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**THE "HERDING EFFECT": EVIDENCE FROM CHINESE STOCK
MARKETS**

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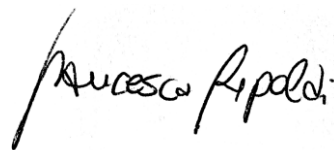
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Firma dello studente

A handwritten signature in black ink, reading "Francesco Ripoldi". The signature is written in a cursive style with a large initial 'F'.

*Cogli le occasioni, sii coraggioso,
la felicità bussava raramente alla tua porta,
e quando accade, la cosa migliore che tu possa fare
è aprire.
Sono le scelte a qualificare noi stessi
e chi vogliamo essere.*

A te, unica e sola certezza

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Observing the decision making process of different actors in the market has always represented a challenging mission for academics and practitioners. The traditional and prevalent principle of efficient markets states that markets are informational efficient, traders build rational expectations about future prices and that each new information collected by the market is immediately integrated into expected prices homogeneously.

However, the efficient market hypothesis has been criticized, both empirically and theoretically, by a growing number of researchers because, above all, it is considered to not be able to modelling the real-life security returns [see among others Shiller (1984)].

Behavioural finance, on the other hand, highlights the various inefficiencies of the markets, which imply, in extreme cases, bubbles and crashes, and come from various cognitive biases, human errors and responses.

According to this perspective, herding activities among investors may be seen as a widespread behavioural explanation for the excess volatility and short-term trends realized in financial markets. Moreover, investor herding is responsible for the deviations from the fundamental values and embodies an important role in the definition of trading strategies and asset pricing models.¹ This is the main reason for its recent relevance.

Human herding behaviour often comes from the tendency to mimic the actions of others. Anyway, the literature does not find an unique method to investigate the herding effect and offers us many different definition of this important phenomenon: for instance, Bikchandani and Sharma (2000) state that it is “an obvious intent by investors to copy the behaviour of other investors”, while Chang, Cheng and Khorana (2000) define it as a “method thanks to which market participants plan their investment decisions only on aggregate beliefs, ignoring their own feelings”.

What about the researchers agree is that each agent is linked to the others through the occurrence of a social network, and thanks to this structure (which can assume many different shapes, creating various types of links between traders) the traders own the possibility to engage in the mechanism of imitation. Moreover, the implications of the interactions among market

¹ For instance, when one trader takes part in a market where other investors are prone to herd around the market consensus, a large number of securities are forced to reach the same degree of diversification than in a herd-free market.

participants in the network may lead to large fluctuations in the aggregate demand driving to heavy tails in the returns distribution and hence to heteroskedasticity.

The mimicking behaviour, furthermore, could be classified as rational or irrational, and it differs from informational cascades (because the latter are distinguished by a sequence of individuals who ignore their private information in the process of decision making, while the herding behaviour is chosen by individuals who imitate other traders but without necessarily ignoring their information) and from flocking (when the herding behaviour adopted among a group of traders).

As the herding behaviour may cause an increasing of the market volatility, an increasing of systemic risk and a decreasing in liquidity, some authors [see among others Ayres and Mitts (2015), Galariotiis *et al.* (2015)] propose to limit this phenomenon introducing some mechanisms to boost separating equilibrium in order to avoid the flattening among the market consensus. In fact, through the provision of licenses, legal menus and tradable permits, regulators can decrease the externalities of excessive pooling.

In this work, we investigate the presence of herding behaviour in the Chinese mainland market by examining the return dispersion of both A and B share markets. The choice of the Chinese country is due to its special macro and microstructure characteristics suggesting an appealing environment for the analysis of investor herding behaviour. In fact, a market commonly identified by unsophisticated retail investors, heavy regulations and lack of transparency and, recently, experiencing huge reforms, makes us interested in the understanding of how investors behave during such situation of transition.

The main outcomes of the empirical analysis indicate that the herding behaviour is not shown in the same amount or with the same importance in each of the scenarios or segments analysed. In fact, we find a general tendency of the Chinese market in showing sheeple behaviour in the sample period studied, except for the Shanghai B market where the degree of development is more emphasized. Furthermore, the occurrence of the herding is decreasing at the reducing of data frequency and over time, apart for the last two years period where, however, we find no causality of the financial crisis. A more detailed digression is necessary for the market asymmetry (return, volume and volatility asymmetry) because the four different markets react differently to the asymmetric conditions.

The remainder of the work is organised as follows. Section 1 describes the environment of the networks. Section 2 defines the herding behaviour, explaining its features and five different methodology of examining the occurrence of mimicking behaviour. Section 3 shows the implications of the herding behaviour on volatility and liquidity and the effects of different regulations on the magnitude of herding effect. Section 5 presents an empirical case study of

the herding phenomenon using the Chinese stock market and analysing the phenomenon from different points of view. Section 6 concludes the research.

Part 1. The value of what is around you

1.1. Definition of networks

Social networks are determining features of the economic result in a wide range of situations including labour markets (find new opportunities, such as jobs or investments), provision of informal insurance, the generation and spread of innovations, disease epidemics, organizational performance and financial markets. In order to tackle the benefits that arise from the networks, agents strategically build and relax links in order to gain a worthwhile position in the social structure.

Figure out, how these strategic choices model the social network, is of primary importance to describe the fundamental properties of networks revealed by empirical studies and to look for the economic implications on the single agent and on the entire society.

The potential complexity of the social networks' structure can be outlined by a little curiosity: a group of just 10 identical agents can form 11.716.571 different connected network architectures [Gallo, E. (2012). Small world networks with segregation patterns and brokers. *Review of Network Economics*, 11(3)]. The network shape depends, above all, on the heterogeneity and the partiality of the knowledge.

Recently, the role of information becomes more and more important because of the development of social networking websites/tools as they give the possibility to agents to crucially improve their knowledge about the social structure they are involved in.

As many sociologists and economists have shown, the familiarity or the neighbourhood effects occupy the top position in individual search. This, in turn, is the cause of a significant correlation across friends, relatives, or neighbours in the most of the different socioeconomic dimensions. The attention of researchers on the importance of economic volatility, the quantity and the quality of social links² is due to their key role in the aim of search and on the reason that justify the adaptability to change.

“The dynamics of network formation can be viewed as a continuous struggle against volatility, with the information arising on new profitable opportunities partially mediated (thus constrained) by the existing network”. [Marsilii (2004)]

“...it takes all of the

² Sometimes referred to as social capital.

*running you can do, to keep in the same place*³

The network structure has some basic attributes that could be grouped into two main classes:

1) Macro (global or aggregate), represented by the density of connections and by the segregation patterns among nodes⁴.

2) Micro (local or individual) characterized by the frequency with which two "friends" of given node are friends with each other or how defined nodes are settled in the network⁵.

The density network is related to the average number of connections among nodes, and erga omnes it is the most responsible element for the diffusion of contagion because it leads to more interactions.

Another important network feature is the segregation pattern defined as the inclination to gather into richly connected, close-knit communities with few links across communities. Specifically Lazarsfeld and Merton (1954) introduced the term "homophily" through which they show the inclination to be linked to each other. About micro pattern of networks, we account for centrality of individual nodes in a network and the local clustering patterns. The clustering coefficient is the proportion of individuals with a common link, who are even connected to each other. The social literature shows that living in a highly interconnected network on a local level is important in encouraging cooperative behaviours. Moreover, in a highly clustered network, if an individual adopts a negative behaviour, everybody will be informed about it.

A general feature of networks is that they are constantly evolving in time. This implies that they are not static structures, but they continuously change adding and/or removing new nodes and links. The consequence is that it is necessary to reveal the dynamical forces that affect the single nodes. The starting point for Bianconi Baràbasi is to postulate a scale-free model that incorporates the fact that network evolution is driven by at least two coexisting components: 1) growth – network expansion depends on the addition of new nodes; 2) preferential attachment - a new node will build links with higher probability to nodes that already have a large number of links.

The scale-free model does not include an important aspect of competitive systems: not each node is equally successful in acquiring links. Bianconi *et al.* (2001) postulate that nodes increase their connectivity in time so that the oldest nodes will gain the highest number of links. This view is hardly substantiated by empirical basis because in real system nodes connectivity and growth rate do not depend only on the age; in fact, in social systems some individuals are able

³ The quote is referred to the Red Queen's Race, an incident that Lewis Carroll tells in the "Through the Looking-Glass" and involves the Red Queen, a personification of a Queen in chess, and Alice constantly running but remaining in the same point.

⁴ They play a crucial role in the process of diffusion and the social learning

⁵ For more details of the properties, see Jackson *et al.* (2014).

to convert a random meeting into a permanent social link in an easier way than others. Take as example the World Wide Web: some documents through a mix of good materials and marketing tricks could reach a large number of links in a very short time, easily overtaking older websites. People are led to link these differences with some innate quality of the nodes, such as the social skills of an individual or the content of a web page, or the content of a scientific article. This phenomenon is called “node’s fitness” and it describes the ability to compete for links at the expense of other nodes.

$$\Pi_i = \frac{\eta_i k_i}{\sum_j \eta_j k_j} \quad \text{Eq. 1}$$

In the model discussed above, Π_i is the probability that a new node will connect to a node i , already present in the network, and it depends on connectivity k_i and on fitness η_i of that node. This means that a node with a higher fitness parameter could enter the system at later time and overcome nodes that have already been in the system for a much longer timeframe.

Tedeschi *et al.* (2012) have developed a structure for the idea of network based on the concept of nodes and edges: in particular, nodes represent agents and edges stand for the links between them. Links are directional because they are oriented towards who is providing the information (information, therefore, travels in the opposite direction). Moreover, links are both created and deleted by agents. In this model the authors decide to limit the number of out-going links to only one, so that agents could receive an advice from only one neighbour. The reason is to found in the will to looking for an easier way to test the network; in fact, a structure with indirect links could entail a problem of synchronisation.

The main variable, according to the view of the authors, is expressed by the fitness parameter focused on the agent’s wealth: every agent, in the beginning, has the same amount of cash $C_{t=0}$ and stocks $S_{t=0}$ and they own, therefore, the same initial wealth defined as $W_{t=0} = C_{t=0} + p_{t=0}S_{t=0}$. The agents, thanks to their talent, could become richer than other, and this “success” is measured by their fitness at time t , i.e. as their wealth relative to the wealth W_t^{max} of the richest agent i_{max} :

$$f_t^i = \frac{W_t^i}{W_t^{max}} \quad \text{Eq. 2}$$

Links are rewinded at the beginning of each period, with this rule: every agent i could delete its outgoing link, with agent k , and forms a new link, with a random agent j , with a probability

$$p_r^i = \frac{1}{1 + e^{-\beta^i(f_t^j - f_t^k)}} \quad \text{Eq. 3}$$

or may preserve its actual link with probability $1-p_r^i$. This rewind mechanism ensures that successful traders, here called gurus, obtain a higher number of incoming links and thus they reach a higher probability of being imitated. Anyway, this algorithm thinks about the concept of randomness, because links with more successful agents have a finite probability to be deleted and substituted with links in favour of less successful agents. “In this way we model imperfect information and bounded rationality of agents” [Tedeschi *et al.* (2012)]. The assumption about the randomness even assists releasing the system from the hypothesis in which all agents are linked to the same guru.

The imitation game assumes a fundamental role, after the generation of the idiosyncratic expectations about spot returns at the beginning of trading period. In fact, exactly in this moment a consultation round begins, and agents revise their expectations by weighing agent i 's own expectation with that of agent j to which i is linked to. In particular, $r_{t_k, t_{k+\tau}}^i = w\hat{r}_{t_k, t_{k+\tau}}^i + (1-w)\hat{r}_{t_k, t_{k+\tau}}^j$ where w measures the impact that agent j 's expectation has on the agent i 's expectation.

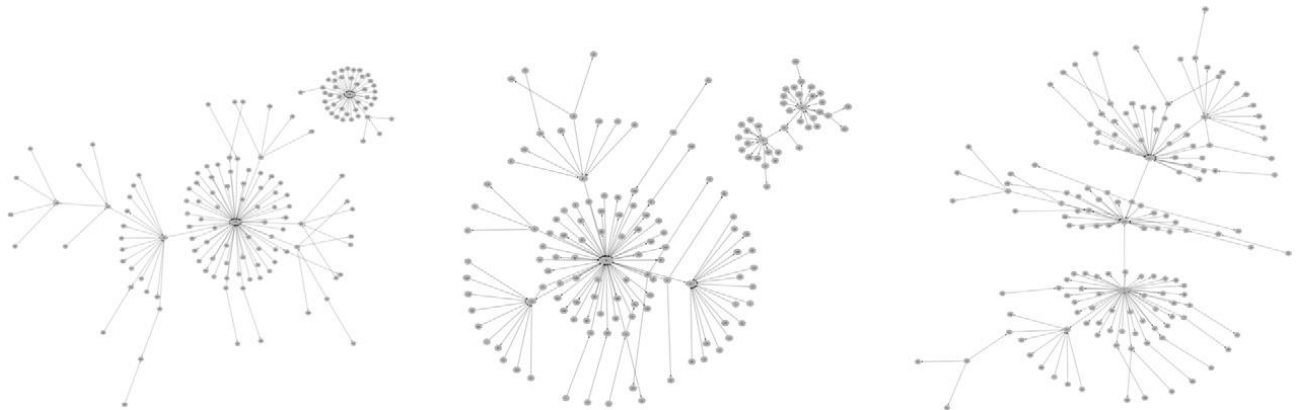


Fig. 1 Network configuration for $w=0.1$ (left side), for $w=0.5$ (centre), and for $w=1$ (right side).
Source: Tedeschi *et al.*, *Journal of Economic Behavior & Organization* 81 (2012) 82–96

Graphs in Fig.1 show that few gurus could work in the same network and contend the fame each other; it is possible to observe that as w goes up, the network assumes a less and less centralized shape with a higher number of smaller gurus. Thus, it is easy to understand how, and how much the network structure depends on the imitation level of w .

Links are created according to preferential attachment⁶ and relative wealth showed in Eq.2, but these are not dependent from w . The weight w , however, affects the profits of the guru, of his followers and, thus, the network formation.

1.2. The communication structure

As matter of fact, the distribution of returns of almost all financial assets, seen as stocks, indexes, and futures, shows a slow asymptotic decay that deviates from a normal distribution. Quantitatively, this behaviour is translated in the excess kurtosis, defined as

$$\kappa = \frac{\mu_4}{\sigma^4} - 3 \quad \text{Eq. 4}$$

where μ_4 is the fourth central moment and σ^4 is the standard deviation of the returns. The excess kurtosis should be zero for a normal distribution, but it falls in a neighbourhood between 2 and 50 for daily returns [Campbell *et al.* (1997), Pagan (1996)] and it is even higher for intraday data.

Studies of returns' distribution exhibit heavy tails, fatter than the normal distribution ones but thinner than a stable Pareto-Lévy distribution [Cont (1998)]. Sometimes, tails have been represented by an exponential form [Cont *et al.* (1997)], while other times they are defined by a power law with tail index between 3 and 4 [Pagan (1996)].

There are many statistical mechanisms used to account for the heavy tails observed in the distribution of asset returns: well-known examples are Mandelbrot's stable-Paretian hypothesis [Mandelbrot (1963)], the mixture-of-distributions hypothesis [Clark (1973)], and models based on conditional heteroskedasticity [Engle (1995)].

It is common knowledge that, in the presence of heteroskedasticity, the unconditional distribution of returns will reveal heavy tails. In most of the models based on the above-mentioned phenomenon, the returns are assumed to be conditionally Gaussian: the shocks are "locally" Gaussian and the non-Gaussian character of the unconditional distribution is an effect

⁶ Simon (1955) showed that power laws arise when 'the rich get richer', when the amount you get goes up with the amount you already have. In sociology this is referred to as Matthew effect (see Merton, 1968) with reference to the biblical edict. Nowadays, this phenomenon is usually known under the name "preferential attachment", created by Barabási and Albert (1999). Bianconi and Barabási (2001) have proposed an extension of Barabasi and Albert. In their model to every new vertex i is given a 'fitness' that represents its attractiveness and thus its propensity to acquire more links. Considering a fitness algorithm, it is true that, even if the fitness increases, this is not the cause of the improvement of site connectivity. In Tedeschi *et al.* (2012) model this intrinsic quality is, precisely, the agents' profit.

of aggregation. The result is achieved by adding a huge number of local Gaussian shocks [Cont *et al.* (2000)]. Thus, unexpected movements in prices are linked to a high value of conditional variance. Moreover, we could affirm that, although conditional heteroskedasticity bring to fat tails in unconditional distributions, ARCH models are not completely able to explain the kurtosis of returns [Hsieh (1991), Bollerslev *et al.* (1992)]; nevertheless, according to the theory, there is no *a priori* reason to postulate that returns are conditionally normal; in fact, even though conditional normality is useful for the estimation of the model's parameters, non-normal conditional distributions reveal the same peculiarities (for example, in terms of volatility clustering) and they lead to a better estimation for heavy tails.

Empirically, Gallant and Tauchen (1989) find significant evidence of both conditional heteroskedasticity and conditional non-normality in the daily NYSE value-weighted index. As well, Engle and Gonzalez-Rivera (1991) reveal which are the effects of the use of a GARCH(1,1) model for the conditional variance of stock returns: among results, they find that the conditional distribution has considerable kurtosis, especially for small-firm stocks. We can account also other authors among the supporter of GARCH-type models with non-normal conditional distributions like Bollerslev *et al.* (1992)].

Stable distributions [Mandelbrot (1963)] represent another alternative possibility to heteroskedasticity for generating fat tails. Models based on such distributions have some benefits but, unfortunately, their infinite variance property is not trackable in empirical data.

A third approach, promoted for the first time by Clark (1973), is to model stock returns through a subordinated process, typically subordinated Brownian motion. The meaning is to transform a complicated dynamic into a Brownian motion or another simple process. Although heteroskedasticity and time deformation partly explain the kurtosis of asset returns, they do not explain it quantitatively: even after considering the implications of these phenomena, there is an amount of kurtosis that it is not already explainable in the resulting transformed time series. Moreover, these theories account for the market as a "black box" and they are not linked to any microeconomic representation of the market phenomenon generating the data that they attempt to describe. [Cont *et al.* (2000)].

In short, we can declare that a wholly statistical explanation to clarify the existence of heavy tails in the distribution of asset returns is a failure. Cont *et al.* (2000) suggest the existence of a more fundamental market mechanism, common to all speculative markets, responsible for heavy tails.

Bak *et al.* (1997) and Lux (1998) outline the heavy-tailed nature of return distributions, as property in a market where fundamentalist traders interact with noise traders. However, there

are two drawbacks: on the one hand, the model is complex and it involves many parameters whose effects are difficult to see on the results obtained, thus decreasing their explanatory power. On the other hand, it is not allowed to reach explicit calculations because of the difficulty of the model, so that it is not easy to compare the parameters with empirical values.

In order to solve these kind of problems, Cont *et al.* (2000) study an alternative approach, which deals with the communication structure between market agents as a random graph. They offer a simple mechanism involving some non-trivial statistical properties of stock price fluctuations.

Although this structure appears much more simplistic than the model of Bak *et al.* (1997), it gives the possibility to perform analytic calculations, and to interpret economically the role of every parameter used in the model. “The basic intuition behind our approach is simple: interaction of market participants through imitation can lead to large fluctuations in aggregate demand, leading to heavy tails in the distribution of returns” [Cont *et al.* (2000)].

In the economic literature, the researchers have often associated “crowd effects” with large fluctuations in market prices of financial assets, but only recently they have been observed by an econometrics point of view. Anyway, many recent studies have considered mimetic behaviour as a possible answer to the excessive volatility existing in financial markets [Bannerjee (1993), Orlèan (1995), Shiller (1989), Topol (1991)].

The network proposed by Cont *et al.* (2000) is made up of the random formation of groups of agents who imitate each other; we have to underline that the independent choices of different groups of agents lead to a heterogeneous market structure. More precisely, the structure considers the interactions among agents as deriving from a random communication structure.

