choice model where a decision maker will act only on the information obtained from previous decisions ignoring private information (as will later decision makers) is discussed by Bikhchandani *et al.* (1992), who argue that, irrespective of the social desirability of the outcome, the reasoning may be entirely rational (see also, Welch, 1992). Note that informational cascades may be linked with partial or complete information aggregation blockages, increased fragility to even small informational shocks, fads and stampedes (Hirshleifer and Teoh, 2003; among others).

In related work, within an experimental research context, Avery and Zemsky (1998) find that herding in the form of an informational cascade is not possible, if simple information structures and a price mechanism are assumed. In case of complicated information structures, however, herding is possible and it may affect asset prices only when the market is uncertain for both the asset value and the information of the average trader. In a laboratory experiment, Cipriani and Guarino (2005) study herding in financial markets and their results are in line with the results of Avery and Zemsky, i.e. when the subjects are trading for informational reasons in a frictionless market herding occurs rarely, although in some cases they observe that subjects follow a contrarian strategy or choose to ignore private information. In an internet experiment with a large number of subjects Drehmann *et al.* (2005) test informational cascades in financial markets and find that herding of this form is not possible in the existence of a flexible market price.

Other authors suggest that investors (or a subset of) are irrational and that the existence of such irrational investors may give rise to bubble-like phenomena and herd behavior. Furthermore, non-rational herd behavior can arise as the consequence of psychological stimuli and restraints, such as pressure from social circles and/or social conventions. For instance, Keynes (1936) argues that investors are affected by sociological factors (e.g. social conventions) that may drive market participants to imitate the actions of others during periods of uncertainty. Baddeley *et al.* (2004)

demonstrate that even experts may resort to herd behavior, given information scarcity, asymmetry and the employment of common heuristic rules.

Other authors, such as Shleifer and Summers (1990), distinguish between arbitrageurs who are fully rational and noise traders (Black, 1986), i.e. irrational investors who act on noise and whose trading behavior suffers from systematic biases. They suggest that some shifts in investor demand for assets and changes in investor sentiment appear to be irrational and not justified by fundamentals, e.g. investors' reaction to pseudo-signals such as advice by "financial gurus." Consider for instance (Shleifer and Summers, 1990) the case where a fraction of investors follows trends. Arbitrageurs, instead of opposing this bandwagon, rationally decide to jump on it. The new higher demand will lead prices even higher and further away from fundamentals, attract more irrational investors, and the rational arbitragers will exit when prices are near the top in order to collect their profits. In other words, the behavior of rational arbitragers, in the short run, will nourish the irrational price bubble. It is interesting to note that irrational noise traders with (unpredictable) inaccurate stochastic expectations may not only affect asset prices but also end up achieving superior returns (for a more detailed discussion see also, DeLong *et al.*, 1990, 1991).

Furthermore, many economists present formal models on how investor sentiment may affect investor trading patterns and behavior and lead to systematic asset misspricings. For instance, Barberis *et al.* (1998) suggest a model of investor sentiment that predicts investor overreaction and/or underreaction to information. Their results are consistent with empirical evidence on the shortcomings of personal judgment under uncertainty. Hong and Stein (1999) propose a theory with two type of boundedly rational market participants. In this model, short-run price underreaction is due to slow information dissemination that is exploited by momentum traders which, in turn, leads to long-term overreaction. Daniel *et al.* (1998) suggest that investors are overconfident regarding their private information and suffer from biased self-attribution. These bisases lead to autocorrelations, excess volatility and return predictability.

Judgments may also be biased, within sequential choice framework models, when people make conjectures regarding observed decisions by previous decision makers while ignoring the influence of non-salient aspects of such decisions (see Simonsohn and Ariely, 2008). In addittion, the bias will be very harmful if these non-salient aspects were indeed relevant for earlier decision makers but are irrelevant for present decison makers. In this case, people may mimic irrelevant decisions. For instance, investors may incorrectly imitate the investment decisions of previous investors which were driven by idiosyncratic rebalancing needs. Such non-rational herd behavior can lead to sub-optimal decisions. In addittion, rational agents may manipulate the environment of early decision makers, seeking to indirectly inuence the decisions of observers[4]. Simonsohn and Ariely use bid data for DVD auctions from eBay and their evidence supports the view of herd behavior behind non-diagnostic decisions.

3. Measuring herding in financial markets

How is herd behavior measured in empirical studies? Generally speaking, we can classify empirical methodologies into two main categories: studies that rely on micro-data or proprietary data and investigate whether specific investor types herd, and studies that rely on aggregate price and market activity data and investigate herding toward the market consensus. We present two of the most commonly used measures of the former first (Lakonishok *et al.*, 1992; Sias, 2004) and then proceed with a discussion

of two of the most commonly used measures the latter (Christie and Huang, 1995; Chang *et al.*, 2000).