Consider a stock market with N agents, included in an integer $1 \leq i \leq N$, trading in a single asset, whose price at time t will be identified by $x(t)$. Take into account that, during each time period, the choice of the agent i could be: buy the stock, sell it, or not to trade. The demand for stock of agent i is described, for each period, by a random variable φ_i , which can take values 0 (agents are not trading), -1 (“bear agents” willing to sell stock), +1 (“bull agents” eager to buy the stock). The randomness of individual demands may be explained either by heterogeneous preferences or by random resources of the agents, or both. For example, the random quality may due to the use of a random utility model [Anderson *et al.* (1993)] or may come from the application of simple decision rules taken by the agents, where each group of agents uses a certain rule. However, in order to concentrate the attention on the effect of herding, Cont *et al.* (2000) decided to not model the decision process characterizing the individual demands, but to

focus only on the result of the decision process as a random variable φ_i . The most important “innovation” is embodied by the default on a binary system, famous in the microeconomics literature, given the possibility to the agents to be inactive, i.e. neither buy or sell during a given time period t . Thus, the aggregate excess demand for the asset at time t is

$$D(t) = \sum_{i=1}^N \varphi_i(t) \quad \text{Eq. 5}$$

The aim is to have a model able to make a comparison with actual market data. The main idea is to create a link between the aggregate excess demand in a given time-frame and the return or price changes during the same given period. If the excess demand is positive (negative), the stocks’ price will rise (fall).

It is common to assume a proportionality between price (or return) change and excess demand:

$$\Delta x = x(t+1) - x(t) = \frac{1}{\lambda} \sum_{i=1}^N \varphi_i(t) \quad \text{Eq. 6}$$

where λ is the market depth and it accounts for the sensitivity of price to fluctuations in excess demand.

Eq.6 reveals the price impact of the order flow in opposition to the other parameters responsible for price fluctuations. In the long run, instead, it is important to underline that some other economic factors – different from short-term excess demand - could influence the evolution of the asset price, causing a mean reversion or other more complex types of behaviour.

In order to estimate the stock returns distribution from Eq.6, it is important to identify the *joint* distribution of the individual demands $[\varphi_i(t)]_{1 \leq i \leq N}$. Let’s analyse the easiest example: the different agents have individual demands φ_i that are independent and identically distributed random variables; this case is commonly known as the “independent agents” hypothesis. According to its simplicity, the joint distribution of the individual demands is, in fact, the product of individual distributions, and, thus, Δx , i.e. the price increment, is the sum of N independent and identically distributed random variables with finite variance. When the Eq.6 includes a huge number of terms, the application of the central limit theorem reveals that the Gaussian distribution is a good proxy for Δx distribution.

Indeed, the good quality of this proxy is valid as long as the individual demand is characterized by finite variance.

Moreover, if we consider the market price changing as the sum of a large number of independent or weakly dependent random effects, the Gaussian distribution could be consider a good proxy; sadly, we observe, empirically, that the distributions both of asset returns [Pagan

(1996), Campbell *et al.* (1997)] and of asset price changes [Mandelbrot (1963, 1997), Cont (1997), Cont *et al.* (1997)] differ significantly from the Gaussian distribution, revealing fat tails and excess kurtosis.

However, the independent-agent model may fit even in a case identified by a distribution with heavy tails, but we have to give up the idea of finite variance for the individual demands. Thus, given the hypothesis of independence (or weak dependence) of individual demands, we will find that the aggregate demand - and so, the price change under the assumption of Eq.6- will follow a stable (Pareto-Lévy) distribution.⁷

The infinite variance is a determine feature because it represents the heterogeneity of the market e.g. the wealth distributions of traders [Levy and Solomon (2000)].

One of the drawbacks of the Mandelbrot's stable-Paretian model is that an infinite variance for stock returns implies that, as more the sample size increases, more the sample variance will raise and the empirical data do not reveal this trend; in fact, Pagan (1996), Cont *et al.* (1997), Bouchaud and Potters (1997) observe that the changing in assets price are characterized by heavy tails and finite variance and suggest the use of exponentially truncated stable distributions.

As a matter of fact, it is not reasonable to affirm that individual agents could produce an outcome⁸ identified by an independent random variable because it would relax an essential element of market organization, i.e. the interaction and communication among agents.

In the reality, people could create groups of different dimensions and use them to share information and behave following coordinate schemes, for example buying or selling the same instruments at the same moment. It is also rational to associate the idea of group to an investment fund where a single fund manager manages the wealth of each investor. Anyway, to catch these effects, it is necessary to point out a new element, which could identify the communication structure among traders. Create a fixed trading-group structure and analyse the resulting fluctuations, would be an option, but this model has two problems: 1) in order to reflect a realistic market structure we have to build a difficult pattern of clusters⁹ that could imply a model not easy to develop analytically; 2) the chosen market structure will affect critically the resulting structure of aggregate fluctuations.

Kirman (1983 and 1996) propose another model, where the market communication structure is treated as a stochastic element. Thus, to construct a random market structure, the

⁷ The above-mentioned analysis for the stable-Pareto model was suggested by Mandelbrot (1963).

⁸ The outcome produced by agents is represented by the result of decisions.

⁹ In financial markets clusters could stand for a group of traders represented by a mutual fund.

authors decide in favour of an amount of traders meeting each other randomly. The “random matching¹⁰” takes place when the agent, who wants to buy, meets a trader willing to sell.

Another opportunity is to assume a random matching process where there is no possibility for the existence of an intra-group trading: in fact, each group decides to adhere to a common market strategy (buy/sell/not trade) and the trade will be between different groups thanks to a centralized market process. This means that trading is between groups and not between agents. In the model of Cont *et al.* (2000) each agent of a given cluster shows the same demand φ_i for stocks; we have to recall the Eq.6, editing the right side and taking account of it as a sum over cluster:

$$\Delta x = \frac{1}{\lambda} \sum_{\alpha=1}^k W_{\alpha} \varphi_{\alpha}(t) = \frac{1}{\lambda} \sum_{\alpha=1}^{n_c} X_{\alpha} \quad \text{Eq. 7}$$

where W_{α} is the size of the cluster α , $\varphi_{\alpha}(t)$ is the individual agent demand involving in the cluster α , n_c is the number of existing clusters and X_{α} could be rewritten as $W_{\alpha} \varphi_{\alpha}$.

We should even consider that taking a couple of agents i and j , the probability that the two agents are linked together is p_{ij} . To create an easier situation, we can assume that $p_{ij} = p$, so that all links are equally probable because of the independency with i and j .

Moreover, we identify the number of links between one trader and the other by $(N - 1)p$. When $N \rightarrow \infty$, we have to choose a value of p such that the limit of $(N - 1)p$ is finite i.e., $p_{ij} = c/N$. What is important to underline, is that the distribution of the clusters is totally dependent by an unique parameter, c , which stands for the willingness of act following the same direction¹¹. If we fix the parameter c close to 1, we are implicitly asserting that every agent is induced to create a link with one other¹² (as a matter of fact, a reasonable assumption). The ratio of

¹⁰ The term was used by some authors in the context of formation of trading groups [Ioannides (1990)], and in the context of stock market model [Bak *et al.* (1997)].

¹¹ It could be interpreted as a ratio that measure the degree of coordination, of intensity of clusters.

¹² Such assumption does not avoid the agents to form large coalitions through binary links, but it excludes the hypothesis that a single agent creates multiple links, as would be in the situation of a centralized communication structure where one trader (the “auctioneer”) is linked to all of the others. The presence of a Walrasian auctioneer identifies a centralized communication structure, for example the “star-like” structure [Kirma (1983)].

excluding a centralized communication structure is the interest to be as close as possible to the reality.

Each coalition is identified by the size W_α and by the “trading decision” of buy/sell/not trade ($\varphi_\alpha \in \{-1,0,1\}$). Moreover, it is reasonable to assert that W_α and φ_α are independent random variables, so that the group size does not affect the choices about trading.

That is why the price fluctuation (Δx) it is no more than a *sum of n_c i.i.d.r.v.'s X_α , $\alpha = 1 \dots n_c$ with heavy-tailed distribution* [Cont et al. (2000)]¹³.

Reconnecting to the starting point, compute the variance and the fourth moment¹⁴

$$\mu_2(D) = n_{order} \left(1 - \frac{c}{2}\right) \mu_2(X_\alpha) \quad Eq. 8$$

$$\mu_4(D) = n_{order} \left(1 - \frac{c}{2}\right) \mu_4(X_\alpha) + 3N_{order}^2 \left(1 - \frac{c}{2}\right)^2 \mu_2(X_\alpha)^2 \quad Eq. 9$$

Now it is possible to compute the kurtosis of the asset returns, which is equal in this model to the kurtosis of the excess demand $\kappa(D)$:

$$\kappa(D) = \frac{\mu_4(X_\alpha)}{n_{order} \left(1 - \frac{c}{2}\right) \mu_2(X_\alpha)} \quad Eq. 10$$

Transforming the kurtosis as a function of c and the order flow, the result is

$$\kappa(D) = \frac{2c+1}{n_{order} (1-c/2) A(c) (1-c)^3} \quad Eq. 11$$

where $A(c)$ is a normalization constant with a value close to 1, tending to a finite limit as $c \rightarrow 1$.

The interpretation of the above ratio is: if the order flow volume decreases, the price variation increases and we observe a wider excess kurtosis (the relation is coherent with the reality, where we observe a large price fluctuation often in less active markets characterized by a small order flow). The effects showed in the Eq.11 constitute the analytical formulation of what happens empirically, as can be seen from various market microstructure models, where, moreover, a wider order flow gives the possibility to the market maker to apply an easier regulation of

¹³ Indeed, if we are talking about reality, we have consider that in a liquid market, like NYSE, the typical order size is $n_c = 100$.

¹⁴ The m.g.f. of the aggregate excess demand D in term of \tilde{f} is: $\mathcal{F}(z) \xrightarrow{N \rightarrow \infty} \exp \left\{ n_{order} \left(1 - \frac{c}{2}\right) [\tilde{f}(z) - 1] \right\}$.

supply and demand. Indeed, it should be useful to focus even on the fact that in the situation showed by the [Cont *et al.* (2000)] model, we observe the same effects of a model in which a market maker is integrated.

A comparison with the deductions of Engle *et al.* (1991) could be useful: in their model, although they take into consideration the element of heteroskedasticity, the conditional distribution for small firms is higher than that one of large firms. The effects observed are coherent with the results of the model of Cont *et al.* (2000) because small firms involve a smaller order flow (identified by the parameter n_{order}).¹⁵

Summarizing, the model justifies a crossover between heavy tails at small timescales and Gaussian behaviour of price variations at large timescales that is created by the growing of the number of the orders during Δt when Δt is gone up. In other words, this statement linked to the Eq.11, reveals a connection between the scaling behaviour of the kurtosis of price variations on the time-frame Δt and the way through which the order flow during the same time interval should increase with Δt .

In conclusion, the use of a simple model characterized by the presence of heavy tails and finite variance for aggregate excess demand and stock price fluctuation unveils a behaviour that is very close to the empirical distributions of asset returns. Since we account for a market model where agents do not interact with each other, the result is the rising of a normally distributed aggregate fluctuations; instead, if we set that agents could have an interaction among each other, the outcome is analytically similar to the empirical findings observed on the stock market returns' distributions. As final point, the aim of the first part of this work was to underline the importance of the networks that everyone is used to create in each aspect of his/her life, and to display the relation between the fatness of the tails of asset returns, measured by the excess kurtosis and the degree of herding among market participants (possible only thanks to the figure of the network) as measured by the parameter c .

¹⁵ Another substantial element of the model is that the kurtosis could be assume a very high value *even if the number of orders is itself large, provided c is close to 1*. If $A(1)$ is close to $\frac{1}{2}$, even for $c=0.9$ and $n_{order} = 1000$, the kurtosis will be, anyway, of order 10, exactly as a very active market on time intervals of tens of minutes reveals.

Analytically, this model shows that $\mu = 3/2$ and the value found is quite similar to that observed in the reality. Indeed, we have to pay attention to the time dependency of the parameter c ; in fact, in a period of great uncertainty we could observe a higher value of kurtosis. When c touches the value of 1, a finite number of market participants experiences the same feelings, and this leads to a market collision.

Part 2. Powerful phenomenon in financial markets

Behavioural finance highlights the typical inefficiencies of the markets such as under or over-reactions to information, which imply market trends and in extreme cases bubbles and crashes. Such reactions may be due to limited investor attention, overconfidence, over optimism, mimicry (herding instinct) and noise trading.

In the following sections, we will focus essentially on the herding behaviour describing each of its features.

2.1. Definition of herding effect



Fig. 2 "Just a normal day at the nation's most important financial institution..." by Kal. This funny cartoon appeared on the cover of the Economist in 1989

Investor behaviour can be responsible for price variations that are not necessarily dependent on the coming of new information to the market but that are, indeed, due to collective phenomena [Shefrin (2000), Thaler (1991)]. This fact guided researchers to look for some theoretical explanations and empirical evidences about different behavioural finance phenomena, including the herd behaviour.

Bikhchandani and Sharma (2000) define herd behaviour as "an obvious intent by investors to copy the behaviour of other investors".

In fact, taking into account the theory of efficient markets, agents construct homogeneous expectations, considering all available information, aware that each investor reaches this public information exactly in the same manner, and that all of them are perfect rational utility

maximizers. The researchers have suggested the herding effect as an alternative evidence of how investors make investment decisions.

Such behaviour, moreover, according to the opinions of policymakers, provokes an increasing in the volatility of returns, and thus, it destabilizes financial markets, especially in crisis conditions.

It is possible to investigate this phenomenon by focusing on the investor's psychology, who may desire to comply with the market consensus [Devenow and Welch (1996)]. Another view offers the idea that other agents may have some information about the return on one particular investment and their behaviour will unveil them [Chari and Kehoe (1999), Calvo and Mendoza (1998) and Avery and Zemsky (1998)]. Furthermore, a third approach underlines the principal - agent relationship where managers may decide to mimic other investors in order to conquer the incentives given by the compensation scheme¹⁶ [Scharfstein and Stein (1990), Rajan (1994) and Maug and Naik (1996)].

The phenomenon of herding effect was treated theoretically for the first time by Banerjee (1992), Bikhchandani, Hirshleifer, and Welch (1992) and Welch (1992). According to these studies, if a relevant number of investors makes the same choices, the investors coming later will decide to disregard their own information, choosing exactly the same behaviour of their predecessors and setting in train a circle of mimicking. As a matter of fact, we have to admit that not always the results of the researchers do agree each other about features and implications of herding.¹⁷

The discipline of behavioural finance was developed in order to underline the limits of classical finance and it is possible to quote a great number of authors, including Kahneman and Tversky (1979).

As above-mentioned and in accordance to behavioural finance theory, investors are influenced by psychological factors when they are making choices. Sometimes, indeed, investors prefer to be affected by their beliefs and feelings, rather than to be confident in the economic models, giving up the rational choices and making asset prices changed compared to the intrinsic value (so that it becomes not easy to discover the underlying value of assets).

Nevertheless, the majority opinion is oriented in stating that the presence of irrational investors does not affect the prices' trend, because of their random behaviour, even if there is who,

¹⁶ e.g. to preserve their reputation or for other benefits about employment.

¹⁷ The lack of consensus about herding may depend, at least partially, on the time horizon chosen for institutional investors, which is usually quarterly. According to Radalj and McAleer (2003), long time frames lead to more problems in the search for herding evidence.

conversely, sustains that their existence is of primary importance. In fact, the mainstream economic theory tells us that rational investors may exploit arbitrage opportunity because irrational investors have similar behaviour, but it is not able to offer a persuasive explanation for financial market frenzies, crashes and panics.

This school of thought adopted as explanation the opinion of Friedman (1953): he stated that, these events, driven by irrational traders, do not produce worthy of attention effects in the long run, because destabilizing speculators would fast fail and be deleted from the market; in a nutshell, according to these authors, the observation of rationale speculators is enough to reveal and understand the behaviour of stock markets. In fact, Friedman (1953) and Fama (1965) state that in the trading activity irrational traders come across rational arbitrageurs who trade against them and, thanks to such meeting, prices go to the fundamental values. Moreover, during the trading section, traders, whose evaluations about the asset values are unable to affect prices (because of errors), lose money to arbitrageurs and thus eventually disappear from the market. The idea is "*that speculation is . . . destabilizing... is largely equivalent to saying that speculators lose money, since speculation can be destabilizing in general only if speculators on ... average sell... low ... and buy ... high*" [Friedman (1953), p. 175]. Noise traders, hence, are not able to affect prices too much and, although they can, they will not do it for a long time.

Vice versa, Shiller (1984), for instance, observing the influence of irrational investors behaviour on the capital market, reached a different result and affirmed that such type of investors may produce prices deviation from their fair values. The turning point, therefore, was to postulate that capital markets might be affected by psychological and sociological elements, concluding that they are not necessarily efficient.

Therefore, it appears evident that the literature does not agree on the importance and on the existence of herding behaviour, so the literary production is not unanimous in giving a unique definition of the phenomenon itself.

Banerjee (1992) gives to the phenomenon the following formalization: he infers that herding is observable when agents "*do what everyone else does, even when their private information suggests they should take a different decision*"¹⁸. Devenow and Welch (1996) and Scubba (2000), moreover, involve behavioural models correlated among agents.

Chang, Cheng, and Khorana (2000) allude to this market feature as a method thanks to which market participants plan their investment decisions only on aggregate beliefs, ignoring their own feelings.

¹⁸ See Banerjee, A. (1992). A simple model of herd behaviour. *The Quarterly Journal of Economics*, 107, 797–817.

Patterson and Sharma (2007, p. 4) underline that “herding” takes place when a group of investors trades on the same market side, being interested in the same securities at the same time-frame or, alternatively, when agents, suppressing their own private information, behave as other investors do.

Although, according to different opinions, many researchers have shown their interest for the search of possible causes about the existence of the herding phenomenon: Hirshleifer, Subrahmanyam, and Titman (1994) state that its occurrence would be due to the propensity of investors to retrieve the information from the sources, giving the same interpretation to the signals conveyed to the market and, hence, reaching analogous financial conclusions. Ergo, if investors are influenced by the same information sources, or they interpret it in an akin way, it will be very likely that correlated behaviour patterns occur.

Among others motivations that support the existence of herding, we may account for the fact that institutional investors negotiate excessively or pay attention to the same group of securities and stand on the same side of the market.

Other authors such as Black (1986), Demirer & Kutan (2006), Patterson & Sharma (2006), Rajan (1994), Scharfstein & Stein (1990) and Trueman (1988) advanced several other explanations for the above-mentioned phenomenon i.e. the will to own similar assets, the compensation schemes, the reputational costs (especially if investors are identified with the figure of managers), the quality of the information dispatched to the market and the degree of market sophistication.

Focusing on another feature of the phenomenon, we have to talk about the rationality of herding. In fact, we can identify two different schools of thought: the first states that this behaviour would be generated by the herding instinct and, therefore, it would be an irrational phenomenon since different groups of investors make the same choices; given this state of mind, it is arduous to recognize and compute the herding effect.

Other researchers, conversely, assert that correlated behaviour patterns could be totally rational because agents decide consciously to make the own choices of other investors; consequently, the relation between rationality and emotion appears significant and the psychological aspect will not be an obstacle in the process of optimisation of investor behaviour.

Empirically, it is not easy to distinguish which herding type prevails, given the great number of parameter that can influence investment choice in a specific stock at a specific point in time.

Although the literature shows many theoretical models that describe the existence and the features of the herding phenomenon in financial markets, the empirical facts, used as prove

them, are not unanimous. In fact, in these studies, we find several measures and indicators, changing the findings of the previous authors or suggesting new methodologies. This is the case of Chang *et al.* (2000), Christie and Huang (1995), Hwang and Salmon (2004, 2009), Lakonishok *et al.* (1992) and Patterson and Sharma (2007) but we have to underline that, most of the times, the result found through the model does not support the existence of herding.

Probably, the problem is about not only the method used for calculating herding, but also about the data sample, among which we find the market type.

Analysing financial markets outlined by a low level of liquidity, the authors are prone to line up with the existence of herd behaviour. For example, Zaharyeva (2009) studies the presence of herd behaviour in the Ukrainian capital market between 1998 and 2008 and she concludes for the existence of it. The results of her studies, moreover, are consistent with what Duasa and Kassim (2008) state observing the Malaysian capital market, another illiquid market and with what Barros (2009), Leite (2011) and Serra & Lobão (2002) find in the Portuguese market.

Further proof is represented by the research of Serra and Lobão (2002) that take a sample of 32 equity mutual funds over the 1998–2000 period and by the studies of Barros (2009) who tests, conversely, a sample of 32 Portuguese equity funds for the period between 1997 and 2007. Both authors found evidence of herding.

Another relevant feature, that influence the existence of correlated pattern behaviour, is the market's degree of sophistication according to Demirer and Kutan (2006), Patterson and Sharma (2006), Rajan (1994), Scharfstein and Stein (1990). The Portuguese market, in fact, is small as regards to the dimension and it is not very liquid; this fact influences the investors to behave in a different way respect to the major world markets, such as the USA one. Especially the illiquidity may influence the investors in their choices, because, sometimes, even if they had wanted to take a different decision, they would be obliged to mimic the market. In support of this theory, the researches of Patterson and Sharma (2005, 2007) confirm that market like the USA, China and Hong Kong do not reveal herd behaviour and they get close to the market efficiency hypothesis.

R. W. Sias (2004) examines also five possible motives that could be at the basis of herding behaviour among institutional investors; he identifies these five categories in informational cascades, investigative herding, reputational herding, fads and characteristic herding¹⁹.

¹⁹See Graham (1999), Nofsinger and Sias (1999) and Wermers (1999) for further discussions of these classifications.

According to his opinion, informational cascades depend on the presence of institutional investors who decide to not account for their own noisy information and to trade with herd, deducing information from each other's trades [Banerjee (1992), Bikhchandani, Hirshleifer and Welch (1992)]. Investigative herding²⁰, conversely, is present when institutional investors' information is positively cross-sectionally correlated, possibly because the agents are influenced by the same signals [Froot, Scharfstein and Stein (1992), Hirshleifer, Subrahmanyam and Titman (1994)]. Reputational herding is due to the fact that if the institutional investors take different decisions from the herd, they will be submitted to some reputational costs [Scharfstein and Stein (1990), Trueman (1994)].²¹

Institutional investors may also herd as a result of fads [Freidman (1984), Dreman (1979), Barberis and Shleifer (2001)] or because they are interested to securities with specific features [Falkenstein (1996), Del Guercio (1996), Gompers and Metrick (2001), Bennett, Sias and Starks (2003)].²²

According to R. W. Sias (2004), observe how institutional investors herd is significant to understand how information, agency problems, fads, and securities features may affect the process of making decisions about investment.

Anyway, none of the reasons regulated in the five categories are considerable mutually exclusive: in fact, agents may herd for a number of different motives.

A special case of "characteristic herding" is represented by "habit investing"²³ and it results from the cross-sectional and time-series correlation in the net flow of funds to groups of institutional investors²⁴. Precisely, if some agents are affected by positive time-series correlation in their net flows, and they invest (divest) flows into (from) their actual portfolios, then these agents will follow themselves into (when flows over adjacent quarters are positive) and out of (when flows over adjacent quarters are negative) the same securities over consecutive quarters.

²⁰ To discriminate informational cascades from investigative herding, R.W. Sias (2004) studied the herding by capitalization quintile. He made use of Wermers's (1999) statement that informational cascades are more likely to be showed in small capitalisation securities (where signals are less noisy). In fact, even if herding is present in every capitalization assets, the phenomenon is stronger in small capitalization securities.

²¹ Another option embodied the behaviour of the investors who engage in herding in order to minimize litigation risk. For instance, bank trusts departments could preserve investments' prudence, showing that other bank trust departments even own the same security.

²² It is useful to mention momentum trading in this category, because institutional investors are interested to (repelled by) securities with high (low) past returns.

²³ Habit investing is a special case of characteristic herding because institutional investors follow each other into and out of the same stock (herd) as a result of their attraction to securities with the same features, so that they own similar portfolios.

²⁴ The capability of habit investing in the explaining the herding behaviour is not inferable only in the R.W. Sias (2004) tests. In fact, if the net flows to subsets of institutional investors show positive cross-sectional correlation and these agents prefer particular stocks (e.g. the securities that they already own), the Lakonishok, Shleifer and Vishny (1992) measure should be positive.

Moreover, if subsets of institutional investors prefer securities with precise features, they will hold more than one security of the same type, and flows to these investors will be characterized by positive time-series and cross-sectional correlation.

Thus, these agents will invest (divest) flows into (from) their actual portfolios and the same actors will incline to go after each other into (when flows over adjacent quarters are positive) and out of (when flows over adjacent quarters are negative) the same securities over consecutive quarters.²⁵

In order to understand if habit investing is able to disclose herding and following their own lag trades, R.W.Sias (2004) studies the correlation²⁶ between the fraction of institutional investors who decide to increment their portfolio weights during the actual quarter and the last one. If institutions emulate themselves and each other into and out the same financial instrument according to *habit investing*, the weights chosen for the portfolio assets should be independent over nearby quarters.

For instance, if the money flow is directed to the technology funds, the funds' manager will buy Microsoft securities. On the other hand, if managers will buy additional shares of Microsoft, proportionally to their current holdings, the combination of portfolio weights, as regards to Microsoft, would not change. Conversely, if traders imitate themselves and each other for reasons divergent by time-series and cross-sectional correlation in net flow, the portion of institutional investors raising portfolio weights will be positively correlated over contiguous quarters.

²⁵ This structure is observable across similar managers according to the same classification. For instance, technology-oriented mutual funds could experience a net inflow of funds over adjacent quarters, while a set of mutual funds that are interested in utility stocks, are submitted to a net outflow over the same quarters.

²⁶ Ottaviani and Sørensen (2000) introduced an exception because they affirmed that reputational herding takes place even without correlated prediction errors in opposition to the famous model of Sharfstein and Stein. They postulate three different scenarios where differential conditional correlation is indeed necessary to obtain herding in a reputational environment: (i) In an investment model with pure private values, only conditional correlation may oblige future investors to condition their behaviour on the predecessors' choices. (ii) In a situation in which investors have intermediate levels of private information about their own ability, correlation is necessary and sufficient to generate herding. (iii) With unbounded private information precision about the state of the world, correlation is not only necessary for herding but also sufficient when the information is characterized by a sufficiently bounded precision on own ability.

2.2. Differences with information cascades

“Small protests began in Leipzig, Germany in 1989 with just a handful of activists challenging the German Democratic Republic. For almost a year, protesters met every Monday growing by a few people each time. By the time the government attempted to address it in September 1989, it was too big to quash. In October, the number of protesters reached 100,000 and by the first Monday in November, over 400,000 people marched the streets of Leipzig. Two days later the Berlin Wall was dismantled.”²⁷

In order to understand the reason hidden in a digression about information cascades in a dissertation focused on the herding effect, we have to make a clarification. In fact, the terms informational cascade and herd behaviour are generally used interchangeably in the literature, but Smith and Sørensen (2000) highlight that there is an important difference between them. We can affirm that an informational cascade takes place when an infinite sequence of individuals ignore their private information in the process of decision making conversely, herd behaviour takes place when an infinite sequence of individuals make an identical decision, not necessarily ignoring their private information²⁸. By the way, this difference appears only as a little knowledge because, as a matter of fact, it is not responsible of great implications.

The concept of information cascades, according to Vieira and Simões (2015), is linked to the repetition of the decisions by several individuals, founded on the observation of the behaviour of other traders. Recently, the literature has underlined the importance of information cascades in the context of economics and the social sciences.

Moreover, Patterson and Sharma (2006) affirm that information cascades are due to trading sequences, begun by a buyer or a seller, higher than those ones that would take place if every actor traded according only to his/her private decision.

Bikhchandani *et al.* (1992) assume also that traders' choices are taken sequentially; this means that, a cascade of investment (disinvestment) will occur only if both the first and the second agent will prone to invest (disinvest). Information cascades, furthermore, give rise to rational

²⁷ Shirky, C. (2008). *Here comes everybody: The power of organizing without organizations*. Penguin.

²⁸ In other words, when people are operating in a herd, they make the same choice, but they may have acted in a different way from one another if the realization of their private signals had been different. Conversely, in an informational cascade, an agent thinks it is better to imitate the behaviour of the predecessors without considering the private signal because his/her belief is so strongly that no signal can go beyond it.

herding when traders become aware that the benefit of having trust on the information they suppose from the actions of other traders [Welch (1992)].

According to Smith and Sørensen (2000), conversely, an information cascade takes place when a non-finite sequence of individuals relaxes their private information in the decision-making process, while sheeple²⁹ behaviour occurs when an infinite sequence of traders makes the same choice, not necessarily disregarding their private information.

The most important implication is that a cascade implies herding, but herding is not necessarily due to a cascade.³⁰

Cipriani and Guarino (2008) assert that informational cascades weaken the information process aggregation and may produce a misalignment between the asset's price and its fundamental value. On the other hand, their research has revealed that the convergence between the price and the fundamental value does not depend significantly on the presence of transaction costs; this is probably due to the decreasing of the trading frequency, which characterizes the irrationality of individuals who trade against their private information.

Recalling Bikhchandani and Sharma (2001), they underline that it is not easy to calibrate the variation in the fundamental value because it may be difficult to compute analytically the intensity and the direction of herding affecting an asset or a market.

Informational cascades grow in a context where imitation will take place with certainty. Even in its simplest form of imitation, they give a very important benefit providing to traders the possibility to take advantages from information owned by others about the environment.

“When a friend is fleeing rapidly, it may be good to run even before seeing the saber tooth tiger chasing around the bend” [Hirshleifer (2003)]. The advantage in mimicking others, and considering consequently the payoff resultant, is of primary importance, as we can deduct even from the behaviour of many different animals.

²⁹ Sheeple is a *portmanteau* of “sheep” and “people” and it is an injurious term, which underlines the herd behaviour of people easily dominated by a governing power which handle them like sheep, herd animals easily to command. The ratio in the use of this word is to describe those who intentionally comply with a scheme without using critical analysis because, mainly, most of people around them are characterized by the same mind-set. Word Spy, the famous website, outlines the phenomenon as *“people who are meek, easily persuaded, and tend to follow the crowd (sheep + people)”*.

The Wall Street Journal, moreover, was the first to report the label in print in 1984; the reporter, in fact, heard the word used by the owner of the American Opinion bookstore.

The term was used even for those, who look like excessively tolerant, or welcoming, about what they hear from the government speaker. In a column entitled “A Nation of Sheeple”, the commentator Walter E. Williams writes: *“Americans sheepishly accepted all sorts of Transportation Security Administration nonsense. In the name of security, we've allowed fingernail clippers, eyeglass screwdrivers, and toy soldiers to be taken from us prior to boarding a plane”*.

³⁰ According to the opinion of Bikhchandani *et al.* (1992), individuals with the access to information, which is less accurate, are prone to follow the lead of individuals that have access to an information set more accurate than they have. Ignoring their own information, such individuals tend to form herds, with the best informed individuals making their decisions first. These decision makers are known as “fashion leaders”, and the phenomenon as “informational cascades”.

Nevertheless the imitation may not be, necessarily, the outcome of a rational analysis and the inclination to adopt a mimicking behaviour could be in harmony with costs and benefits thanks to the leading role of natural selection.

The word imitation is largely used to take into account sub-rational mechanisms that lead an individual to mimic the behaviour of another individual.

Both in psychology and in zoology we find a huge literature on imitation regarding many animal species, both in the wild and experimentally [see, e.g., Gibson and Hoglund (1992), Giraldeau (1997), and Dugatkin (1992)]. Imitation, moreover, has been certificated among birds, fishes, mammals in foraging and diet choices, selection of mates, selection of territories, and in means of avoiding predators.

The beginning of an informational cascade may even dry to a complete information blockage.

Take into account a sequence of ex ante identical agents who handle analogous decisions, paying attention to conditionally independent and identically distributed private information signals³¹, considering that they are able to see the actions but not the payoffs of previous individuals. Now, assume that agent i is in a cascade and that later traders know this information. Thus, the agent $i + 1$ does not reach any information by the observation of i and he/she is, informationally, in the same situation of i .

So $i + 1$ will even take the same decision despite of his private signal. By induction, we can spread this mechanisms to all later agents, i.e. the collection of information undergoes a screeching halt when a cascade rises.

Hirshleifer (2003) specifies that the idea for what information is blocked forever without any “development” is, absolutely, excessive, for the following reasons:

- A publicly observable shock could remove a cascade;
- If agents are not ex ante identical, then the occurrence of an agent with different information or preferences may imply the end of the cascade;
- For the rising of a cascade is necessary that agents do not own an arbitrarily precise signal. [Bikhchandani, Hirshleifer and Welch (1992)].
- Each decision in the cascades leads to a payoff, which, if revealed, may become a public information making the cascade removed.³²

³¹ Agents may observe private signals without paying any costs, or they may employ resources to achieve signals. Many social learning approaches choose the costless options, but the costs of achieving signals may lead to little accumulation of information in the social pool for essentially the same reason as in other cascades or herding models. Agents are less prone to examine private signals if the main benefit of making use of such signals is to obtain some information that later individuals, will easily achieve. [see Burguet and Vives (2000) who study social learning model with investigation costs].

³² However, bad cascades need not be dislodged with certainty; see Cao and Hirshleifer (2000).

Hence, what we can deduce, is that basic cascades model reveals an information aggregation overly slow respect to what theoretically we expect firstly and that the presence of the blockages could last for a long time-frame [Gale (1996)].

In closing, a generalization of the cascades concept is the so-called *behavioural coarsening*: the term implies any occurrence in which an agent makes the same choice for multiple signal values, where, instead, the actions reveal only partially the information.

Moreover, behavioural coarsening is able to create a partial information blockage. In fact, a cascade is a limit case where the coarsening identifies each possible signal value, leading to a complete blockage.

The poor aggregation of information in this structure makes even the result lousy, although the signal observed by the agents may be good in delineate the right choice with virtual certainty.

Because of the full rationality of the model, each trader is totally aware that the public set of information implicit in the predecessors are not very precise. Thus, even rather modest public shock may lead to long-term change in individuals' decisions.

Even if the agents, learning about much public information, improved their choices, the occurrence of a signal, obtained through a public disclosure, would paradoxically worsen the situation.

In fact, since further information can drive agents to fall into a cascade easier, aggregating the information of fewer individuals, it is not straight assuming that the signal will improve choices about investment in the cascade [Bikhchandani, Hirshleifer, and Welch (1992)].

Similarly, individuals that are able to notice past actions with low noise instead of high noise, or agents that may know not only the past actions but also the resultant payoffs, could make, on average, poorer choices [Cao and Hirshleifer (1997, 2000)]³³

*"A little knowledge is a dangerous thing"*³⁴

Indeed, in a real investment environment, the assumption of basic cascades model, where the timing and the sequence of actions is exogenously given, is not realistic. If we give to traders the possibility to delay their actions, we may observe long periods without any investment succeeded by unforeseen opposite choices: in fact, suddenly, an individual can decide to invest in a project triggering the exercise of a real option by other agents [Chamley and Gale (1994)].³⁵

³³ Even the possibility to learn by observing predecessors may worsen the followers ability to decide about investment, by making the signal noisier and decreasing their incentives to look for more and better information [Cao and Hirshleifer (1997)].

³⁴ Pope, Alexander. *An essay on criticism*. Clarendon Press, 1909.

³⁵ See also Hendricks and Kovenock (1989), Bhattacharya, Chatterjee, and Samuelson (1986), Zhang (1997) and Grenadier (1999).

Anyway, we can include most of the concepts above-mentioned in the social learning models where, however, cascades do not take place.

Another feature of the information aggregation is its propensity to be self-limiting: when the public pool of information does not convey any information, individuals are very confident in private signals, so that each move contributes to the public pool with many information (acquired through the observation of past actions or of their results). As the environment becomes more and more informative, the private signals become less and less significant for the agents. Thus, the lack of sensitivity of actions to private signals could also create an unexpected change, represented by sudden variation from the full trust in private signals to a completely opposite behaviour [Banerjee (1992), Bikhchandani, Hirshleifer, and Welch (1992)]. Conversely, it could occur also gradually leading to the conditions for a complete blockage or not.

In a nutshell, it is the economic structure to influence the flow of information, i.e. whether the information aggregation become quickly or only gradually clogged or whether the blockage is complete or partial; moreover, we are also able to prove that individuals can herd even for long time periods although upon poor decisions, because of a tendency of behavioural convergence. Conversely, individuals who decide to invest according to their private signals, offer to the other agents a positive externality about what everybody could draw inferences.

The informational cascade model described by Banerjee (1992) or Bikhchandani, Hirshleifer and Welch (1992) is supported by the idea that the public pool of information dominates the individual's private signals even if an unbounded ratio of private signal likelihood could overturn this mechanism. Moreover, taking into account the informational cascades theory, endorsements can be really important if the endorser is well known thanks to his/her precision, and if the endorsement is about tangible information given by the expert. The endorsement could assume different shapes: the expert could behave in a similar way (selling a stock), or put into play the reputation giving a recommendation about it. Obviously if a big-five auditor, a top-rank investment bank or a venture capital decides to certificate a firm spending their own reputation, it will drive investors to be confident in that firm.³⁶

³⁶ See the models of Titman and Trueman (1986), and Datar, Feltham, and Hughes (1991), and the evidence of Beatty and Ritter (1986), Booth and Smith (1986), Johnson and Miller (1988), Beatty (1989), Carter and Manaster (1990), Feltham, Hughes, and Simunic (1991), Simunic (1991), Megginson and Weiss (1991), Michaely and Shaw (1995), and Carter, Dark, and Singh (1998). A relevant and recent example of this certification effect is represented by the decline of 36% in the shares of Emex when First Boston disclaimed Emex that it was their investment banker (Remond and Hennessey (2001)).

Furthermore, exactly as shopping mall ownership takes advantage from “anchor” stores to attract other stores, McGee (1997) states that some IPO underwriters have been using the names of popular investors as “anchors” to raise interest other investors.³⁷

We can mention many powerful investors, some more fair than others. For instance, in an article published on the 5th of July 1992 and defined as “*Pied Piper of Biotech Keeps Followers Happy with Cut-Rate Stock*”, the Wall Street Journal says that “*Wherever David Belch invests his money, a crowd of stockbrokers and money managers is sure to follow*”. “*David Blech is the single most important force in the biotech industry*”, asserts Richard Bock, a stockbroker... “*I follow whatever stock he goes into, knowing it will be a success*”.

Some brokers try even to attract individuals in cold-calls using as incentive the fact that some famous investors are owning that financial product [Lohse, D. (1998). *Tricks of the trade: “Buffett is buying this” and other sayings of the cold-call crew. Wall Street Journal, 6(1), 98*]. Indeed, since Warren Buffett is essentially a passive investor, his behaviour creates the impression that he is well informed, instead of revealing that he will reorganize the firm.

For example, Davis (1991) underlines that the occurrence about Buffett involved in an investment, was used as an advertising mean for a stock; when the public heard that Warren Buffet bought about 20% of the 1997 world silver output, The Economist (1998) affirm that silver prices went “soaring”.

Furthermore, when Warren Buffets divulged to have increased his holding position in American Express, and in PNC Bank, these shares rose by 4.3% and 3.6% respectively [O'Brien and Murray (1995)].

Quoting Sandler and Raghavan (1996), “whether Warren Buffett has been right or wrong about a stock, investors don't like to see him get out if they're still in. Some investors in Saloman are focusing almost entirely on the famed Omaha, Neb., multibillionaire's decision, announced Sept. 12, ...” to convert Salomon preferred shares into common shares instead of withdrawing money.