A common metric of institutional investor herding behavior is the one proposed by Lakonishok *et al.* (1992; LSV hereafter)[5]. The notion behind the LSV measure is straightforward: if there is a tendency of money managers to disproportionately buy (sell) an individual stock (i.e. end up on the same side of the market) then it can be concluded that there is herding at the level of individual stocks. They compute herding as the proportion of net buyers (money managers who increase their holdings in a stock during a given quarter) relative to the total money managers who trade that stock minus an adjustment factor that declines as the number of money managers active in that stock rises. If no herding exists the expected value of this metric should not vary from period to period; in the presence of herding there should be significant cross-sectional variation in this measure. The LSV herding measure, H, is calculated as:

$$H(i) = |B(i)/(B(i) + S(i)) - p(t)| - AF(i) \tag{1}$$

In (1), $B(i)$ is the number of money managers who are net buyers, $S(i)$ is the number of money managers who are net sellers (i.e. decrease their holdings), $p(t)$ is the expected proportion of money managers buying in that quarter relative to the number active, and the adjustment factor, $AF(i)$, is the expected value of $|B/(B+S)-p|$ under the null hypothesis of no herding. LSV point out that, for any stock, AF declines as the number of money managers active in that stock rises (Lakonishok *et al.*, 1992, pp. 29-30).

In the same spirit, Sias (2004) argues that the proportion of institutional investors buying this quarter will covary (across assets) with the proportion of institutional investors buying last quarter, if institutional investors herd or follow their own trades into and out of the same securities; thus, herding can be evaluated by estimating the cross-sectional correlation between demand for an asset by institutional investors last quarter and demand for the asset by institutional investors this quarter. Sias starts by estimating every institutional investor's position in every asset as a fraction of the asset's shares outstanding at both the beginning and the end of each quarter. If an institutional investor increases (decreases) ownership in the stock this investor is defined as a buyer (seller). Then for each stock quarter the portion of investors that are buyers is estimated. This ratio is denoted as the "raw fraction of institutions buying" and is estimated as in the following equation:

$$Raw\Delta_{k,t} = \frac{BI_{k,t}}{BI_{k,t} + SI_{k,t}} \tag{2}$$

In (2) BI is the number of institutions buying asset k during quarter t, and SI is the number of institutions selling asset k during quarter t. In order to allow aggregation over time and comparison for different market capitalizations and investor types, Sias standardizes the fraction of institutional investors buying asset k in quarter t as follows:

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

Next the following cross-sectional regression (4) is evaluated as follows:

$$\Delta_{k,t} = \beta_t \Delta_{k,t-1} + \varepsilon_{k,t} \tag{4}$$

The idea here is that "If institutional investors follow each other into and out of the same securities (herd), or if individual institutional investors follow their own last-quarter trades, then the fraction of institutions buying in the current quarter will be positively correlated with the fraction of institutions buying in the previous quarter" (Sias, 2004, p. 172). As Sias points out, the key difference between the LSV and the Sias measure is that while the former tests indirectly for cross-sectional temporal dependence within periods, the latter is a direct test of whether institutional investors follow each other's trades during the following periods.

A different approach is suggested by Christie and Huang (1995, CH hereafter), who propose a metric that measures investor herding toward the market consensus. They argue that during periods of extreme market movements investors are most likely to suppress their own beliefs and follow the market consensus. In this case returns will not deviate too far from the market return and thus return dispersions should be relatively low; when stocks sensitivity toward the market is different rational asset pricing suggests that dispersions will increase. Their approach starts with the estimation of cross-sectional standard deviation (CSSD) as a metric of herd behavior, which is calculated as:

$$CSSD_t = \sqrt{\frac{\sum_{i=1}^{N} \left(R_{i,t} - R_{\mathrm{m},t}\right)^2}{N-1}} \tag{5}$$

In (5), $R_{i,t}$ is the observed asset return on asset i at time t, and $R_{m,t}$ is the cross-sectional average of the N asset returns in the aggregate market portfolio at time t. In other words, the CH metric captures the particular asset return closeness to the realized average. CH then employ the following regression in order to examine whether the dispersion of returns is significantly lower during periods of extreme market movements:

$$CSSD_t = \alpha + \beta^{\mathrm{L}} D_t^{\mathrm{L}} + \beta^{\mathrm{U}} D_t^{\mathrm{U}} + \varepsilon_t \tag{6}$$

In (6), D_t^{L} is a dummy variable that takes the value of 1 if the market return on day t is positioned in the extreme lower tail of the distribution and the value of 0 otherwise, D_t^{U} is a dummy variable that takes the value of 1 if the market return on day t is positioned in the extreme upper tail of the distribution and the value of 0 otherwise, and α is a constant term. The use of the dummy variable approach allows the identification of differences in the behavior of investors in extreme positive and negative market conditions against normal market conditions. According to CH, rational asset pricing implies positive coefficients on the dummy variables during periods of extreme market conditions, while statistically significant and negative coefficients may suggest that investors herd during extreme market conditions. A comparable methodology is proposed by Hwang and Salmon (2004) who employ the cross-sectional dispersion of asset sensitivity to various fundamental factors rather than asset returns. This measure can discriminate between price adjustments to information about fundamentals from herding behavior due to shifts in market sentiment.

A methodology similar in spirit to the CH approach is proposed by Chang *et al.* (2000, CCK hereafter). They argue that if investors tend to follow aggregate market behavior during periods of large average price movements, then the linear and increasing relation between dispersion and market return will no longer hold and it can become non-linearly increasing or even decreasing. Thus, they utilize a non-linear regression specification to estimate the relation between the cross-sectional absolute deviation of returns and the market return. They start with the conditional version of the Black (1972) CAPM to define the expected cross-sectional absolute deviation of stock returns (ECSAD) in period t as follows:

$$ECSAD_t = \frac{1}{N}\sum_{i=1}^{N} |\beta_t - \beta_{\mathrm{m}}| E_t(R_{\mathrm{m}} - \gamma_0) \tag{7}$$

In (7), R_{m} is the return on the market portfolio, γ_0 is return on the zero-β portfolio, β_{m} is the systematic risk of an equally weighted market portfolio, and β_i is the systematic risk on any asset i. CCK then demonstrate (Chang *et al.*, 2000, p. 1656) that the increasing and linear relation between dispersion and time-varying market expected returns is:

$$\frac{\partial ECSAD_t}{\partial E_t(R_{\mathrm{m}})} = \frac{1}{n}\sum_{i=1}^{N} |\beta_i - \beta_{\mathrm{m}}| > 0 \tag{8}$$

$$\frac{\partial^2 ECSAD_t}{\partial E_t(R_{\mathrm{m}})^2} = 0 \tag{9}$$

Based on (8) and (9) they propose a test of herding behavior that also requires a parameter to capture any possible non-linearity in the relation between asset return dispersions and the market return. CCK use the cross-sectional absolute deviation at time t ($CSAD_t$) in order to proxy for the unobservable $ECSAD_t$. CSAD is estimated as the average absolute value of deviation (AVD) of each stock relative to the return of the equally weighted market portfolio. The notion behind this approach is that if herding is present during periods of extreme market conditions then there should be a less than proportional increase (or even decrease) in the CSAD measure. Note here that CSAD is not used as a metric for herding: herding is identified through the relationship between CSAD and the market return. CCK then run the following regressions (10) and (11) in order to examine whether the degree of herding behavior is asymmetric in rising (UP) and falling (DOWN) markets:

$$CSAD_t^{\mathrm{UP}} = \alpha + \gamma_1^{\mathrm{UP}} |R_{\mathrm{m},t}^{\mathrm{UP}}| + \gamma_2^{\mathrm{UP}} \left(R_{\mathrm{m},t}^{\mathrm{UP}}\right)^2 + \in_t \tag{10}$$

$$CSAD_t^{\mathrm{DOWN}} = \alpha + \gamma_1^{\mathrm{DOWN}} |R_{\mathrm{m},t}^{\mathrm{DOWN}}| + \gamma_2^{\mathrm{DOWN}} \left(R_{\mathrm{m},t}^{\mathrm{DOWN}}\right)^2 + \in_t \tag{11}$$

If during periods of extreme market conditions investors tend to herd toward the market a negative non-linear relation between CSAD and the average market return should exist which is captured by the coefficient on the non-linear term.

4. Herding in financial markets: institutional investor herding

In their important early study, Lakonishok *et al.* (1992) use US data on 769 tax-exempt funds and the LSV measure to examine herding and positive-feedback trading and find that pension fund managers do not strongly engage in either herding or positive-feedback trading, although they do find some evidence of herding for smaller stocks (with no destabilizing effect on stock prices). Grinblatt *et al.* (1995) examine the US mutual fund industry for momentum and herding behavior, using the LSV herding measure, and find evidence consistent with momentum but not herding. Wermers (1999) also finds little evidence of herding by US mutual funds in the average stock; however, the results suggest a much higher level of herding in trades of small stocks and in trading by growth-oriented funds. In other words the early evidence only weakly supports the notion that funds tend to buy and sell the same stocks at the same time. Note, however, that Nofsinger and Sias (1999) find a positive relation between annual changes in institutional ownership and returns in the US markets. This, they suggest, may be due to either higher positive-feedback trading of institutional investors compared to individual investors or due to the higher impact on prices of institutional herding compared to individual investor herding. They find evidence that both factors play a role in explaining the relation.