Among different forms of endorsement, we find also investing in human capital; for instance, when the news that John Scully was appointed as chairman and CEO of the little known society named Spectrum Information Technologies Inc., its stock jumped by close to

³⁷ “As any fashion house knows, stitching a designer label on a pair of jeans allows it to charge two or three times the going rate for pants. Now, battling to set themselves apart from the crowd, and entice more investors to their initial public offerings of stock, fledgling technology companies with unproven products and no earnings are bragging of their ties to stock-market winners like Microsoft Corp., Cisco Systems Inc. or American Online Inc. Never mind that some of these anchor investors do not appear to be picky; they invest in bunches of smaller companies because they know that not every investment will pan out. The fact is, the hype works...” The article gives several examples where tech stock analysts and investors may have been let influenced by the cachet of anchor investors.

46%.³⁸ We can suggest a meaning of what we report above: the impact of a “gurus” in a stock market is comparable to a form of endorsement, although sometimes, famous but incompetent analysts irrationally affect individuals. This is due, for instance, to a wrong match between the visibility fame of the analyst and his/her ability; a would-be guru may even makes use of outlandish publicity stunts to gain notoriety (to gain more information, see, for example, the description of Joseph Granville's career in Shiller, 2000b).

Indeed, stock prices are influenced by the trades’ news of insiders [Givoly and Palmaon (1985)] and it is obvious that these trades give information to the investors, who change, eventually, their trading activity as result. The relevance whose insiders could enjoy, offers them the possibility to manipulate prices, as reflected on the analysis of Fishman and Hagerty (1995).³⁹ Agents are even affected by private conversations with peers; for example, Fung and Hsieh (1999) affirm that “a great deal of hedge fund investment decisions are still based on *recommendations from a reliable source*”. We can also state that individuals are induced to modify their decisions through implicit endorsements, as in the case of default settings for contributions in 401(k) plans.⁴⁰

³⁸ John J. Keller (10/14/1993). *Sculley Becomes Chief of Spectrum, Placing Bet on Wireless Technology*, Wall Street Journal. A later Business Week investigation inferred that the CEO of Spectrum was “a manipulator who duped John Sculley and milked the company” (Schroeder (1994).

³⁹ See Fried (1998) for a dissertation about the “copycat theory” where insiders make use of imitators by trading without private information.

⁴⁰ See Madrian and Shea (2000).

2.2.1. Model based on Bayes rule

In line with the idea of herd phenomenon, herding behaviour derives from a clear investors' purpose to copy other investors. This phenomenon should be differentiated from “*spurious herding*” where groups handling similar problems and owning the same information set, make similar choices. Furthermore, spurious herding is considered an efficient result, while “*intentional herding*” is not necessary to be efficient even if we have to underline that it is not easy to divide empirically “spurious herding” from “intentional herding”; in fact, several factors have the possibility to affect an investment choice.

For instance, spurious herding may occur if interest rates suddenly rises and stocks appear less desirable to invest in. Thus, individuals could prefer to own a smaller percentage of those stocks in their portfolio, but this behaviour cannot be identified with the main definition of herding because individual choices are not taken after the observation of other agents.

Spurious herding may also occurs if the opportunity sets of several investors differ: assume that there are two groups of agents, D domestic and F foreign investors, who invest in a country's stock market; because of restrictions on capital account convertibility in the country, type D invest only in S_d , the domestic stock market, and in B_d , the domestic bond market. Moreover, agents F invest in S_d , B_d and even in S_f , a foreign country's stock market and in B_f , the foreign bond market.

If, in the foreign country, interest rates drop or agents are not confident of future earnings of firms, the trader F may augment the share of S_d and B_d in his portfolio. Therefore, the investor F looks like member of a “buying herd”, while the trader D looks like to be included in a “selling herd”. Yet, the investment choices of agents F and D are individual decisions and they may not be affected by the choices of other investors. Additionally, this behaviour is efficient under the capital convertibility constraints, which the agent D is forced to.

By the way, Sharma and Bikhchandani (2000) are not interested in not fully rational agents⁴¹, but only in the mimicking behaviour due to the exploitation of signals by the investors.

⁴¹The only exception is represented by one category of herd behaviour, which use momentum investment strategies [see even Grinblatt, Titman and Wermers (1995), Froot *et. al.* (1998), Choe *et.al.* (1999), Kim and Wei (1999a, 1999b)]. A momentum investment strategy shows the agents' propensity to buy and sell financial products taking into account the past returns of the stocks, i.e., to buy recent winners and sell recent losers.

This type of herd phenomenon is not rational under the efficient market hypothesis since we suppose that market prices reveal all available information. Thus, “momentum investment” or “positive-feedback” strategies could amplify price movements and increase volatility.

Now we examine an inform cascades' case based on the Bayes rule where it is well explained the sequence's mechanism due to the exploitation of sequential different signals related to the coming of new information.

Assume that many investors choose, in sequence, if make an investment in an individual stock (or in an industry or in a country). Every agent's compensation is proportional to the payoff given by the investment.

Assume that V is the payoff given by the investment to each agent. The value that V could take are either $+1$ or -1 with the same probability; the order of investors' investment choices is exogenously given.

Every agent observes a private signal, which may be good – G – or bad – B – about the investment payoff. If $V = +1$, the probability that the signal received is G is equal to p and, consequently, the probability that the signal received is B is equal to $1 - p$, considering that $0.5 < p < 1$. On the other hand, if $V = -1$, we observe the signal B with probability p (and G with probability $1 - p$)⁴².

Other than the private signal, every investor is able to observe the choices (not the private signals) of other predecessors.

Using Bayes' rule, the posterior probability of $V = +1$ after receiving the signal G is

Eq. 12

$$\begin{aligned} \text{Prob}[V = +1|G] &= \frac{\text{Prob}[G|V = +1].\text{Prob}[V = +1]}{\text{Prob}[G|V = +1].\text{Prob}[V = +1] + \text{Prob}[G|V = -1].\text{Prob}[V = -1]} \\ &= \frac{p \times 0.5}{p \times 0.5 + (1 - p) \times 0.5} = p > 0.5 \end{aligned}$$

Thus, the first investor, Simon, will follow his signal: if he identifies G , then he will make the investment; if, conversely, the type of signal is B , then he will not make the investment.

Natalie, the second investor, is aware of this kind of behaviour and she infers signal from his choice. If her signal is G and she looks at Simon investing, then she will make the investment. On the other hand, if she receives the signal G and she observes that Simon does not make the investment, then a different application of Bayes' rule leads her posterior probability of $V = +1$ to 0.5 (the same outcome is achievable if Natalie have received two type of signals: G and B) and she flips a coin.

Actually if Simon invests and Natalie does not, Susan will suppose that Simon receives the signal G and Natalie B ; if, on the other hand, both Simon and Natalie make the investment,

⁴² Individual signal are independent respect to the true value.

Susan, the third trader, will suppose that Simon receives G and Natalie is more likely to receive G than B .

In the residual two cases, in which Simon does not make an investment and Natalie does or does not make an investment are symmetric.

As above-mentioned, now assume that both Simon and Natalie invest, Susan infers that Simon and reasonably Natalie have received good signals but a different use of Bayes' rule reveals that Susan will invest even if her signal is B .

Now we add a new member, Donald, who do not know anything about the fulfilment of Susan's signal from her investment choice. Donald addresses the same situation of Susan and he will make the investment too despite the realization of his signal and consequently, even Emma, Frank, Greta, Harry, etc.

According to this example, Sharma and Bikhchandani (2000) state that *invest cascade* begins with Susan, and that, if both Simon and Natalie do not make an investment, Susan will begin a *reject cascade*.

However, if Simon and Natalie make contrasting choices, Susan will be sure that one of them received the signal G and the other the signal B . Thus, her prior belief (a state of mind, which foreruns the observation of the signal) considers $V = +1$ and $V = -1$ equally likely and she will make the same choice of Simon (being in the same position), i.e. follow the signal.

Generally, an agent will be in an invest cascade (reject cascade), if and only if the number of forerunners, who make the investment, overtakes the number of forerunners, who do not make the investment, by two or more. Thus, it is more likely that a cascade begins after the first few individuals.

According to Sharma and Bikhchandani (2000), although the signal is arbitrarily noisy (i.e. p is arbitrarily close to 0.5), a cascade begins after the first four (eight) investors with a probability bigger than 0.93 (0.996). However, particularly for noisy signals, the probability that the cascade is inaccurate (i.e. a reject cascade when $V = +1$ or an invest cascade when $V = -1$) is significant. For example, if $p = 0.55$, the probability that a mistake will occur in the cascade estimation is 0.434, only a bit less than 0.45, i.e. the probability of an agent to make the wrong investment choice without the observation of the forerunners.

The information collected by the investors, if aggregated and interpreted accurately, would lead them to a much more precise forecast of the true value. For example, if we assume that, in a set of hundred agents, the second through the tenth agent decides to relax the information derived from their forerunners, following their private signals, we may affirm that a more precise information is achievable to the eleventh through the hundredth individuals.

Hence, the agents, who receive the more accurate information, are more prone to herd if it is much more likely to do the right choice (compared to a situation where agent two from ten exploit the information received).

Moreover, the most important element for giving rise to a cascade is not how many “good” and “bad” signals arrive, but the order in which they arrive. For instance:

- if signals are received in the order GGBB..., each agent will make the investment because Susan will start an invest cascade;
- if the signals are received in the order BBGG..., agents will not make any investment because Susan will start a reject cascade;
- if the signals are received in the order GBBG..., there will be a probability of 0.5 that Natalie makes the investment and Susan starts an investment cascade.

Hence, the researchers have proved that an invest or reject cascade is path-dependent and idiosyncratic.

Moreover, when a cascade begins, agents will stop to aggregate public information, because their preponderance to investing or rejecting makes the further investors to relax their private signals, which, hence, never reaches the public pool of knowledge; even the public pool of information should not be much attractive if it makes agents relaxed their private signals.

Furthermore, although the public pool information becomes a little bit more informative, agents decide to herd giving rise to a cascade; this means that cascade is not robust to small shocks. Yet, we may list different types of shocks that could remove a cascade: for instance, the appearance of better informed agents, or the announcement of new public information and change in the underlying value of investing versus not investing. Moreover, when agents understand that they are in a cascade, they are conscious that the cascade depends on little information respect to the information held by private individuals. Hence, the main feature of the cascade is the fragility with respect to small shocks; they even start quickly, idiosyncratically and smash easily.

Implementations of the researches of Sharma and Bikhchandani (2000) are given, for example, by Chari and Kehoe (1999), who prove that information cascades are involved in a model characterized by an endogenous timing of individual decisions, continuous action space and the possibility of sharing information among agents.

Calvo and Mendoza (1998) analyse a model where investors can make an investment in N different countries, but agents are obliged to incur in a fixed cost to collect information about the returns on investment in country A . The payoff realized by investors, exploiting the information received, drops as N , the number of countries (i.e. the investment opportunities)

goes up. Furthermore, if N is large enough, the number of agents informed about the country A will drop significantly, and agents will herd in their investment choices not paying attention on country A .

Another implementation came from Avery and Zemsky (1998), who add another element to the underlying uncertainty in the basic model. Assume the existence of two types of agents, H and L ; the investor H has very precise information (p_H is close to 1) and the investor L has, conversely, very noisy information (p_L is close to 0.5). Moreover, assume that the market participants are not perfectly informed about the proportion of two types of agents and, above all, this proportion is not discoverable by the market-makers.

Therefore, even if the stock market prices always reveal all public information, the prices do not reflect the private information of every previous agent.

Avery and Zemsky underline that exist the possibility to observe a sequence of equal decisions in a well-informed market (where the most of the agents are attributable to the category H) because most of the traders receive the same (very informative) private signal realization.

Unlike the case when we observe a poorly informed market (where the most of the agents are attributable to the category L) because the sequence of identical decisions is due to the herding behaviour of agent L , who wrongly concludes that the most of other traders belongs to the type H .

Hence, informational inefficient herd phenomenon may take place and drive to bubbles and mispricing, if the market is not informed about the presence (or the absence) of precision of information. In fact, investors could imitate the forerunners trusting that they know something. Finally, we may therefore affirm that if the uncertainty is only about the underlying asset, the stock market price will be informational efficient, and we will not observe herding phenomenon; conversely, if other than the uncertainty is added an additional dimension – called uncertainty about the accuracy owned by market traders – a one-dimensional stock price will be no more efficient and we will observe the herding phenomenon, despite the agents rationality.

This method has been used even for other shapes of the herding phenomenon, i.e. it was born to explain the information-based herding and cascades but it may fit for the reputation-based herding [as Sharfstein and Stein (1992) explain] and for the compensation-based herding [as Maug and Naik (1996) show].

2.3. Various computations of herding effect

“The reaction of one man can be forecast by no known mathematics; the reaction of a billion is something else again”⁴³

Now we want to examine some different computational models realized, across time, by different researchers in order to demonstrate the presence of herding effect in the market.

Each method is innovative in some of its elements and it observes the problem from a different point of view. As matter of fact, we want to underline that the models, about we will discuss later, are inclined to admit the existence, almost partially, of herding.

2.3.1. Imitation model based on realized returns and on utility

De Long and J. Bradford (1990) developed a model based on a stripped-down overlapping generation model with two-period-lived agents. In order to simplify, the model does not involve first-period consumption, labour supply decision, and bequest. This implies that the resources invested by agents are exogenous and that the only choice undertaken by investors is about portfolio.

Going deeply in the analysis of the model’s assumptions, the economy involves two assets, which pay the same amount of dividends.

The first is a safe asset s , it pays a fixed real dividend r (represented by the riskless rate), it is in perfectly elastic supply and a unit of it can be turned back into a unit of the consumption good in any period. Considering the consumption of each period numeraire, the price of the safe asset remains fixed at one.

The second asset u , the unsafe one, pays the same dividend of the asset s (i.e. r). The discrepancy, respect to the safe asset, is that u is not in elastic supply: it is fixed, unchangeable and normalized at one unit.

p_t is the price of u at time t ; if each asset price is equal to the net present value of its future dividends, it will imply that u and s are perfect substitutes and that they would be sold at the price of one. However, this mechanism is not valid if noise traders enter in the market.

Then we can affirm that in the market, there are two types of investors: sophisticated individuals (represented by the letter i), identified by rational expectations and noise traders (represented

⁴³ Asimov, I. (2010). *Foundation: Foundation and Empire; Second Foundation* (No. 332). Everyman's Library
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by the letter n). Moreover, the portion of noise traders in the economy is μ , while the portion of sophisticated is $1 - \mu$, and all agents of a given type are identical.

Sophisticated traders young in period t , owning the risky asset, observe carefully the returns' distribution, so that they can maximize its expected utility. On the other hand, noise traders, young in period t , have wrong observation on the expected price of the risky asset, making use of an independent and identically distributed normal random variable:

$$\rho_t \sim N(\rho^*, \sigma_\rho^2) \quad \text{Eq. 13}$$

where ρ^* is the amount of the average “bullishness” characterizing noise investors and σ_ρ^2 is the variance misperception per unit of the risky asset's expected return.⁴⁴

Hence, noise investors maximize their own expected utility considering the next-period dividend, the one period variance of p_{t+1} , and their wrong belief that the price distribution of u has a mean equal to ρ_t above its true value.

The model of De Long and J. Bradford (1990) gives also the possibility to both noise and sophisticated traders to reveal a negative demand: in fact, they can choose to own a short position if they want. Although traders own only positive quantities of both assets, the chance of un-bounded returns creates the possibility to realize a negative final wealth.

Given these assumptions, the model reveals that the demand for the risky asset is proportional to observed excess return and inversely proportional to its observed variance, taking into account that the additional term in the noise traders' demand function has to be linked to their misperception of the expected returns.⁴⁵ Indeed, if noise investors overestimate expected returns, they will demand a bigger quantity of the risky asset respect to a sophisticated trader; if, conversely, they underestimate the expected return, they will gain a smaller amount of it. The uncertainty about the price for the risky asset, affects each investor, regardless of their beliefs about expected return, thus limiting how much individuals bet against each other.

Conversely, the certainty about the next period price would lead sophisticated and noise traders to behave differently about expected returns, having as consequence a never-ending bet

⁴⁴ The assumption that noise investors have wrong perceptions about the expected price conceals the fact that the expected price is itself a function of the parameters ρ^* and σ_ρ^2 . Hence, the researchers are implicitly postulating that noise investors know how to factor the effect of future price volatility into their calculations of values (the ratio of the hypothesis is to reach simplicity). De Long and J. Bradford (1990) have even created a more complex model, which parameterizes noise investors' beliefs through their expectations of future prices, instead of through their misperceptions of future returns and, anyway, the results are equally reliable.

⁴⁵ $\lambda_t^i = \frac{r + {}_t p_{t+1} - (1+r)p_t}{2\gamma({}_t \sigma_{p_{t+1}}^2)}$, $\lambda_t^n = \frac{r + {}_t p_t - (1+r)p_t}{2\gamma({}_t \sigma_{p_{t+1}}^2)} + \frac{\rho_t}{2\gamma({}_t \sigma_{p_{t+1}}^2)}$

between the two categories. This two option, underline that an equilibrium would not take place.

$$p_t = \frac{1}{1+r} [r + {}_t p_{t+1} - 2\gamma({}_t \sigma_{p_{t+1}}^2) + \mu \rho_t] \quad \text{Eq. 14}$$

Eq.14 shows the risky asset's price in period t as a function of period t 's misperception by noise traders ρ_t , of the technological r and behavioural γ parameters of the model, and of the moments of the one-period-ahead distribution of p_{t+1} . But after developing the Eq.13, we can obtain an equation where the price depends only on exogenous parameters and on public information regard to present and future misperception by noise trader:

$$p_t = 1 + \frac{\mu(\rho_t - \rho^*)}{1+r} + \frac{\mu \rho^*}{r} - \frac{(2\gamma)\mu^2 \sigma_p^2}{r(1+r)^2} \quad \text{Eq. 15}$$

The second term in Eq.15 analyses the variations in the price of the risky asset u , due to the fluctuations of noise traders' misperceptions: if a generation of noise traders is more bullish than the average one, they will bid up the price of u ; if, conversely, they are more bearish, they will bid down the price.

When noise investors own their average misperception – i.e. if $\rho_t = \rho^*$ - the term will be zero. The third term of Eq.14 reveals the deviations of p_t from its fundamental value: in fact, if noise investors are bullish on average, the “price pressure” inferred, leads the price of the risky asset higher than it could otherwise be. However, optimistic noise traders bear a bigger than average of price risk. In fact, since sophisticated investors assume a smaller share of price risk, they look for a lower expected excess return and, as a consequence, they may pay a higher price for the asset u .

Anyway, the bigger is the portion of noise investors relative to sophisticated ones, the more volatile the asset prices are.

However, it is the fourth term, the most important one: indeed, sophisticated traders are not willing to own the risky asset without being compensated of taking the risk that noise investors will become bearish and the risky asset price will drop.

The problem is that both noise investors and sophisticated traders in period t are prone to think about a mispricing of the asset u , but because of the uncertainty of p_{t+1} , no one of them is willing to wager too much on the mispricing.

Thus, the return due to the increasing of one's position in an asset, which is unanimously considered mispriced (even if not everybody thinks about the same mispricing) is balanced by the further price risk that must be run. Noise investors, hence, “create their own space”: in fact,

we do not know what noise investors will think over the next period, and this uncertainty drives the asset u to a riskiness degree that otherwise it would not exist, leading even its price down and its return up.⁴⁶

The equilibrium exists until there will be the uncertainty about the risky asset's returns. In fact, no agents could wait as long as the risky asset's price increases again before selling.

An overlapping generation structure could represent a very useful model to consider the implications on prices of many different institutional features, such as recurring estimations of money managers' performances, which may drive rational market investors to worry about short-term rather than long-term performance.

In the model built by De Long and J. Bradford (1990), the time-horizon of the typical market participants is important because, if the sophisticated trader has a long horizon relative to the extent of the noise traders' optimism or pessimism about risky assets, they may buy low, trusting that they will be able to sell high when prices revert to the mean. In fact, noise trader risk is a significant deterrent to arbitrage only if the duration of noise investors' misperceptions is of the same size as sophisticated traders or longer than their horizon.