More recently, Sias (2004) finds that institutional investors tend to follow each other in buying and selling the same securities and their own lag trades and that they tend to follow momentum strategies, although little of their herding results from momentum trading. Also there is no evidence that institutional herding drives prices away from fundamental values. Sias argues that the results are most consistent with the hypothesis that institutions herd as a result of inferring information from each other's trades. The US institutional herding in the American Depositary Receipt (ADR) market is studied by Li and Yung (2004) who find a significant positive relation between changes in institutional ownership and ADR returns that persists even after they control for momentum. Strong empirical evidence of US institutional industry herding is reported by Choi and Sias (2009): there is a cross-sectional correlation between the fraction of institutional traders buying an industry one quarter and the fraction buying the previous quarter of, on average, 39 percent. They also show that institutional industry herding stems from managers' decisions, is behind institutional industry momentum trading, is more pronounced in smaller and more volatile industries, and may drive industry market values away from fundamentals. Gutierrez and Kelley (2008) point out that institutional purchase may have a more permanent effect than institutional sells, since the former may be motivated by information about intrinsic stock values while the later may be driven by liquidity needs. They use data between 1980 and 2005 and a herding measure that is based on the LSV measure to find that prices are destabilized by buy herds and stabilized by sell herds.

Other studies examine institutional investor herding in non-US markets and the results indicate that in smaller markets herding may be more prevalent. For example, Wylie (2005) finds that there is only a modest amount of UK equity fund manager herding and only for extreme capitalization individual stocks, with little herding detected for other capitalizations or stocks aggregated by industry, while Kim and Nofsinger (2005) find a lower level of institutional herding in Japan than the USA. This seems to depend on economic conditions and the regulatory environment, while herding appears to have a more significant impact on price movements. Similar results on the impact of herding on stock prices in Japan are reported by Iihara *et al.* (2001) who use the yearly change in ownership as a proxy for investor herding. They also find

that both institutional and foreign investors herd. Chang and Dong (2006) show that in Japan both institutional herding and firm earnings are positively related to idiosyncratic volatility. Walter and Weber (2006) find evidence of herding and positive-feedback trading by German mutual fund managers, with a significant portion of herding being related to spurious herding as a consequence of changes in benchmark index composition.

In a study that examines Polish pension fund managers Voronkova and Bohl (2005) show that managers are to a greater extent involved in herding and positive feedback trading than managers in mature markets. Order flow data are used by Chang (2010) in order to examine the behavior of qualified foreign institutional investors in emerging markets and finds that when they increase (decrease) their investments in particular sectors other market participants such as margin traders and mutual funds follow the same action during the same and subsequent periods. Chang argues that this behavior can be destabilizing since asset prices initially overshoot and later revert. Bowe and Domuta (2004) use data from the Jakarta Stock Exchange to investigate the investment patterns of foreign and domestic investors for evidence of herding and positive feedback during the 1997 Asian crisis, They find that both foreign and domestic investors herd with the former herding more than the later especially after the crisis; they further argue that herding does not destabilize the market. The Korean market is examined by Choea *et al.* (1999) who employ order and trade data between 1996 and 1997 and find significant evidence of evidence of herding (and positive feedback trading) by foreign investors before the crisis. As Bowe and Domuta for Indonesia, they report no evidence that trades by foreign investors have a destabilizing effect on Korea's stock market. Recently, Holmes *et al.* (2013) employ the Sias (2004) methodology and monthly institutional holdings data for Portugal and find evidence of herding; further analysis under different market conditions indicates that institutional herding is intentional rather than spurious and due to reputational reasons.

There is also evidence to indicate that hedge fund managers may herd. For example, Brunnermeier and Nagel (2004) examine the portfolio holdings of hedge funds during the sharp rise in the prices of NASDAQ stocks (1998-2000) and their findings are consistent with the notion that these sophisticated institutional investors intentionally chose to ride the technology stock bubble capitalizing on the predictability of investor sentiment and the limits to arbitrage; in addition, they report that hedge funds decreased their exposure before the collapse in prices. The findings of Fung and Hsieh (2000) indicate that hedge fund trading is significant and may impact market prices during some episodes of market volatility (e.g. ERM crisis in 1992) but not others (e.g. the Peso crisis in 1994). Overall, however, they report no evidence that hedge funds intentionally lead other investors to herd in similar trades. Brealey and Kaplanis (2001) do find evidence on hedge fund herding in currency and emerging market funds, however, their tests cannot clearly indicate whether this herding behavior is more significant than for other types of funds. The results of other studies (Boyson, 2010) indicate that for senior hedge fund managers that diverge from the industry average the probability of failure increases significantly. Boyson uses different herding proxies and the results indicate that herding is more prevalent among more experienced fund managers, consistent with Graham (1999). Boyd *et al.* (2010) find similar levels of herding among hedge funds and floor market participants in US futures markets. They argue that reasonable herding levels by hedge funds tend to stabilize futures prices.