Thus, the difference between noise and sophisticated traders' total returns, considering the same wealth at the beginning of the period, is the product of difference between the amount of risky asset u owned and the excess return given by a unit of the risky asset u .

We can even compare the expected excess total return of the two types of agents analytically:

$$E(\Delta R_{n-i}) = \rho^* - \frac{(1+r)^2(\rho^*)^2 + (1+r)^2\sigma_\rho^2}{(2\gamma)\mu\sigma_\rho^2} \quad \text{Eq. 16}$$

The first term is related to the *price pressure effect*, the numerator takes into account the *Friedman effect*⁴⁷, and the denominator shows as it is possible to *create space* (if the opinion of the noise traders becomes more diversified, the price risk will raise).⁴⁸

⁴⁶ The vision to the effect that traders in the risky asset "ought" to look for higher expected returns because they embody the significant social function of risk bearing, disregards to take into account that noise traders' speculation is the only source of risk. Conversely, if we consider the whole economy, there is no risk to carry.

⁴⁷ Friedman effect is the phenomenon of buy high – sell low. In fact, noise traders' misperceptions are stochastic, so that they are affected by the worst market timing. They start buying the most of the risky asset u only when other noise investors are buying it, exactly when they are most likely to suffer a capital loss.

⁴⁸ The two forces *-hold more and create space-* make usually increased noise traders' relative expected returns; conversely, the two elements *-the Friedman and price pressure effects-* make noise traders' relative expected returns dropped.

Noise traders' expected returns compared to sophisticated traders ones are going up when noise investors, on average, own more of the risky asset and they gain a larger share of the benefits by the risk borne.

If ρ^* is smaller than zero, the fluctuating misperceptions of noise traders still make risky the asset u which is essentially riskless and they make the expected return of asset u increased. However, the benefits of taking the risks are not proportionally shared among sophisticated traders, who, on average own a bigger amount of the risky asset, respect to noise traders.

We have to underline that, if sophisticated traders want to exploit the noise traders' misperceptions, they must bear a higher risk; as long as sophisticated traders are risk averse, they decide to bound the extent of their bet against noise traders in response to the bigger risk.

It is important, in any case, remember that, sophisticated traders achieve a bigger health if noise investors occur in the model. In fact, conversely, the only opportunity for sophisticated traders is to choose the investment at the riskless rate r . Thus, the occurrence of noise traders provides to sophisticated investors the possibility to enlarge their chances, because they can carry on investing in the safe asset, but they can also receive profits from the trading on the risky asset; moreover, having more chances make the sophisticated traders' expected utility increased.⁴⁹

De Long and J. Bradford (1990), after analysing the model taking into account the relative expected returns of the agents involved, decide to adopt even another point of view: the relative utility levels.

In fact, in order to obtain a higher expected return, the noise traders are obliged to have portfolios characterized by a higher variance, thus reaching a lower expected utility. As sophisticated traders maximize true expected utility, each trading strategy different from theirs, which gains a higher mean return, has to reveal an enough higher variance to make it not desirable. The average amount that old noise investors have to hold in order to obtain the ex-ante utility of sophisticated traders is

$$\frac{(1+r)^2}{(4\gamma)\mu^2} \left(1 + \frac{\rho^{*2}}{\sigma_\rho^2} \right) \quad \text{Eq. 17}$$

This ratio is inversely proportional to the variance and directly proportional to the square of the mean of the noise traders' misperceptions. The size of their error raises with the increasing of ρ^* , but the risk penalty, due to the will of taking an advantage from their errors, increases with

⁴⁹ If we relax the exogeneity of the risky asset's stock, sophisticated traders may be worse off in the case of the noise investors' occurrence. If noise traders attenuate the capital risk and the risk's price, they will decrease the opportunity set of sophisticated investors and their wealth [De Long *et al.* (1989)].

σ_ρ^2 . The average realized utility for noise traders is the same both in the case of $\rho^* = x$ and $\rho^* = -x$; the difference is about the average returns, because, if $\rho^* > 0$, they may receive higher average returns, if $\rho^* < 0$, viceversa.

As we state before, sophisticated investors are undoubtedly better off in the occurrence of noise investors because, otherwise, they can invest only in the safe asset; noise investors acquire higher average consumption than sophisticated traders do, and sophisticated traders acquire higher average consumption than in fundamental equilibrium. Still, resources like the labour per period, the capability of society to create the asset s are not affected by the occurrence of the noise activity.

In order to explain the extra returns, we can observe the results of an experiment; suppose that before the time τ , noise traders are not in the market; as far as the time τ , the risky and the safe asset are sold at the unitary price. Moreover, at time τ , investors are informed about the enter of noise traders' next generation in the market, so that the price p_τ of the asset u plunges. As a consequence, who own the asset u , at time τ , will be affected by a capital loss, which is the origin of the excess returns and of the higher consumption in the equilibrium with noise. During the time τ , young investors have more to trade on the asset s , because they spend less money for buying the asset u from the old traders.

If, at time ω , the market is informed about the stable withdrawn of noise traders, those who owned the asset v at time ω would obtain the present value of what would have been, in different conditions, the future excess returns (i.e. $p_\omega = 1$). This supernormal return would also be acquired by a generation that gains the possibility to "bust up" the risky asset transforming it in the same amount of the riskless asset.

The fact that, trading in the market, bullish noise investors may gain higher returns than sophisticated traders, leads not only to justify the hypothesis that the Friedman "market selection" argument is incomplete⁵⁰, but also to foresee the existence of herding phenomenon, which is, after all, the point of our interest.

In fact, the researchers have just showed us that noise traders obtain higher expected returns than sophisticated traders, proving, as their lack of their importance over time is less probable. Even if De Long and J. Bradford (1990) model does not allow to account for the accumulation of wealth of noise traders, we can allude to the succession of agents' generations as families. Hence, the new agent gathers the data about the performances of the previous generation and

⁵⁰ In fact, as noise investors' wealth may rise faster than sophisticated traders one, it does not make sense postulate that noise traders lose money and eventually significance.

Moreover, the shift of the sophisticated traders' demand curve relative to the presence of more noise traders and the consequent increasing in risk is the main divergence with Friedman's (1953) model.

choose the strategy to adopt; one of the hypothesis states that the new trader is interested only to the recent returns gained by several investments strategy and he cannot appraise the ex-ante risk assumed. In the second hypothesis, conversely, the traders decide their investment strategies in relation to recent utility levels realized for these strategies.

The first approach assumes that each trader's generation gains exogenous labour income when young and, once aged, they decide to consume all of its wealth. The strategy of noise and sophisticated traders are observed by the same amount of agents in each generation other than few traders who decide to shift their choices because of the past relative performance realized by the two categories. If, in each period, noise investors gain a higher return, a portion of the agents who would, generally, have lined up with sophisticated traders, will prefer to be a noise trader and *vice versa* if, in each period, sophisticated traders achieve more wealth than noise traders do. Obviously, the higher the variation in realized returns in each period, more agents reverse their choice. Analytically, we assume that μ_t is the power of attraction of noise traders, R_t^n and R_t^s are, respectively, the realized returns of noise and sophisticated traders, thus

$$\mu_{t+1} = \max\{0, \min[1, \mu_t + \zeta(R_n - R_t)]\} \quad \text{Eq. 18}$$

where ζ is the rate of "noise transformation" per unit difference in realized returns.⁵¹

The equation states that success leads to a mimicking behaviour: in fact, the investment strategy that gives to their followers the opportunity to be richer would encourage the switch. According to the main idea, how agents decide to invest their money when they enter the market is not completely known. In fact, if sophisticated traders have gained a higher return lately, new traders are willing to build their investment strategy imitating sophisticated investors, or to commit their money to them.

If, conversely, we observe the opposite situation, new agents imitate noise traders largely.

The main argument is that if the popularity of noise traders decreases, sophisticate investors will be better disposed to bet against them. Thus, sophisticate traders will be better off thanks to their capitalization on noise traders' misperceptions and to the negative difference

⁵¹ Bray (1982) postulate a different learning rule, interpreting ζ as a function of time: $\zeta_t = \zeta_0/t$. Through this conversion rule noise investors share is included in the set $\{0,1\}$ without fundamental risk.

between noise and sophisticated traders expected returns. If the noise trader popularity μ_t is less than

$$\mu^* = \frac{(\rho^{*2} + \sigma_{\rho}^2)(1+r)^2}{2\rho^*(\gamma\sigma_{\rho}^2)} \quad \text{Eq. 19}$$

then μ_t decreases. Conversely, if μ_t is bigger than μ^* , noise traders make the price risk increased so that sophisticated traders are loath to bet against them. Thus noise investors become richer and more numerous. Moreover, in the long-run, noise investors reveal themselves as winners or exit from the market as shown in the figure below

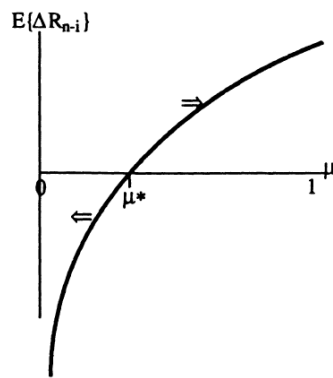


Fig. 3 Dynamics of the noise traders. De Long and J. Bradford (1990)

Another imitation rule is embodied by justifying the occurrence of noise traders in the market with the difference in utilities realized during the last period according to the divergent strategies developed by the two different traders' categories.

The main deviation from the strategy based on realized returns, is that, with concave utility, there is a higher shift away from a strategy that realized low returns rather than toward one that obtained high returns. By applying this method, the popularity of noise traders disappears (reaching zero) when $\zeta = 0$. In fact, as sophisticated traders maximize the true expected utility, on average, the realized utility of sophisticated traders is higher than the noise investors' one. The implications are that the more elevated variance, caused by noise traders, appears as a malus since it reduces their popularity because of the drop in term of average utility.

According to the researchers, De Long and J. Bradford (1990), it is more valuable to focus on wealth-based imitation rule because it is more credible that traders associate the higher return of an investment strategy to the market timing skills of its agents and not to its greater risk. This concept acquires a great importance when we are going to examining why investors modify their investment strategies, which have just gained high returns.

As long as enough traders make advantages of the pseudo-signal of realized returns in order to decide their investment strategy, noise investors will remain in the market. Moreover, this point of view underlines the inaccuracy of Friedman (1953) who stated that noise traders gain lower average realized returns and, then, they exit from the market.⁵²

⁵² Friedman (1953), moreover, state that noise traders would loose share and popularity because they are not able to deserve attention of potential imitators, since new agents would think that luck rather than skills are responsible for their success.

2.3.2. Linear factor model focusing on cross sectional volatility betas

After the general dissertation on mimicking behaviour presented by De Long and J. Bradford (1990), in this paragraph we will proceed to the analysis of another approach with the aim to investigate the presence of herding effect, making advantage of statistical instruments. Hwang and Salmon (2001), in fact, create a new measure of herding adopting linear factor models.

The model recalls the method of Christie and Huang (1995), hereafter called CH method, exclusively when they capitalize on the information revealed by the cross-sectional movements of the market. However, the focal point is about the cross-sectional variability of factor sensitivities rather than the returns themselves and it, furthermore, elaborates an explicit statistical testing procedure for exploit herding based on their measure. This test should be easy enough to compute because it is based on returns data, while for the LSV⁵³ and PCM⁵⁴ models are necessary reports of detailed trading investments features of portfolios variations which, often, may not be reachable. Hwang and Salmon (2001) prefer to gauge market-wide herding than herding relative only to a group of agents. Their test employs the cross-sectional standard deviation of factor loadings relative to the assets using a linear factor model. In a model characterized only by one factor, in which the factor embodies market returns, the herding degree is determined from the individual betas. In fact, when herding takes place “*toward the market portfolio*”, the cross-sectional variance of the estimated betas will drop.

Moreover, employ a linear factor model, in the research for herding behaviour, is useful even to take into account different factors linked to the market such as growth and value factors.

Another difference with CH model is that Hwang and Salmon (2001) automatically check for information on fundamentals by examining the cross-sectional fluctuations in the betas instead of the factor returns themselves; this method leads to a measure of the intentional herding rather than the correlated adjustment to fundamentals, which considers even the implications of the variations in the time series volatility included in the cross-sectional variance.

Chang, Cheng and Khorana (2000) have lately proposed a variant of the CH model; in fact, they explain that under CAPM hypothesis, rational asset pricing models reveal that the equity return dispersion, estimated by the cross-sectional absolute deviation of returns, should be a linear function of market returns.

⁵³ Lakonishok, Shleifer, Vishny (1992) set their model on the trading choices made by a subset of market agents during a period of time.

⁵⁴ Portfolio-Change Measure developed by Wermers (1995) and designed to account for both the direction and intensity of investors' trading.

Thanks to this method, they demonstrate the occurrence of herding behaviour in South Korea and Taiwan.

Anyway, we have to underline that the method advanced by Chang, Cheng and Khorana (2000) does not take into account neither the time-varying properties of beta in the CAPM nor the herding behaviour affected by other factors, which may be significant to describe the asset returns.

These researches implicitly reveal that observing herding in an absolute way is not possible; we have to examine it in a relative sense and be certain that no market is totally exempt by herding phenomenon.

Yet, market stress does not essentially mean that the entire market should reveal either large or negative returns. For instance, we could mention periods of large swings in both Dow Jones and the NASDAQ and at the same time the stock market as a whole has not reveal any impressive variation in the aggregate. Thus, without any big change in the entire market, we can note significant reallocations in specific sectors.

Since we delineate the herding effect as the phenomenon that occurs only when big positive or negative returns take place, we are implicitly reject these significant examples of herding behaviour and regressing the cross-sectional volatility of returns on the two dummies will lead to deceptive conclusions.

Moreover, as the model does not involve any mechanism to check for fundamentals' movements, it is not possible to decide if it deals with herding or independent fundamental adjustment and thus if the market is going to the efficiency or not.

There is another difficulty with the use of the simple cross-sectional standard deviation of individual stock return as in CH model because it is not independent from time series volatility.

Furthermore, Hwang (2000) reveals that cross-sectional volatility and time series volatility show theoretically and empirically a significant positive correlation and thus, the uncertainty of return predictability drops with cross-sectional volatility. Therefore, although the data show a small cross-sectional volatility of returns, we may not be confident if it is due to the reduction of uncertainty about future or to herding behaviour.

Assume that the excess return r_{it} of asset i follows the linear factor model:

$$r_{it} = \alpha_{it} + \beta_{imt}r_{mt} + \sum_{k=1}^K \beta_{ikt}f_{kt} + \varepsilon_{it} , \quad i = 1, \dots, N \text{ and } t = 1, \dots, T \quad \text{Eq. 20}$$

where α_{it} is a constant that changes over time, β_{imt} and β_{ikt} are respectively the coefficients on the excess market portfolio return and on factor k at time t , r_{mt} and f_{kt} are respectively the excess market portfolio return and the realised value of factor k at time t . Because the model is

a conventional linear factor one, we assume that the explanatory variables r_{mt} and f_{kt} are uncorrelated and it is not necessary to demand for an efficient market or in equilibrium.

Moreover, the factors considered in the equation may be take into account the risk or the anomalies; they may refer to countries, industries, currencies, styles, macroeconomic variables, or other significant anomalies.

We now show the measure of the herding effect based on the cross-sectional variance⁵⁵ of the factor loadings of the individual assets. Through the model developed by Hwang and Salmon (2001), we observe that the herding realized toward market portfolio, will be identified by a decrease in the cross sectional dispersion of the beta on the market portfolio β_{imt} .

For instance, if at a certain point in time, agents decide to choose a strategy, which mimic the general market behaviour, then the cross-sectional volatility of β_{imt} should appear smaller respect to the a situation in which herding does not take place.

As the cross-sectional volatility of r_{it} , $var_C(r_{it})$, relaxes the implications of market returns' heteroskedasticity, r_{mt}^2 , the measure is robust, against the effects of volatile market movements. Thus, we can say that our measure is not dependent on the market returns' time series volatility, but it is affected by any variations in the relationships between individual stock returns and the market return. This means that the market is not completely efficient, and this market feature is exactly why we are focusing on herding instead of on correlated fundamental adjustments, which would not influence the cross-sectional dispersion.

Furthermore, β_{imt} is even the analytic representation of the systemic risk, and its variations over time, usually, are justified by the financial leverage [see Black (1976) and Christie (1982)].

Cho and Engle (1999), in fact, show that both idiosyncratic and market news make betas risen if bad news occur and, conversely, make the betas dropped if good news occur. Given this outcome, we are able to illustrate why our herding measure is robust to herding through correlated fundamental adjustments built on rational decision making, so that the measure reflect the herding behaviour that we are trying to explain.

The idiosyncratic news, theoretically, affect the cross-sectional statistics of investors' betas only in an insignificant way and we foresee that the cross-sectional average and variance

⁵⁵ $var_C(r_{it}) = E_C[(r_{it} - r_{mt})^2] = E_C[\alpha_{it}^2] + r_{mt}^2 E_C[(\beta_{imt} - 1)^2] + \sum_{k=1}^K f_{kt}^2 E_C[\beta_{ikt}^2] + E_C[\varepsilon_{it}^2] + Cov_{Ct} = var_C(\alpha_{it}) + r_{mt}^2 var_C(\beta_{imt}) + \sum_{k=1}^K f_{kt}^2 var_C(\beta_{ikt}) + var_C(\varepsilon_{it}) + Cov_{Ct}$

Hwang and Salmon (2001) apply the cross-sectional variance of β_{imt} (or β_{ik*t}) as a measure of herding for the factor. Generally, we may adopt Gini's mean difference developed by Yitzhaki (1982) or Shalit and Yitzhaki (1984).

of the new betas are expected to keep unchanged until the implications of idiosyncratic news will be negligible on average.⁵⁶ Conversely, the sharing of market news among each asset leads us to think that individual betas change in unison relative to the market, according to the occurrence of bad or good news. The agents' returns may differ but, given the hypothesis of the model, we cannot affirm that the cross-sectional variance of the betas should deviate.

Hence, in the cross-section, we do not presume that the degree of dispersion of the individual betas fluctuate significantly over time because of idiosyncratic or fundamental news.

This result means that any quick or relevant fluctuations in the cross-sectional variance of the betas and, as a consequence, our measures will reveal herding and not aggregate actions due to fundamental news. Moreover, any quick deviations in the factor loadings, instead of variations in the factor values, that would take place naturally, are linked to the factors revealing herding in specific directions.

With the linear factor model, represented in Eq.20, we can examine even the potential herding towards other factors over the herding towards the market factor. For instance, herding toward some factor k , is measurable by the cross-sectional variance of the coefficient β_{ikt} ; thanks to this method, we can examine, for example, the herding toward developed or emerging market stocks.

Then Hwang and Salmon (2001) define the herding measure toward the market and toward some factors as:

Herding "toward the market portfolio", $H(m, t)^$, is defined as a reduction in*

$$H(m, t)^* = \text{var}_c(\beta_{imt}) \quad \text{Eq. 21}$$

and herding "toward factor k ", $H(k^, t)$, is defined as an increase in*

$$H(k^*, t)^* = \text{var}_c(\beta_{ik^*t}) \quad \text{Eq. 22}$$

When $H(m, t)^*$ goes up, a lot of the individual β_{imt} will be significantly divergent by one, so that the individual stock returns spread more widely around the market return, introducing less similarity and thus herding.

Conversely, when $H(k^*, t)^*$ rises, several β_{ik^*t} will be significantly different from zero.

⁵⁶ The statement used looks like to the one exploited by Connor (1984) to develop an approximate arbitrage pricing model.

Hence, any important change of the coefficients from zero reveals herding behaviour towards the factors, and if we take into account that this occurs at time t , we will find a large value of $H(k^*, t)$ ⁵⁷.

The researchers, anyway, underline that the above definitions do not stand for absolute measure of herding so that, since the criteria show variations over time, we may remark the presence of almost more or less herding effect.

⁵⁷ Furthermore, Hwang and Salmon (2001) prove that the drop and the increment in herding is statistically significant thanks to the use of OLS estimator.