The discussion so far has concentrated on institutional investor herding. Note, however, that there is also evidence to indicate that individual (small) investors herd as

well. For example, Kim and Wei (1999) study the behavior of investors in Korea and find that institutional investors herd significantly less than individual investors and that resident institutional and individual investors herd significantly less than non-resident investors. Furthermore, Barber *et al.* (2009) argue that small trades may be a proxy for individual investor trades and analyze tick-by-tick transaction level data for US stock markets. Among other things, their findings indicate that order imbalance based on TAQ/ISSM (Trade and Quotes; Institute for the Study of Security Markets) data indicates strong herding by individual investors, that small trade order imbalance is correlated with retail broker order imbalance, and that small trade order imbalance forecasts future returns. Tan *et al.* (2008) examine the behavior of stock market investors in China and find evidence of herding for both A-share markets which tend to be dominated by domestic individual investors and B-share markets in which foreign institutional investors are dominant. In another study of Chinese investors Li *et al.* (2009) argue that for institutional investors with better information herding behavior is more intense compared to individual investors, indicating more selective trading by institutions vs individual investors who allocate their investments more evenly across stocks. They also find that while both types of investors herd toward the market, individual investors tend to rely more on public information and attention-grabbing evens.

5. Herding in financial markets: aggregate market activity

Another strand in the relevant literature attempts to uncover herding behavior using aggregate market data. The most commonly used empirical methodologies to test for herding toward the average, as discussed in Section 3, are suggested by Christie and Huang (1995) and Chang *et al.* (2000). The initial results for daily and monthly US data are not consistent with the presence of herd behavior during periods of large price movements (Christie and Huang, 1995). Also Chang *et al.* (2000) find no evidence of herding for the USA and Hong Kong, partial evidence of herding in Japan, and significant evidence of herding for South Korea and Taiwan. Chang *et al.*, also find that for the markets that do exhibit herding it is information related to macroeconomic fundamentals (rather than information at the firm level) that influences investor behavior.

In a study that employs a similar methodology but at the same time allows the evaluation of the cross-sectional dispersion of asset sensitivity to various fundamental factors, Hwang and Salmon (2004) find, for the USA and South Korean equity markets, significant movements and persistence of herding in the direction of the market; this does not depend on market conditions and fundamental macroeconomic variables. They also report that market crises seem to reduce herding behavior. Specialized markets, such as exchange traded funds (ETFs), are studied by Gleason *et al.* (2004) who use intraday data on nine sector ETFs traded on the American Stock Exchange in order to examine whether traders herd during periods of extreme market movements. Their empirical approaches are based on either the extreme up market and down market periods or on a non-linear regression specification as in Chang *et al.* (2000). They find that ETF investors do not herd during periods of extreme market movements. Tan *et al.* (2008) examine dual-listed Chinese stocks and find evidence of herd behavior by both domestic individual investors and foreign institutional investors.

In studies of European equity markets, Caporale *et al.* (2008) also use the CSAD approach and the non-linear regression of Chang *et al.* (2000) in order to test for herd behavior in extreme market conditions in the Athens Stock Exchange. Their results

(on daily, weekly and monthly data) suggest herd behavior that is more pronounced over daily time intervals. In addition, Economou *et al.* (2011) utilizing the same methodological approach test for herding behavior in the Portuguese, Italian, Spanish and Greek market. They use daily data that cover the period between 1998 and 2008 and an interesting feature of the study is that it examines whether the return dispersion in one market is affected by the return dispersion in the rest of the markets. Their findings suggest that herding becomes more intense during the financial crisis of 2007-2008. The CSAD approach is also employed by Caparrelli *et al.* (2004) to evaluate herding effects in the Italian Stock Exchange; they find that herding is present in extreme market conditions, a result consistent with Christie and Huang (1995). Applying the same methodologies, Henker *et al.* (2006) examine market wide and industry sector herding with intraday data on Australian equities and find evidence that is inconsistent with intraday herding.