2.3.3. Cross sectional absolute deviation or dispersion of returns

Mobarek and Mollah (2014) have focused on a different prospective respect to their predecessors: they find a strong link between the occurrence of a crisis and the spread of herding behaviour.

In fact, in the aftermath of the global financial crisis, some researches [e.g. Bakaert (2011)] have shown a certain contamination among countries characterized by similar features as an addition to the wakeup call hypothesis [Goldstein (1998)].

The wakeup call hypothesis affirms that market participants wake up after a crisis and takes into account that similar market main elements, which characterize different markets, (i.e. the same level of market transparency, level of regulation, and industrial structure) drive to similar market behaviours.

Furthermore, countries that present weak macroeconomic key elements are vulnerable to the spread of financial crises. Since everything goes well, traders usually are not too much anxious about the fundamentals; on the other hand, when a crisis arises somewhere in the world, suddenly, everybody starts making predictions about the next potential victims, and the most likely targets are identified with the countries characterized by similar macroeconomic weaknesses.

We can assume that different European markets do not share the same level of information spread and transparency according to the heterogeneous firms, industry structure and market efficiency. Thus, we may rely on a heterogeneous pattern configuration for herd behaviour among continental, Nordic and the PIIGS countries and similar herd behaviour within them, on the basis of the wakeup call hypothesis.

Therefore, Mobarek and Mollah (2014) develop a theory based on the next hypothesis:

1. *Country-wise herding implications are not the same among the continental, Nordic and PIIGS countries for the entire sample period.*

Moreover, another main feature of studying herd behaviour is the possibility to pay attention on scattering the cross-sectional correlation of stock returns due to the asymmetrically changing market conditions. According to the studies about the information asymmetry observed in stock markets, researchers have shown that traders in these kinds of markets are more prone to reveal herd behaviour. If we take into account countries with different features relative to boom, bust and market asymmetry within a long sample period, we will observe the herding phenomenon developing differently across divergent country groups because of overreaction, momentum and information asymmetry. This outcome drives us to test the asymmetry of the market up and

down, with positive and negative returns signalling good news and bad news, high and low volume, volatility etc.

Hence, the second hypothesis showed by the researchers is the following:

2. *Herd behaviour arises similarly in different market conditions across different country groups in Europe.*

Furthermore, herd behaviour plays a key role in analysing and studying the markets from both regulatory and investment views. As remark before, it is common knowledge, that similar sub-group of European countries may show similar institutional, cultural, economic and financial connections, which change across different groups of markets. This consideration gives to the authors the reason for postulating our third hypothesis as follows:

3. *There is no cross-country herd behaviour among similar and divergent country groups.*

Finally, we have to underline that the herd behaviour showed in foreign markets during the global crisis [see, for instance, Economou *et al.* (2011)] was the trigger that started the study relative to the European countries because of the Eurozone crisis that flattened the European countries. Country-wise herding behaviour, in fact, could be affected by foreign markets other than the domestic markets because of the flights to quality [see, for instance, Allen and Gale (2000)], portfolio rebalancing [Brunnermeier and Pederson (2005); Brunnermeier and Pederson (2009)], liquidity channels, and risk premium channels under the contagion literature [Longstaff *et al.* (2010)]. Additionally, during the periods of market turbulence, herd behaviour may turn out to be a threat to financial stability since initial negative shocks may be worsened and increased through pro-cyclical market mechanisms, which drives us to propose our final hypothesis, i.e.:

4. *Country-wise herd behaviour is not subject to change during the Global Financial Crisis and the European Zone Crisis.*

Given the above hypothesis, Mobarek and Mollah (2014) postulate that traders are more likely to relax their private information and act according to the market consensus during periods of market distress. Thus, they use the cross-sectional standard deviation (CSSD) method, introduced by Christie and Huang (1995), making some changes in order to reveal their findings:

$$CSSD_t = \sqrt{\frac{\sum_{i=1}^N (R_{i,t} - R_{m,t})^2}{(N-1)}} \quad \text{Eq. 23}$$

where $R_{i,t}$ is the observed stock return of asset i at time t and $R_{m,t}$ is the cross-sectional average of the N returns in the aggregate market portfolio at time t . The dispersion measure computes the average proximity of individual returns to the realized average⁵⁸.

Chang *et al.* (2000) assert that a linear and increasing relation between dispersion and market returns, as proposed by the standard asset pricing models, is not valid when we observe large average price movements. Hence, herd phenomenon around the market consensus during periods of large price movements is sufficient for transforming the linear relation into a non-linear one. Thus, in order to include this effect, we introduce the cross-sectional absolute deviation (CSAD) as a measure of return dispersion, which was used by Chang *et al.* (2000) in the following form:

$$CSAD_t = \frac{1}{N} \sum_{i=1}^N |R_{i,t} - R_{m,t}| \quad \text{Eq. 24}$$

Eq.24 give us only the possibility to compute the CSAD; if we want to introduce a non-linear framework for showing the relationship between individual stock return dispersions and the market average, we have to use the following model:

$$CSAD_t = \alpha + \gamma_1 |R_{m,t}| + \gamma_2 R_{m,t}^2 + \varepsilon_t \quad \text{Eq. 25}$$

in which the squared market return $R_{m,t}^2$ is a parameter introduced to take into account the non-linearity in the relationship, α is the constant, γ_1 and γ_2 are coefficients, and ε_t is the error term at time t . This model is built to test the first hypothesis and Eq.25 is evaluated for every country (i). Moreover, if herding effect does not occur, Eq.25 shows $\gamma_1 > 0$ and $\gamma_2 = 0$. Instead, if herding phenomenon takes place, $\gamma_2 < 0$ (negatively significant).

Since, as above-mentioned, the relationship between CSAD and market returns may be asymmetric, we are interested in analysing herd behaviour in relation to market returns, trading volumes and return volatility observing if the phenomenon is more evident when these parameters are high. We mimic the approach of Chiang and Zheng (2010) and Chiang *et al.* (2010), who make use of a dummy variable approach in a single model⁵⁹.

⁵⁸ Previous studies underline that the dispersion in returns will rise with the absolute value of the market return given the normal information flow because market traders make their investment because of private information. However, during crisis periods, agents follow market collective actions, so that individual stock returns tend to cluster around the overall market return, herding behaviour conquers the market and return dispersion decrease.

⁵⁹ This model, in fact, is considered by the authors more robust than the Tan *et al.* (2008).

Yet, Mobarek and Mollah (2014) decide to test the second hypothesis separately for returns, volume and volatility using the following equations.

In fact, the asymmetric behaviour of return dispersion in relation to market returns is computed as follows:

$$CSAD_{i,t} = \alpha + \gamma_1 D^{up} |R_{m,t}| + \gamma_2 (1 - D^{up}) |R_{m,t}| + \gamma_3 D^{up} (R_{m,t})^2 + \gamma_4 (1 - D^{up}) (R_{m,t})^2 + \varepsilon_t$$

Eq. 26

where D^{up} is a dummy variable, which takes value of 1 for days with positive market returns and value of 0 for days characterized by negative market returns. The difference with the previous equation is that Eq.26 give us the possibility to take into account even the second hypothesis of the authors. If herding phenomenon is not revealed by the market, the Eq.26 will shows $\gamma_1 > 0$ and $\gamma_2 > 0$. If herding behaviour is present, instead, $\gamma_3 < 0$ and $\gamma_4 < 0$ with $\gamma_4 < \gamma_3$ if this phenomenon is more relevant during the days with negative market returns. Moreover, the behaviour's asymmetry of return dispersions, taking into account the trading volume, can be estimated as follows:

$$CSAD_{i,t} = \alpha + \gamma_1 D^{Vol-High} |R_{m,t}| + \gamma_2 (1 - D^{Vol-High}) |R_{m,t}| + \gamma_3 D^{Vol-High} (R_{m,t})^2 + \gamma_4 (1 - D^{Vol-High}) (R_{m,t})^2 + \varepsilon_t$$

Eq. 27

where $D^{Vol-High}$ is 1 for days characterized by high trading volume and 0 otherwise.

Eq.27 is used to test the second hypothesis and the trading volume on day t is considered high if it is bigger than the previous 30-day moving average and low, if it is smaller than the previous 30-day moving average. If herding effect does not occur, Eq.27 assumes $\gamma_1 > 0$ and $\gamma_2 > 0$; conversely, if the herding phenomenon takes place, we will find $\gamma_3 < 0$ and $\gamma_4 < 0$, with $\gamma_3 < \gamma_4$ if these effects are more pronounced during days with a high trading volume.

Moreover, according to the asymmetric behaviour of return dispersion in relation to the market volatility, we can implement the model as follows:

$$CSAD_{i,t} = \alpha + \gamma_1 D^{\sigma^2-High} |R_{m,t}| + \gamma_2 (1 - D^{\sigma^2-High}) |R_{m,t}| + \gamma_3 D^{\sigma^2-High} (R_{m,t})^2 + \gamma_4 (1 - D^{\sigma^2-High}) (R_{m,t})^2 + \varepsilon_t$$

Eq. 28

where D^{σ^2-High} is represented by the value 1 in relation to days with high market volatility and 0 otherwise. Market volatility on day t is defined high, if it is larger than the previous 30-day

moving average and low, if it is smaller than the previous 30-day moving average. If herding effect does not occur, Eq.28 will reveal $\gamma_1 > 0$ and $\gamma_2 > 0$. If herding phenomenon takes place, we will find $\gamma_3 < 0$ and $\gamma_4 < 0$, with $\gamma_3 < \gamma_4$, if these effects are more pronounced during days with high market volatility.

Further, markets that show a certain degree of co-movement with correlated cross-sectional return dispersions are even able to reveal synchronized herding patterns in order to test the third hypothesis.

In fact, according to Economou *et al.* (2011), Mobarek and Mollah (2014) revise Eq.25 by adding explanatory variables for taking into account the cross-sectional dispersions of the n markets included in our sample as follows:

$$CSAD_{i,t} = \alpha + \gamma_1 |R_{m,t}| + \gamma_2 (R_{m,t})^2 + \sum_{j=1}^n \delta_j CSAD_{j,t} + \varepsilon_t \quad Eq. 29$$

This model is used to test the third hypothesis: δ_j is the CSAD coefficient to take into account the other countries (j). The cross-country herding effect will occur if $\delta_j < 0$.

Finally, the authors study even if the herding phenomenon is more remarkable during periods of financial crises. They introduce, in Eq.25, a dummy variable D^{CRISIS} , which takes the value 1 for days of crisis and 0 otherwise as follows:

$$CSAD_{i,t} = \alpha = \gamma_1 |R_{m,t}| + \gamma_2 (R_{m,t})^2 + \gamma_3 D^{CRISIS} (R_{m,t})^2 + \varepsilon_t \quad Eq. 30$$

The model is created to test the fourth hypothesis so that the Eq.30 shows both GFC (Global Financial Crisis) and EZC (Euro-Zone crisis) dummies separately. Moreover, herding phenomenon is more remarkable during the crises' periods and differs among country groups; if the crisis coefficient, γ_3 , is less than 0 as regard to both periods of *impasse*, we may affirm that the herding phenomenon occurs.

The model is characterized by significantly positive coefficients for $|R_{m,t}|$ relative to all countries, so that we prove that the cross-sectional absolute dispersion (CSAD) of returns rises with the magnitude of the market return.

The regression outcome shows that 77 of 110 country coefficients are statistically significant; this means that common herding forces occur across a great number of markets in Europe.

Finally, the comparative country-wise analysis of herd phenomenon among European countries implies that herding is not limited to emerging Europe because it also takes place in developed European countries.

2.3.4. Counting buyers and sellers and compare offers on volatility

...I explained to you the instability of [stock] prices and the reasons therefore...

and discussed the frenzy and foolishness of speculation.

...As there are so many people who cannot wait to follow the prevailing trend of opinion ...

they think only of doing what others do and following their examples...⁶⁰

The essence of herding behaviour is that traders switch their positions in the same direction. Moreover, we know that the tendency of traders to move in the same direction at the same time is a necessary but not sufficient constraint for herding because such parallel choices may be a result of the variations in common information sets. According to the research of Weiner (2006), the simplest measures for catching the tendency of traders to buy or sell when other investors are doing the same are:

- counts of traders buying and selling simultaneously
- correlation across traders of changes in open position

Through this simple model, under the null hypothesis of no herding, we take into account the number of speculators buying, B , and selling, S , considering that each day should be equal, and deviations from equality are due to chance.

The adjustment factor, μ , shows that even under the null hypothesis, the expected value of an absolute difference is positive.

$$H = \left| \frac{B}{B+S} - 0.5 \right| - \mu$$

$$\mu = E[|B/(B+S) - 0.5| \text{ no herding}]$$

Eq. 31

Under the null hypothesis of no herding, μ is readily computed, because the sample fraction buying $B/(B+S)$ has a binomial distribution with probability of success 0.5 and number of trials $B+S$. Moreover, the adjustment factor, μ , decreases with the sample size.

Fotini *et al.* (2015) widen the discussion by studying the method with more depth. In fact, they give their contribution to the research on the herding phenomenon, analysing the institutional

⁶⁰ De la Vega, J. (2009). *Confusión de confusiones*. Editorial Maxtor.

herding in relation to the propensity of fund managers to herd in frontier markets, topic that nobody takes into account before in the literature.

The most important element is the fact that, unlike the developed and emerging markets, the frontier ones are very small relative to the size of both their fund-industry and their capitalization/volume.

The original measure, used in the literature in order to determine the herding phenomenon among fund managers, was the one proposed by Lakonishok, Shleifer and Vishny (1992): the herding effect is calculated making use of the fraction of funds, which buy the stock i during a given period t as follows:

$$H_{i,t} = [|B_{i,t}/(B_{i,t} + S_{i,t}) - p_t|] - AF_{i,t} \quad \text{Eq. 32}$$

In the Eq.32, $B_{i,t}$ ($S_{i,t}$) stands for the proportion of funds increasing (decreasing) their positions in stock i (as a matter of fact, the fraction of buyers and sellers, respectively) in the given period t ; p_t represents the number of “buyers” relative to the total number of active⁶¹ funds presented in the market across all stocks during the period t . Hence, p_t is computed by averaging $B_{i,t}/(B_{i,t} + S_{i,t})$ across all stocks in a given period, giving as result, the average institutional demand for stocks during that period, or similarly the expected proportion of buyers for that period [Wermers (1999)]. If funds make investments independently from each other (i.e. there is no herding), $B_{i,t}/(B_{i,t} + S_{i,t}) = p_t$ for all the stock i within the period t .

Moreover, to consider the random variations of $B_{i,t}/(B_{i,t} + S_{i,t})$ around p_t , Lakonishok *et al.* (1992) add an adjustment factor, $AF_{i,t}$, which represents the expected value of $|B_{i,t}/(B_{i,t} + S_{i,t}) - p_t|$ under the hypothesis that $B_{i,t}$ follows a binomial distribution with a probability of “success” $p = p_t$.

Thus, the occurrence of herding phenomenon, in this case, is stated through the deviations of $|B_{i,t}/(B_{i,t} + S_{i,t}) - p_t|$ from its expected value (showed through the $AF_{i,t}$).

The Lakonishok *et al.* (1992) method has been widely used in many herding studies, although some researchers have discovered that it is affected by some drawbacks (listed below), making it less pertinent for the context of our study.

- The method implicitly assumes the possibility that short-selling occurs, but some features of frontier markets, such as the rudimentary institutional pattern and the

⁶¹ The term “active” is used to include only those funds, which have modified their position in stock i during the period.

relatively low trading volume imply that short-selling is an activity either not allowed or not feasible in these kind of markets. If short-selling is not allowed or feasible, then the buy-side in the Lakonishok *et al.* (1992) measure will be stronger (i.e. the fraction of funds selling a stock at the end of every period will never be more than the fraction of funds holding the stock at the beginning of the same period). This implication would drive to distortions in the binomial distribution of $B_{i,t}$ and, finally, increases bias in $B_{i,t}$ – and, thus, herding⁶².

- The measure presumes that the ex-ante probability of a fund manager buying a stock is affected only on the degree of herding [Wylie (2005)]; as a matter of fact, the low trading volume typical of frontier markets could create a very bigger problem to the fund managers' buy decisions, because illiquidity can insert frictions in the trading process by deferring the execution of a buy-order, regardless of whether the order was justified by herding or not.
- The measure reveals the fund managers' preferences to trade in a given direction over and above what would be expected from them if their trading activity is characterized by randomness and independency, regardless of the fact that this correlation in institutional demand may be come from herding as much as habit-investing⁶³.

Still, separate the funds that follow each other and the funds who follow their past trades, need a study of institutional demand since the method proposed by Lakonishok *et al.* (1992) observes herding within and not across periods.

These three clarifications lead Fotini *et al.* (2015) to observe herding by exploiting the idea advanced by Sias (2004) – rather than the Lakonishok *et al.* (1992) one – which endeavour to find herding through the temporal dependence of institutional demand and which, according to this study, has been used in order to investigate [Gavriilidis *et al.* (2013), Holmes *et al.* (2013)] about the intentionality of herding.

In Sias (2004) model, in fact, institutional demand is seen as the raw fraction of funds buying security k in period t and it is indicated by $Raw\Delta_{k,t}$ as follows:

$$Raw\Delta_{k,t} = \frac{\text{Number of funds buying security } k \text{ during period } t}{\text{Total number of funds active in security } k \text{ during period } t} \quad Eq. 33$$

If a fund raises its position in security k in period t respect to the period $t - 1$, it will be considered as a “buyer”, while if the fund reduces its position, it will be considered as a “seller”.

⁶² For a concise analysis of this topic, see Wylie (2005).

⁶³ The case of funds who decide to follow their own trades from previous periods.

Then, a significant step is to standardize $Raw\Delta_{k,t}$ by subtracting in every period from every $Raw\Delta_{k,t}$, its cross-sectional (across all active stocks in that time-frame) average and dividing the result by its cross-sectional standard deviation:

$$\Delta_{k,t} = \frac{Raw\Delta_{k,t} - \overline{Raw\Delta_t}}{\sigma(Raw\Delta_{k,t})} \quad Eq. 34$$

Sias (2004) postulate that $\Delta_{k,t}$ follows an autoregressive process of order one in order to evaluate the temporal dependence involved in the institutional demand structure, as showed below:

$$\Delta_{k,t} = \beta_t \Delta_{k,t-1} + \varepsilon_{k,t} \quad Eq. 35$$

Eq.35 is standardized both on the left and on the right, and as it involves only one explanatory variable, $\Delta_{k,t-1}$, its slope coefficient, β_t , identifies the cross-sectional correlation between institutional demand in periods t and $t - 1$ respectively.

Sias (2004) develops the slope-coefficient so that it can be divided into two components: the first part is related to funds following their own past trades and the second part is related to funds, which follow the trades of their peers (herding):

$$\begin{aligned} \beta_t &= \rho(\Delta_{k,t}, \Delta_{k,t-1}) \\ &= \left[\frac{1}{(K-1)\sigma(Raw\Delta_{k,t})\sigma(Raw\Delta_{k,t-1})} \right] \times \sum_{k=1}^K \left[\sum_{n=1}^{N_{k,t}} \frac{(D_{n,k,t} - \overline{Raw\Delta_t})(D_{n,k,t-1} - \overline{Raw\Delta_{t-1}})}{N_{k,t}N_{k,t-1}} \right] \\ &+ \left[\frac{1}{(K-1)\sigma(Raw\Delta_{k,t})\sigma(Raw\Delta_{k,t-1})} \right] \times \sum_{k=1}^K \left[\sum_{n=1}^{N_{k,t}} \sum_{m=1, m \neq n}^{N_{k,t-1}} \frac{(D_{n,k,t} - \overline{Raw\Delta_t})(D_{m,k,t-1} - \overline{Raw\Delta_{t-1}})}{N_{k,t}N_{k,t-1}} \right] \end{aligned} \quad Eq. 36$$

For the sake of a greater clarity, we give a little description of the parameters involved in the Eq.36:

- $N_{k,t}$ stands for the total number of funds considered active in stock k during the period t ;
- $D_{n,k,t}$ is a dummy variable whose value equals one if fund n is a buyer of stock k in the given period t and zero if it is a seller;
- $Raw\Delta_{k,t}$ stands for the raw proportion of funds buying stock k in period t ;

- $\sigma(Raw\Delta_{k,t})$ represents the cross sectional standard deviation of $Raw\Delta_{k,t}$ across all active securities in period t and $Raw\Delta_t$ is the cross-sectional average of $Raw\Delta_{k,t}$ in period t .
- The first additive element stands for that part of β_t , which shows if funds have followed their own past trades; if it is bigger than zero, funds within the period t will trade according to their past trades. Conversely, if it is less than zero, funds will trade in the opposite direction respect to the previous period.
- The second additive element stands for that part of β_t , which reveals if funds imitate other funds (herding phenomenon); if the value is bigger than zero, funds will follow other funds. If it is less than zero, instead, funds will trade against funds' trades of the previous period.