Many authors link herd behavior with the creation of asset bubbles. During a speculative bubble asset prices are usually considerably higher compared to their intrinsic values and the volume of trading and market volatility is also at high levels. Investing in popular or "hot" stocks during these periods indicates investing in identical assets as other investors, implying herd behavior (Dass *et al.*, 2008). In fact, it has also been suggested that this behavior leads not only to the creation of the bubble but also to the bubble burst and the price decline afterwards. For example, Johansen and Sornette (1999) argue that herd behavior by investors is not only evident and leads to speculative bubbles but also that this behavior leads to "anti-bubbles" where the market valuations are falling after the all-time high levels achieved during the bubble. They employ parametric and non-parametric tests in order to examine this proposition with the Nikkei stock index and gold future prices and report that the values obtained for the after bubble period are comparable to the values obtained for the bubbles leading to crashes.

6. Herding in analyst recommendations: empirical evidence

Do analysts herd when making recommendations? Some theories suggest that career concerns (e.g. reputation, compensation) or the imitation of analysts with higher abilities may lead to underweighting of private information and herding behavior toward the consensus (Scharfstein and Stein, 1990; Trueman, 1994; Graham, 1999; see Section 2 for a discussion). In a related study, Hirshleifer *et al.* (1994) examine security analysis and investment decisions in the case where private information becomes available to some (risk averse) market participants before others. Their model suggests a tendency toward herding.

These theoretical predictions seem to be supported by the results of empirical studies. For example, Graham (1999) employs newsletter analyst strategies for the period between 1980 and 1992 in order to examine herding toward the advice of value line and the results confirm the theoretical predictions of his model. The results of Cote and Sanders (1997) also indicate that reputation concerns and the credibility of the consensus forecast is positively related to herding behavior while forecast ability is reversely related to herding behavior. Hong *et al.* (2000) employ an I/B/E/S data set of 8,421 US security analysts, who produced earnings forecasts between 1983 and 1996, in order to examine how their forecasting ability is related to career concerns. They report that, on average, inexperienced analysts who make bold forecasts that deviate from the consensus are more likely to be terminated compared to more experienced analysts. More importantly, their forecasts tend to deviate less from consensus

forecasts; in other words, younger analysts tend to herd more compared to their experienced counterparts. The authors argue that these findings are consistent with career motivated herding theories which point out that an agent facing more career concerns may herd more than an agent facing no career concerns. Note that other studies report that herding is not related to age: Ashiya and Doi (2001) find that macroeconomic forecasters in Japan exhibit herding behavior irrespective of the age of the forecaster[6].

In a similar study for fund managers, Chevalier and Ellison (1999) also argue that younger managers have incentives to herd into popular sectors and their findings support this argument. Welch (2000) employs the Zacks' Historical Recommendations Database which covers 226 US brokers between 1989 and 1994. The findings indicate that the recommendations of security analysts have a positive influence on the next two analysts' revisions. In addition, the results indicate that the influence of the consensus is less strong when the consensus forecasts accurately subsequent price movements (consistent with models where analysts herd due to scarce information). The influence of the consensus on analyst recommendations is also stronger during bullish market conditions, indicating a poorer aggregation of information during favorable market conditions (see also Clement and Tse, 2005; DeBondt and Forbes, 1999; for similar results on analyst herding).

There is also evidence to indicate that the more difficult the task of the analysis the higher the level of herding: Kim and Pantzalis (2003) examine the period between 1980 and 1998 and find that herding seems to be more pronounced among analysts that concentrate on diversified companies. Furthermore, investors seem to penalize herding behavior by analysts since the market value of the companies covered by herding analysts tended to be lower. In addition, Olsen (1996) points out that the effect of herding is positive bias and inaccuracy in analyst earnings forecasts. According to Olsen, investors can mistake the reduced dispersion in forecasts for reduced risk and the positive bias for high expected returns. This can result to abnormally low returns for stocks with unpredictable future earnings.

A two-period model in an efficient market where it is possible to differentiate between herding based on imitation and herding based on information is suggested by Jegadeesh and Kim (2010). They argue that while the former could introduce noise and destabilize stock prices the latter may not. Furthermore, the market is able to recognize whether the analyst tends to herd or not while revising a recommendation. They test their model with sell-side analyst recommendations contained in the I/B/E/S database for the period between 1993 and 2005, and the results indicate analyst herding. More specifically, herding seems to be more pronounced for analysts from large brokers, analysts that cover stocks with a low recommendation dispersion, and analysts that do not revise their recommendation frequently. Their results on the reaction of stock prices on analyst revisions indicate that an analyst's tendency for herding is recognized by the market. They also show that there is a positive (negative) relation between the stock price reaction and the deviation of the analyst's recommendation from the consensus if the analyst has an incentive (disincentive) to herd. Based on their results, Jegadeesh and Kim doubt whether herding has a destabilizing effect on prices.