After having looked for the occurrence or not of herding, Fotini *et al.* (2015) decide to study if herding is intentional or not. According to this purpose, they relate it with several elements, which represent the market conditions (market returns, market volatility and market volume).

According to the market returns, for instance, if the market shows negative performances, the probability to suffer a loss will increase, so that “bad” managers decide to mimic “good” peers. “Bad” managers may decide to herd not only during bearish market, but also in a period of bullish market, because it could be easy to identify their poor ability. Hence, if the herding phenomenon is intentional (i.e. caused by informational and professional reasons), it will exist a relation between herding and market return (i.e. differences in herding between periods of positive and negative market returns). Conversely, if herding phenomenon is spurious (due, for instance, to homogeneity or characteristic trading), we could not explain these difference with herding significance.

The same idea is linked also to the market volatility because, if the volatility market is high, the public pool of information becomes more difficult to examine and “bad” (with low skills, for example) managers will imitate the good ones. Instead, if market volatility is low, “bad” managers may prefer to be confused with “good” managers⁶⁴ [Holmes *et al.* (2013)].

As regard to market volume, finally, we can state that trading volume is seen as an effective information flow proxy [Jiang and Kryzanowski (1998)] because high trading activity boosts the participation of informed traders⁶⁵. Thus, within period of high volume, it is easier for “bad” managers to mimic the “good” ones, in order to obtain their visibility.

⁶⁴ Consequently, if herding phenomenon is due to intentionality, we can foresee a relationship between herding and market volatility.

⁶⁵ According to Romano (2007), a high trading volume gives to informed traders the possibility to trade more easily on their information by decreasing the friction in the trading process.

However, as before, it is possible to observe institutional herding even during a period characterized by low trading activity⁶⁶.

We underline that, on the one hand, “*herding drives fund managers to choose portfolio allocation that may be sub-optimal, hence not acting in the interests of their clients*” and on the other hand, “*the leverage commanded by funds and the relatively low turnover of frontier markets can lead their herding to cause price pressure and potential destabilization*” [Fotini *et al.* (2015)].

As we will discuss later, the role of regulators in the market is important because they have to understand the above risks and take measures in order to limit the herding phenomenon in the investment conduct. A possibility, according to Gavriilidis *et al.* (2013), is to spread periodical statements which deal with the level of correlation in funds’ holdings at the same time as each fund’s expense-fees so that the investor could be informed about the level of fund’s herding phenomenon before making an investment.

⁶⁶ Fund managers, indeed, could not be satisfied if their orders have been executed within a low volume period, because they address an increased liquidity risk and performance-related issues.

The latter takes place when a fund manager hopes to rid his portfolio off precise stocks (for instance recent losers) and he cannot sell them, because of the low volume of market trading which prevents the transaction. Thus, actually, making an investment into (or out of) the same stocks as the peers is a rational option.

2.3.5. A naïve approach: herding intensity

In the research for an optimal measure of herding, Vieira and Simões (2015) suggest a model, called herding intensity, which is directly linked to the sentiment investor and take into account two different approaches.

First, the researchers imitate the methodology advanced by Patterson and Sharma (2006), applied to a Portuguese sample. It involves intraday order sequences, generally considered to offer the ideal frequency for testing the occurrence of herding behaviour.

If news are received by the market on an intraday basis, traders are not able to make advantages of analytical models to interpret the news because of the lack of time, so that they may not forecast future price movements.

Hence, their choices could not depend on rationality and traders are prone to follow the attitudes of other investors [Orlean (1995)].

However, according to the opinion of Patterson and Sharma (2006), an information cascade can be revealed by a sequence of negotiation begun by buyers or seller, which are higher than sequences where traders decide only according to the available information. Thus, Vieira and Simões (2015) choose the approach of Patterson and Sharma (2006) for three main reasons:

- An intraday measure, being a daily parameter, is a proper instrument for testing the occurrence of herd behaviour;
- The researchers do not postulate that herding phenomenon fluctuates during extreme market conditions;
- This approach considers each type of investors rather than only the institutional ones.

In order to build the herding intensity measure, we have to recognize each trade settled in a trading day within the sample period, counting the number of sequences that takes place in the same day, in each stock. Hence, Patterson and Sharma statistic take into account for herding intensity analysing the number of runs represented by the following random variable:

$$\chi(i, j, t) = \frac{(r_i + 1/2) - np_i(1-p_i)}{\sqrt{n}} \quad \text{Eq. 37}$$

where r_i is the number of runs relative to type i (up, down or zero), n is the total number of trades settled on stock j on day t , $1/2$ is the parameter to adjust for discontinuity and p_i is the probability of determining a run from type i .

Under asymptotic conditions, the statistic $\chi(i, j, t)$ has a normal distribution with zero mean and variance equal to:

$$\sigma^2(i, j, t) = p_i(1 - p_i) - 3p_i^2(1 - p_i)^2 \quad \text{Eq. 38}$$

In order to define the herding intensity in the capital market, we need to choose the type of day for each stock sequence, which is associated to the corresponding market index. Hence, we compute the daily return of every stock, deciding whether it is a sequence of the type up (*i*), down (*ii*) or zero (*iii*) and whether the security's return is positive, negative or zero, respectively.

In fact, the daily return of stock *j* on day *t* is analytically computed in the following way:

$$\text{return}_{j,t} = \frac{CP_{j,t} - CP_{j,t-1}}{CP_{j,t-1}} \quad \text{Eq. 39}$$

where $CP_{j,t}$ is the closing price for the security *j* within the day *t*, $CP_{j,t-1}$ is the closing price for the security *j* within the day *t*.

Hence, the herding intensity statistic is the following:

$$H(i, j, t) = \frac{\chi(i, j, t)}{\sqrt{\sigma^2(j, t)}} \rightarrow N(0, 1) \quad \text{Eq. 40}$$

where *i* assumes three different values according to the fact that:

- i. The trade is a buyer-initiated (up)
- ii. The trade is a seller-initiated (down)
- iii. The trade is zero tick (zero)

If traders are involved systematically in herding, the statistic should be negative and statistically significant, since the number of initiated sequences (runs) will be lower than expected [Patterson and Sharma (2006)]. Thus, as more negative is the statistic, as bigger become the probability of observing the herding behaviour.

We have to explain that, according to the opinion of Patterson and Sharma (2007), a trade belongs to the category "buyer-initiated", if the current trade price is higher than the previous trade price (and *vice versa*, it belongs to "seller-initiated" if the current trade price is lower). Moreover, if the current trade price does not change relative to the previous one, we have zero-tick.

Therefore, we observe three series of *H* statistics:

- $H_i = \text{series of statistic values for up runs (buyer)}$
- $H_{ii} = \text{series of statistic values for down runs (seller)}$

- $H_{iii} = \text{series of statistic values for runs with no price changes (zero)}$

In conclusion, we can postulate that in large sample $H_{j,t}$ has a normal distribution with zero mean and unitary variance, but we do not forget that in the application we can incur in the problem of missing values.

We have seen that when people are linked by a network, it is possible for them to affect each other behaviour and choices. In the second part, we have examined the herding behaviour, looking at the phenomenon from several points of view. In fact, we have underlined the differences with other two shadows of the herding behaviour i.e. informational cascades and flocking and we have seen several computational models with the aim of find a measure of herding in the market.

2.4. Herding vs Flocking

We have seen that herding is a widespread social phenomenon, and we may explain it even in a metaphoric way: this behaviour may be explained, in fact, by the image “*people that decide to buy a book title because it is on bestseller lists*”.

Moreover, as explained in the previous section, during the past decade we have attended to an important progress in the development of theoretical models focused on herding behaviour, both in general and in financial markets in particular⁶⁷.

However, we want to give some information even about another phenomenon that we present as appendix to the herding phenomenon. In fact, the finance literature introduces even two hypotheses about the herding phenomenon among groups of traders, known as flocking.

The researches on the topic address, in fact, the problem relative to who are the types of speculators that are most likely prone to flock, making possible the creation of tests designed to distinguish between them.

According to Weiner (2006), the *information asymmetry hypothesis* defines flocking as rational behaviour chosen by relatively poorly informed traders⁶⁸, who look at their better-informed traders mates wishing to be able to take similar positions⁶⁹.

If this hypothesis is correct, then the “smart money” – often used as the symbol of institutional investors – has less probability to flock due to the greater (or faster, or more accurate) access to information and capability for analysis of its price implications.

Indeed, individual investors are apt to flock⁷⁰, above all the traders who physically attend on the floor of the exchange, where they can readily monitor the behaviour of other agents.

Conversely, the *monitoring/incentive hypothesis* states that institutional investors are the group most likely to flock. In fact, institutional investors are subject to industry benchmarking – fund managers’ evaluation and incentives, for instance, usually depended on their performance relative to other managers – and, hence, they will try be involved in the flock

⁶⁷ See Devenow and Welch (1996) for a survey of the literature.

⁶⁸ Here flocking is defined “rational” because it implies higher expected returns for poorly informed traders respect to the situation where they are trading on their own information. Furthermore, “poorly informed” is an attribute refers to some market traders who have access to information about changes in market fundamentals less rapidly or more expensively than others do.

⁶⁹ In the natural context, members of a flock of birds may escape from predators by watching each other and acting in parallel, rather than wasting energy on vigilance against the source of danger itself.

⁷⁰ For instance, about the trade press, Briese (1994, 38) observes that “...*some market books recommend following the large speculators under the theory that they must be pretty good traders to get that large.*” He also remarks the counterargument that “*the growth of these funds (the large speculators) can be attributed more to a knack for fundraising than trading.*”

[Scharfstein and Stein (1990)]. In fact, a useful method to achieve this result is to buy the securities that other fund managers are buying.

Of course, as the authors underline, these two hypotheses are not mutually exclusive: institutional investors and individuals can be flocking among themselves at the same time but for different reasons.

Part 3. Implications of herding effect

After reporting some of the several methods used to prove the occurrence of sheeple behaviour and to compute analytically its amount, we are going to examining one measure, which is able to limit the adoption of this kind of behaviour and some of the implications that we can observe in the market whether the traders decide to imitate each other's.

3.1. Impact of regulation changes

“A 1 percent probability of failure means either that 1 percent of the banks fail every year or, alternatively, that the whole banking system fails every hundred years – quite distinct outcomes. Therefore it is crucial for regulators to find ways of discouraging herding behaviour by banks.”⁷¹

Even during the recent years, we have been witnesses of the worst chaos in the international financial system after the second world war. The “Asian Crisis” and the “Russian Crisis” of the late 1990s succeeded the “Tequila Crisis”, occurred in the mid-1990s. The possible explanations of financial turmoil are various. One school of thought is interested on “fundamentals” – focusing on the weaknesses in social, political, and economic systems. An alternative view believes that crises are produced by the financial system itself, due to “speculative excess”, “contagion”, “flocking” or “herding” – everything that implies that the underlying fundamentals are basically distorted.

In fact, if speculators worsen (or even give rise to) financial instability, then society would profit from policy measures which limit their activity. Such legislative measures are several and different, varying from the “Tobin Tax” on speculative activity advanced by the Nobel prize winner James Tobin, in order to enforce government regulation, and to close down markets entirely. The aim is to “throw sand in the wheels of international finance” [Eichengreen *et al.* (1995) and Haq *et al.* (1996)]. On the other hand, if speculation is able to reduce volatility, then trading should be supported.

⁷¹ Dewatripont, M., Rochet, J. C., & Tirole, J. (2010). *Balancing the banks: Global lessons from the financial crisis*. Princeton University Press.

Yet, the literature faces considerable challenges in testing theories that consider speculators as essential to the working of the international financial system versus to the researchers that view them as superfluous at best, and destroying at worst.

These challenges are of two types. In *primis*, most of speculative behaviours is not easily recognizable – neither policymakers nor researchers usually get to know information with respect to speculators' decisions and actions, which are private. In fact, only the outcome of their behaviour is observable.

In *secundis*, many of the results may be justified equally well by the hypothesis that show that speculators are responsible for market turmoil or by the theory focused only on fundamentals.

Demirer and Kutan (2006) examine the Chinese market and its relationship in regulation changes; in fact, they take into account several different occurrences.

On January 1994, the State Planning Committee declared an annual quota of US \$ 700 million for the new issued, an amount, which was lower respect to what the market had forecasted. Moreover, the China Securities Regulatory Committee (CSRC) temporarily prevented many state-owned corporation new issues and trading recorded for more than 15% of total market capitalization.

On July 1994, furthermore, the CSRC introduced a series of measures in order to promote the market liberalization. These consist of:

- A prohibition on new listing of shares (type A) for the rest of 1994;
- The provision of a US \$ 1.15 billion credit line for qualified security firms in order to boost trading;
- Promoting new mutual funds and possible foreign participation in the domestic A-share market
- A promised merger of the A and B-share categories within 5 years. In fact, on June 1995, the CSRC halted futures' market trading on government bonds and, simultaneously, the central bank fixes an upper limit to the interest rate for corporate and municipal bonds.

Consequently, a large number of funds were shifted from the bonds markets into the stock markets.

The researchers, hence, decide to introduce a dummy variable for each of these regulation changes, but they find significant values only for the ECB measures. In fact, the outcome indicates that CSRC regulatory changes may be better discounted by market participants, whereas the actions of the Bank is harder to predict.

Another different interpretation of the outcome obtained is that market participants are prone to speculate on the government actions in the market. Yet, a trader requires owning more information about the purposes that the central bank policies want to achieve and about the intervention before making these claims, “as they are somewhat subjective and subject to interpretations” [Demirer and Kutan (2006)].

Even Galariotis, E.C. *et al.* (2015) face the problem, and through the use of statistic tests, they show that during the EU crisis period, macroeconomic information announcements, fluctuations in the Bank of England rate, and variations in the US federal funds rate push market participants to herding; interestingly, Galariotis, E.C. *et al.* (2015), unlike Demirer and Kutan (2006)], state that there is no herding during ECB rate fluctuations.

The authors make use of a dummy variable that assumes the value of one on a day when important macroeconomic news is announced and zero otherwise.

If herding behaviour is revealed, the coefficient on the dummy variable should take negative value and be statistically significant. For the dummy variable, we consider days where the following informational events occur: rate changes due to the will of the European Central Bank, the Bank of England, the US Federal Bank, and macroeconomic information release dates such as the days when Eurostat issues the “Data for Short Term Economic Analysis”. These releases consist of monthly updates of several basic macroeconomic indicators, i.e. Euro area GDP, inflation and unemployment⁷².

| Period | β_2 | p-Value | β_3 | p-Value |
|---|-----------|---------|-----------|---------|
| <i>Panel A. DUM = ECB rate changes</i> | | | | |
| 2000–2013 | 31.353 | (0.00) | 0.5385 | (0.98) |
| 2000–2006 | 0.7220 | (0.75) | 31.199 | (0.00) |
| 2007–2013 | 26.216 | (0.00) | –16.596 | (0.66) |
| <i>Panel B. DUM = US federal rate changes</i> | | | | |
| 2000–2013 | 31.212 | (0.00) | –55.326 | (0.00) |
| 2000–2006 | 0.5089 | (0.82) | –3.6688 | (0.60) |
| 2007–2013 | 26.035 | (0.00) | –78.429 | (0.01) |
| <i>Panel C. DUM = UK rate changes</i> | | | | |
| 2000–2013 | 31.242 | (0.00) | –55.295 | (0.01) |
| 2000–2006 | 0.4803 | (0.83) | –4.2590 | (0.70) |
| 2007–2013 | 26.020 | (0.00) | –83.870 | (0.01) |
| <i>Panel D. DUM = EU macro announcements</i> | | | | |
| 2004–2013 | 27.637 | (0.00) | –31.219 | (0.04) |
| 2004–2006 | 1.6322 | (0.48) | 10.480 | (0.04) |
| 2007–2013 | 26.018 | (0.00) | –35.747 | (0.05) |

Table 1 Testing for herding when macroeconomic information is announced.
Source: Galariotis, E.C. *et al.* (2015)

⁷² The “data for short term economic analysis” considers the period from July 2004 to January 2013 (sources: European Central Bank, Bank of England, Federal Reserve, and Eurostat). More precisely, the Eurostat releases “Eurostatistics — Data for short term economic analysis”, i.e. a monthly review which shows the economic activity evolution in the European Union, euro area and Member states.

Table 1 shows the outcome of the test created for testing in fundamental macroeconomic information releases drive to sheeple behaviour. Panels A to C show what will happen if the dummy variable stands for the variation in the ECB base rate, the US Federal Funds rate and the Bank of England rate respectively.

Panel D, furthermore, exhibits results for the case, in which the dummy variable assumes a value of one during the European macroeconomic information announcement days and zero otherwise. We examine the full sample period and the two sub-periods (pre and post crisis).

We can see that regardless of the ECB rate changes, in all other cases there is a strong evidence of herding due to fundamental macroeconomic information acquired during the recent European crisis.

This result shows that, during the European crisis period, macroeconomic information release drives bond market investors to adopt herding behaviour. The same outcome is worth even for days characterized by a change in the Bank of England rate and the US federal funds rate: in fact, during the European crisis period, bond market investors are prone to herd when rate variations become public.

Interestingly, for ECB rate changes there is no statistically significant evidence of investor herding. Yet, this may be surprising, but it is congruous with earlier studies that see international factors as the major determinants of intra-euro area government bond spreads [Barrios, Iversen, Lewandowska and Setzer (2009)], or euro area yield spreads as strongly depended by the US (instead of the Euro) level and slope of the default-free term structure, suggesting that US interest rates play an important role in the corporate bond markets.

Another approach has been developed by Ayres and Mitts (2015), who state that anti-herding regulation can generate two kinds of benefits. In primis, anti-herding regulation can decrease the systemic risk, which takes place when there is excessive behavioural uniformity. For instance, if essentially each homeowner (through low-down payment first-mortgages or equity-stripping second mortgages) owns less than 5% equity in their homes, then a 10% decline in housing prices is able to produce a destabilizing wave of defaults. Secondly, anti-herding regulation can drive to socially beneficial information. In fact, “provoking separating equilibria among the regulated can, for example, avoid the inefficiency of informational cascades and help steer both private and public actors toward better evidence-based outcomes” [Ayres and Mitts (2015)]. More extensively, we state that regulators should be consistent with systemic effects of regulatory pooling on the information generation and on the creation of systemic risk.

We have to underline that pooling is normally a good thing; in fact competitive markets pool on a single price and highways are safer when drivers choose to drive at the same speed⁷³. However, the authors outline the situations where regulations should actively try to lead to behavioural diversity.

Anti-herding regulation must be prone to address the bigger problem of driving similar entities to behave in a different way. For this purpose, we propose different alternatives that government can use to incentivize, with a mix of carrots and sticks, the deviation from a pool. According to this purpose, we take into account the hypotheses of limited licenses and regulatory changes that lift a regulatory burden for a subset of regulated subjects. For instance, the Treasury might reinforce its risk-retention rule by the selling of a limited number of licenses freeing who hold them from securitizing prohibitions. Furthermore, a limited number of tradable licenses can assure an ex ante equal protection and, at the same time, it guarantees the ex post diversity in regulatory burdens.