A different view is expressed by Bernhardt *et al.* (2006) who argue that the clustering of analysts' recommendations and forecasts may not necessarily imply analyst herding. For example, among other things, relying on the same information sources or due to common unexpected market wide extreme events most forecasts will be too high or too low relative to actual earnings. They use the I/B/E/S database for the

period between 1989 and 1999 and design a test that accounts for correlated information, common market-wide shocks, information arrival over the forecasting cycle, and systematic optimism or pessimism. They find evidence consistent with the notion that analysts bias their earnings forecasts in the direction of their private information in an attempt to differentiate and over-emphasize their private information relative to the consensus (i.e. analysts "anti-herd"). Zitzewitz (2001) studies the behavior of I/B/E/S analysts and also finds evidence inconsistent with herding: analysts tend to exaggerate their differences with the consensus. The results of recent empirical studies seem to confirm the "anti-herding" view: Pierdzioch *et al.* (2013) analyze thousands of forecasts for nine metal prices and report heterogeneity of forecasts with anti-herding being the source of the heterogeneity; Pierdzioch and Rülke (2012) examine herding among forecasters of the S&P 500 stock price index and find evidence consistent with anti-herding which is inversely correlated with forecast accuracy.

7. Discussion: open issues and empirical limitations

This paper reviews a number of papers that study herding behavior in financial markets either at a theoretical or an empirical level. The main conclusions that emerge from the discussion are as follows. First, the empirical evidence is inconclusive. As regards to institutional investor herding, on the one hand many studies find limited evidence of herding (Lakonishok *et al.*, 1992; Grinblatt *et al.*, 1995; Christie and Huang, 1995; Gleason *et al.*, 2004; Wylie, 2005), while on the other hand there is also evidence to suggest that US institutional investors herd (Choi and Sias, 2009), that institutions herd as a result of inferring information from each other's trades (Sias, 2004), or that German institutional investors are engaged in spurious herding (Walter and Weber, 2006). As regards to herding toward the market consensus there are studies reporting the existence of herd behavior (Hwang and Salmon, 2004) especially for southern European markets (Economou *et al.*, 2011; Caparrelli *et al.*, 2004). On the other hand, Chang *et al.* (2000) find no evidence of herding for the US and Hong Kong, partial evidence in Japan, and significant evidence of herding for South Korea and Taiwan.

A similar case can be made for the issues of analyst herding and of whether herding destabilizes prices. For example, a number of studies report evidence consistent with analyst herding for various reasons (Graham, 1999; Cote and Sanders, 1997; Hong *et al.*, 2000; Ashiya and Doi, 2001; Welch, 2000), while more recent studies reporting opposing evidence and argue that analysts "anti-herd" (Bernhardt *et al.*, 2006; Pierdzioch *et al.*, 2013; Pierdzioch and Rülke, 2012; Zitzewitz, 2001). As regards to the effect of herding on prices, Lakonishok *et al.* (1992) argue that the amount of herding they detect has no destabilizing effect on stock prices, Jegadeesh and Kim (2010) doubt whether herding has a destabilizing effect on prices (see also Bowe and Domuta, 2004, for Indonesia; Choea *et al.*, 1999, for Korea; Boyd *et al.*, 2010, for hedge funds). Choi and Sias (2009), on the other hand, find that herding may drive industry market values away from fundamentals (see also Chang, 2010).

Second, there are limitations to the existing measures of herding in financial markets; perhaps this explains to some extent the inconclusive empirical evidence. For example, many empirical studies employ the LSV measure which provides important insights into fund manager behavior, however, it has certain drawbacks: it may suggest herding when merely a small number of investors are active, it is not a direct test for dependence in institutional demand, it does not separate between managers that follow their own trades and managers that follow the actions of others,

it assumes short selling, and requires access to detailed information on fund holdings that may not always be readily available (see, Wylie, 2005; Sias, 2004; Hwang and Salmon, 2004). Furthermore, it is not informative of the intensity of herding behavior since it does not consider the volume of trading and also it cannot reveal whether herding is followed by the same funds over time (Bikhchandani and Sharma, 2000). The Christie and Huang (1995) herding measure (and similar measures) essentially employs one fraction of the total return (at the firm level) to capture herding toward the market consensus. In other words, it tests for one specific form of herding and ignores herding in other contexts. When applied in empirical studies and the results are not supportive for the existence of herding one must bear in mind that what is rejected is merely herding toward the market consensus.

Another limitation as regards to the means employed in the literature for detecting institutional investor herding stems from the heterogeneity of the sector (mutual funds, pension funds, hedge funds, unit trusts, investment trusts, investment banks, etc.). Even within each type of fund there is no homogeneity. Take mutual funds, for example. There are so many different investment strategies and styles within the sector (diversified equity, index tracking, emerging markets, growth, value, momentum, contrarian, technology stock, quantitative, fund of funds, etc.) that detecting herding may be a difficult task. More specifically, fund managers may herd on different investment styles but, if studied as a group (as is often done), no herding is detected (on average) since these strategies may cancel each other out. For example, consider the effect of aggregating the transactions of fund managers that follow contrarian and momentum strategies and have similar investment horizons.

Third, one can notice a discrepancy between theoretical advances, on the one hand, and the development of appropriate methodologies and/or suitable data sets to empirically evaluate the theoretical predictions, on the other hand. Take informational cascades, for instance. There are important theoretical approaches to informational cascades that assume either sequential or simultaneous trading and examine a range of theoretical issues in order to understand the development of informational cascades and/or informational blockages: the rate of learning in financial markets, the endogeneity of asset prices, the bid-ask spreads, the motives that investors have for trading (e.g. non-speculative trading), transactions costs, discrete trades, the cost of information acquisition, the availability of information and the role of biases such as the locality bias, etc. (for a detailed review see Hirshleifer and Teoh, 2003). Unless the researcher has access to detailed databases on investor private information before the trade it is problematic to directly test many of these issues. For instance, one cannot easily test whether investors actually disregard their information and mimic the behavior of others or not (unless one has access to the available information before the trade), what are the reasons for this behavior, what biases dominate during the decision-making process (if at all), etc. Empirical tests can only be performed indirectly and with assumptions. As a result, many empirical papers on herding in financial markets essentially opt for methods to quantify investor transaction and decision clustering. Clustering, however, may take place due to a variety of reasons.

Fourth, many empirical studies do not make an attempt to investigate whether their results are attributable to spurious or intentional herding. As Graham (1999) points out the type of herding one investigates may lead to very diverse definitions of the dependent variable and the testing methodology employed. A related issue is the time-variation of herd behavior: do people herd for the same reasons over time? Many empirical studies neglect to investigate whether it is the same factors that lead to herd

behavior over time. For example, Baddeley (2010) argues that herding behavior may be the result of an interaction of cognitive and emotional factors and calls for interdisciplinary attempts to study herding.

Finally, "silent" or "passive" herding is ignored in empirical studies which essentially measure "active" herding. As Bikhchandani and Sharma (2000, p. 280) put it: "Intuitively, an individual can be said to herd if she would have made an investment without knowing other investors' decisions, but does not make that investment when she finds that others have decided not to do so." In order to test herding, empirical studies usually look at various metrics for correlated trading and/or clustering of prices and/or investment decisions. In other words, they ignore "silent" herding, i.e. herding that is expressed with an investment decision not to proceed with an action (e.g. a trade) after observing others having done the same. For example, consider an investor that has picked a stock for investment and then he/she observes that other investors do not invest and avoid that stock. If he/she does not proceed with the investment, and thus ignores private information, then this investor is herding. This type of herding behavior, however, will not be picked up in empirical studies.

The discussion above indicates a number of open issues for future research. For example, defining clearly what form of herding is tested and devising appropriate methods for testing each form of herding can perhaps resolve the issue of the inconclusive evidence. Studies that deal with institutional investor herding could differentiate by the type of fund and investment style, in order to resolve the issue of losing information due to the aggregation of transactions. In addition, more attention should be paid on the interaction between investor types, such as individual and institutional investors or domestic and foreign investors; different investors may be in possession of different information and/or react to different signals. Future studies that deal with time-series price data could employ empirical methodologies that allow for time-variation in parameter values. It is also important to know whether it is the same investors that herd over time, and why: are the reasons behind herding the same over time? More research is needed on emerging stock markets and institutional investors in these markets or markets such as commodity, derivative and real estate markets. Finally, silent herding: arguably, it is difficult to measure this form of herding; however, it may be a challenge for economists to device an appropriate methodology in order to test for this form of herding.

Notes

1. See article: Bloomberg, Neuger, J., and Kennedy, S., www.bloombeg.com/news/2010-11-29/ireland-s-eu-financial-rescue-fails-to-stem-contagion-as-spain-bonds-drop.html
2. For a detailed discussion on rational herding theories see also Devenow and Welch (1996).
3. Note that fund manager remuneration is usually performance-related and linked to market or industry benchmarks.
4. For example, "[…] restaurants could offer happy hour promotions precisely because they wish to generate a nondiagnostic signal that will be erroneously interpreted as diagnostic by latecomers" (Simonsohn and Ariely, 2008, p. 1625).
5. LSV point out that during 1989 about 50 percent of the equities in the USA was held by institutional investors and that their trading accounted for 70 percent of the trading volume on the New York Stock Exchange (Lakonishok *et al.*, 1992, p. 24).
6. Ehrbeck and Waldman (1996) argue in favor of behavioral explanations for forecast bias.

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