On the other hand, regulatory menus and heterogeneous altering rules can imply similar separating effects.

A simple financial measure as setting progressive extra fees on certain mortgage terms that are incline to worsen systemic risk⁷⁴ can restrict excessive pooling on those terms without entirely eliminating activity.

Thus, we can state that regulatory intervention interrupts informational cascades by leading separating equilibria and it decreases the externality of an informational market failure.

In fact, by compelling separation, regulators oblige subsequent contractors to make a decision, which depends on the information other than probabilistic inference from similar transaction terms, giving to the society the benefit of taking better-informed decisions. This mechanism might offset the previous benefits of pooling equilibria⁷⁵, but it is not easy to understand whether relying on previous benefits will drive to an efficient cost reduction as opposed to ignorance-promoting informational cascades.

These researches do not want to suggest that regulators should prohibit pooling equilibria tout court, but that sometimes creating separating equilibria is useful in order to prevent the dangerous consequences of excessive pooling equilibria, of which informational cascades are

⁷³ Highways are not, however, safer if all drivers choose to drive at the same time.

⁷⁴ About interest, low down-payment and interest-reset terms, which worsen systemic risk in relation to the traditional fixed-rate writing off loans, see Ayres, I., & Mitts, J. (2014). Three Proposals for Regulating the Distribution of Home Equity. *Yale J. on Reg.*, 31, 77.

⁷⁵ Ian Ayres, *Making a Difference: The Contractual Contributions of Easterbrook and Fischel*, 59 U. CHI. L. REV. 1391, 1405 n.30 (1992) where the author quotes Jeffrey N. Gordon, *The Mandatory Structure of Corporate Law*, 89 COLUM. L. REV. 1549, 1565-66 (1989).

only one example. The society can reap benefits as a whole by adding information regard as more socially efficient alternatives in the present and in the future⁷⁶.

To resume what we show above, we exhibit three different mechanisms by which regulators may lead to separating equilibria in private contracting i.e. direct manipulation of incentives through licensing and subsidies, menus, and heterogeneously impeding altering rules.

Anyway, in a recent article, Ian Ayres and Joshua Mitts have advanced a system of leverage licenses, which drive to separation in the distribution of home equity⁷⁷.

In fact, licenses have been broadly preferred as the best way to control environmental externalities such as carbon emissions⁷⁸, and academics have suggested licensing regimes for several fields e.g. patent rights⁷⁹, energy credits⁸⁰ and hunting rights⁸¹. The benefits of using licenses over traditional “command-and-control” regulation (i.e., simply forbidding a certain behaviour) are strictly linked to the reasons that lead us to postulate the need of creating separating equilibria: in fact, there are important benefits in the allowing some quantity of a beneficial phenomenon, which is characterized even by some undesirable side effects rather than preventing it completely.

Such “partial” regulation typically has been supported by the theory to which the socially efficient level of an activity is less than would otherwise arise without any regulation but nonetheless nonzero. Initially, in fact, economists suggested the government intervention using a Pigouvian tax, i.e. a simple fee on transactions that decreases the output to the socially efficient level⁸².

Yet, succeeding studies had proved that tradable permits – seen as limitations to the licit quantity of an activity – were often better than price mechanisms⁸³.

However, although licenses and Pigouvian taxes are equally useful in decreasing the output to a socially efficient level, they are not equally effective to drive to separating equilibria and resulting in stability and informational benefits. In fact, as a matter of fact, taxes drive to

⁷⁶ This may also benefit parties to the contract by compelling them to bear a risk and possible discover an alternative set of transaction terms from which they can reap the benefits.

⁷⁷ Ayres & Mitts, *supra* note 74 at 66

⁷⁸ See generally, e.g., Tietenberg, T. H. (1990). *Economic Instruments for Environmental Regulation*, 6 OXFORD REV. OF ECON. POLICY, 1.

⁷⁹ See for instance, Ayres, I., & Parchomovsky, G. (2007). *Tradable Patent Rights*. *Stanford Law Review*, 863-894.

⁸⁰ See Berry, D. (2002). *The market for tradable renewable energy credits*. *Ecological Economics*, 42(3), 369-379.

⁸¹ See MacMillan, D. (2004). *Tradeable hunting obligations – a new approach to regulating red deer numbers in the Scottish Highlands?*. *Journal of environmental management*, 71(3), 261-270.

⁸² See, for instance, Pigou, A. C. (1932). *The economics of welfare*, 1920. *McMillan&Co., London* and Baumol, W. J., & Oates, W. E. (1971). *The use of standards and prices for protection of the environment*. *The Swedish Journal of Economics*, 42-54.

⁸³ See e.g. Dales, J. H., & Pollution, P. (1968). *Prices: An Essay in Policy-making and Economics*; Martin L. Weitzman, *Prices vs. Quantities*, 41 REV. ECON. STUD. 477 (1974); Stavins, R. N. (1995). *Transaction costs and tradeable permits*. *Journal of environmental economics and management*, 29(2), 133-148.

separating equilibria only if certain assumptions occur as regards to contractors' demand curves.

Licensing, however, is not the unique way to directly handle incentives to reach separating equilibria. Sometimes it is useful to combine the “stick” of regulatory prohibitions with the “carrot” of subsidies and payments in order to obtain the required behaviour⁸⁴.

A complementary strategy to ask licenses for limiting pooling equilibria, moreover, is to arrange subsidies earmarked to the occurrence of diversity in contracting terms. For instance, regulators could provide several measures to boost transactions other than those that are commonly known in the marketplace.

Among the examples of targeted subsidies, we report Ayres and Mitts' suggestion to create variation in the “conforming mortgage” definition used by Fannie Mae and Freddie Mac⁸⁵.

They propose to permit the GSEs in order to induce beneficially varying conformity by directly setting the price they are willing to offer for mortgage products at each level. In fact, thanks to the submitting of not identical prices for mortgages at different equity levels, the GSEs would lead to a profitable separation in the distribution of equity.

Furthermore, legal menus are another measure to attenuate externalities by inducing separation⁸⁶.

In fact, the hearth of our anti-herding suggestion is the idea that comparable actors should be treated divergently or persuaded to behave divergently. Exactly as in the case of licenses and subsidies, menus can decrease the externality of excessive pooling by creating more separation than would occur considering only the possibility of contracting around a traditional default.

“A menu is the communication of at least two simultaneous offers” [Ayres and Mitts (2015)] and an example of a contractual menu, which comes from everyday life is represented by the document showing the restaurant's food supply, where a customer has the possibility to choose one or more of the listed dishes or nothing at all. Moreover, if the client does not accept one of the listed meals, no contract has been stipulated.

Menus that at the same time offer a higher-price paired with a low-regulation alternative or a lower-price coupled with higher-regulation alternative can lead regulated entities to split themselves on whether the lower regulatory deserve the cost of the higher price. In fact, altering the quality price mixture (or varying two quality dimension of a regulation) can discourage herding behaviour. Hence, menus combined with clearly communicated altering rules could

⁸⁴ About incentives and anti-incentives see Ayres, I. (2010). *Carrots and sticks: Unlock the power of incentives to get things done*. Bantam.

⁸⁵ Ayres & Mitts, *supra* note 74, at 66

⁸⁶ See generally Ayres, I. (2006). Menu matter. *U. Chi. L. Rev.*, 73, 3.

speed up the separation by decreasing the cost of contracting around the default to a privately higher-valued option⁸⁷. In a nutshell, menus can drive to separating equilibria every time that the cost of individualized negotiations for an alternative set of terms rises above the cost of contracting under the menu.

Finally, a third possibility to lead to separation is a generalization of the ideas that the authors have used about the menus, and it includes the use of heterogeneously impeding altering rules.

⁸⁷ Scholars have shown how separating menus are able to speed up efficiency by decreasing altering costs for suppliers, making use of the facts of *Hadley v. Baxendale* as an example: “When high-type valuations are intermediate [compared to low-type ones], carriers will offer separating menus because the gains from discriminating between the high and low types is now greater than are the costs of contracting.” [Ayres & Gertner (1992)]. In this example, menus lead to separation by offering to suppliers a low-cost mechanism to contract with beneficiary with a lower valuation that is private information, deleting the problem between excluding these beneficiaries at all and employing in individualized negotiations with prohibitive costs.

3.2. Impact of herding on volatility

According to the opinion of De Long and J. Bradford (1990) when noise traders occur in the market, we observe an asset price excessively volatile in the sense that it fluctuates more than we are able to explain taking into account only the changes in fundamental values.

They state that it is difficult to account for all the volatility of asset prices in terms of news. Although Shiller's (1981) declares that the stock market extremely violated variance bounds forced by the requirement that prices be discounted present values depended on controversial statistical procedures [Kleidon (1986)]; another prove that asset price movements do not all reflect changes in fundamental values.

Roll (1984) observes the orange juice futures market, where the main source of important news is weather. He proves that a substantial share of the movement in prices cannot be associated to news about the weather that is relevant for fundamental values.

Campbell and Kyle (1987), furthermore, figure out that a great portion of market fluctuations cannot be linked to news about future dividends or discount rates. Such excess volatility is even better to justify if we relax the hypothesis that all market participants are either noise traders or sophisticated investors – as in the model of De Long and J. Bradford (1990) – who bet against them. A more reasonable hypothesis is that many market participants try to attain passive strategies, neither responding to noise nor betting against noise traders.

If a large fraction of investors allocates a constant share of their wealth to stocks, then even a small portion of noise traders can have a great impact on prices. When noise traders try to sell, only a few sophisticated traders are willing to hold extra stocks, so that prices have to fall substantially to make it possible. The fewer is the proportion between sophisticated and noise traders, the larger is the impact of noise⁸⁸.

Another approach is the one advanced by Park and Sabourian (2009) where they deal with the implications of switches in behaviour due to herding on price volatility. As a matter of fact, the authors introduce the following questions: “will buys move prices less with than without herding? Will sales move prices more with than without herding?” [Park and Sabourian (2009)]. In order to find the answers to the previous questions, we use a model involving a comparison between the prices relative to the occurrence of herding behaviour and prices due to the actions of informed traders who take the same choices that they would take at the initial history.

⁸⁸ We report a little example to explain in a better way. Assume that each trader is persuaded that the market is efficient. They will hold the market portfolio. Now, assume that one trader decides to employ his wealth disproportionately to a single security. Its price will go to infinity.

In this hypothetical economy, informed traders behave as if they do not observe prices and past actions of other market participants; we will refer to this world as the opaque market. Conversely, in the standard framework traders examine and learn from the predecessors' actions. To underline the discrepancy, we refer to the standard case as the transparent market. The following figure shows specific sequences of simulated transaction prices for the two markets.

In this simulated figure, we observe that volatility is higher in the transparent market than in the opaque one and this outcome holds even when the herding phenomenon occurs.

In fact, when the average price after a buy is the last period's ask price, and the average price after a sale is the last bid price, we may see that when herding starts, the first trade has a bigger impact on the average price in the transparent market than in the opaque one (the average price is higher after a buy and lower after a sale).

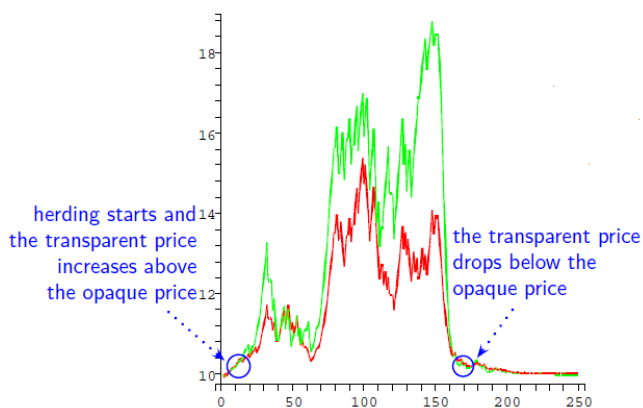


Fig. 4 Simulated Transaction Prices.

In the panel the green line plots the outcome of the simulated prices for the transparent market (where there may be herding) and prices during herding can move up substantially. The red line plots transaction prices for the same sequence of traders, but for an opaque market.

Source: Park, A., & Sabourian, H. (2011). *Herding and contrarian behaviour in financial markets*. *Econometrica*, 79(4), 973-1026.

Blasco *et al.* (2012) decide to develop the impact of the sheeple behaviour on volatility splitting it in historical, realized and implied volatility.

The starting point is the evidence that volume traded and return volatility are positively correlated [Karpoff (1987), Gallant, Rossi and Tauchen (1992), Jones, Kaul and Lipson (1994)]. The two paradigms that try to describe this relationship are the mixture of distributions [Epps and Epps (1997)] and the microstructure paradigm [O'Hara (1995)]. Among different empirical studies, which use dissimilar measures of volume to test these paradigms, we use Jones, Kaul and Lipson (1994) and Chan and Fong (2000, 2006). Following these approaches, we make use of three different measures of volume: the traditional measure of volume traded in Euros, the number of trades, and the average trade size in Euros.

Considering the existing debate in the literature about which of these elements actually have an effect on volatility, Blasco *et al.* (2012) think it makes sense to take into account all of these measures, in order to assure more robustness to the results⁸⁹.

When the variable involved in the regression is volume traded in Euros, we can observe a positive influence on volatility for all the measures of historical volatility. Moreover, when trading volume is measured in terms of the number of trades, we can even see a significant positive effect on volatility in each term, in which it was measured. However, when volume is measured in terms of average trade size, every significant effect of volume on volatility that rises is negative. In a nutshell, volatility rises with increases in volume traded, but it drops with increases in trade size.

Both Easley and O'Hara (1987) and Admati and Pfleiderer (1988) infer that informed traders are involved in higher volume trading than uninformed traders do. Hence, the bigger is the trade size, the higher is the amount of informed trading and consequently the less is volatility that we can assume to observe in the market. [Hellwig (1980) and Wang (1993)].

After studying the three series of volatility, we can focus on the different residual series in order to compute the extent of the linear effect of herding intensity on calculated volatility on day t ⁹⁰. Generally, we note that all three types of herding show a significantly negative effect on all the volatility measures regardless as the implied volatility.

In the model we see that the level of herding intensity increases as the coefficient becomes more negative, and the negative coefficients relative to the herding intensity variable in regressions imply that markets that show higher levels of herding intensity will also reveal higher volatility.

⁸⁹ The following equations identify, respectively, the historical, the realized, and the implied volatility.

$$\begin{aligned}\sigma_{it} &= \alpha_i + \alpha_{im}M_t + \sum_{j=1}^{12} \rho_{ij}\sigma_{it-j} + \varphi_i V_{it} + v_{it} \\ \sigma_{it} &= \alpha_i + \alpha_{im}M_t + \sum_{j=1}^{12} \rho_{ij}\sigma_{it-j} + \theta_i NT_{it} + \eta_{it} \\ \sigma_{it} &= \alpha_i + \alpha_{im}M_t + \sum_{j=1}^{12} \rho_{ij}\sigma_{it-j} + \gamma_i ATS_{it} + \tau_{it}\end{aligned}$$

where σ_{it} is the value on day t of each of the volatility measures considered, taking into account that i can take ten different values; M_t is a dummy variable that takes a value of 1 for Mondays and zero for the remaining days of the week; V , NT and ATS are the volume measures described above. v_{it} , η_{it} , τ_{it} are the residuals of the regressions that become the new series after the removal of Monday and volume effects.

⁹⁰ The following equations represent the residuals of the previous series.

$$\begin{aligned}v_{it} &= \omega_{it} + H_{ist} + \lambda_{it} \\ \eta_{it} &= \omega_{it} + H_{ist} + \lambda_{it} \\ \tau_{it} &= \omega_{it} + H_{ist} + \lambda_{it}\end{aligned}$$

Where ω_{it} is a constant, H_{ist} is the PS (2006) herding intensity computed at the day t where s can assume three different values, according to whether the herding has taken place during an up run, a down run or a zero run.

The outcome is consistent with what Avramov, Chordia and Goyal (2006) reveal in the researchers.

In fact, the results for the measures of historical and realized volatility are very similar, regardless of which volume proxy is used. The parameters used to measure herding intensity seems to influence the volatility created that day.

Furthermore, the outcome given by the measures of historical and realized volatility reveals that a higher level of herding (which might be seen as uninformed trading) implies greater price changes (volatility), which means less stability. Herding traders either add momentum to price fluctuations or make prices exceeded the fundamental price, ensuing in more volatile and, maybe, less informative prices. Nevertheless, these traders also provide liquidity to markets.

The outcome for the implied volatility measure is not so clear. The differences existing between the results for implied volatility and the remaining measures used reveals that the occurrence of herding influences current volatility but not the expected one, which is gauged by implied volatility.

The main explanation of implied volatility is represented by the market's future volatility forecast.

In fact, implied volatility mainly gathers expectations about factors such as market price, fear of sharp drops or interest rate, which, hence, relies on future information.

The option prices and, thus, the implied volatility evaluations, also include other factors such as the expiration date, the strike price, the bearish/bullish state of the market, liquidity problems in the options traded, volatility price skews due to buy/sell fees, excessive leverage effects or wide bid/ask spreads [see, for instance, Peña *et al.* (1999) or Serna (2004)].

The research reveals that implied volatility, by definition, does not consider herding effect.

Many studies have shown that volatility increases with uninformed or liquidity trading [Hellwig (1980) and Wang (1993)] and some authors have directly connected volatility increments to herd trading [Froot, Scharfstein and Stein (1992)], Avramov, Chordia and Goyal (2006)].

Although, the outcomes deriving by the use of short-term implied volatility offer to the topic new information, which has not been shown in former studies.

3.3. Impact of herding on liquidity

After observing the impact of sheeple behaviour on volatility, we want to examine its implication on liquidity, since the two phenomena are strictly related. Park and Sabourian (2009), in fact, address even this topic, and in order to analyse the impact of social learning on liquidity, they make a comparison between price movements in the transparent economy and the ones in a hypothetical economy, called opaque (which is exactly alike the initial one, as we exposed in the previous paragraph, with only one exception: informed traders do not switch their behaviour in relation to the actions of others). Furthermore, we do not observe social learning either since market participants do not hold information about the others' behaviour or since they are not able to extract any information about the true state from the behaviour of others.

According to the tradition of Glosten and Milgrom (1985) liquidity is estimated by the size of the bid-ask-spread because a bigger spread causes higher adverse selection costs and thus lower liquidity. The authors make a comparison between the measure of liquidity when a (rational) informed trader herds with that one when the market participants decide to not change their behaviour according to the theory (anyway, prices always precisely reveal the behaviour of traders). The result of the studies shows as the former situation makes the price higher than in the latter.

To prove the previous sentence, we observe the case of buy herding by a signal type S . A simple intuition hints that buy herding hampers the information transmission so that the ask-price will be lower when the herding candidate changes his/her behaviour respect to the case where he/she does not switch. The idea is that when S type decides to buy herding "there are more types that are buying, compared to when he does not switch and therefore a buy conveys less information in the former case than in the latter one" [Park and Sabourian (2009)].

Yet, this intuition is deceptive and the ask-price is higher in the presence of herding respect to the case in which there is no reversal in traders' behaviour. The reason lies in the herding candidate's U shaped conditional signal distribution⁹¹: the difference in the ask prices in the two cases reflects the fact that the herding candidate S buys in one state and not in the other one. When buy herding begins the likelihood of V_1 ⁹² is small relative to both V_2 and V_3 . Since

⁹¹ U shaped conditional signal distribution is characterized by: $Pr(S|V_1) > Pr(S|V_2)$ for $i = 1, 3$.

In fact, the possibility of herding for any informed agent with signal $S \in \mathbb{S}$ depends substantially on the shape of the conditional signal distribution of S .

⁹² The liquidation value is denoted by V , which assumes one of the sets of three potential values $V = \{V_1, V_2, V_3\}$ with $V_1 < V_2 < V_3$.

type S sets larger weight on signal V_3 respect to V_2 , thus, it implies that within the case where S buys the ask-price must be higher.

According to the previous arguments, the bid price is lower when the type S (rationally) buy herds respect to the case where the type S sells: in fact, when buy herding begins, the relative likelihood of V_1 is small; as type S sets larger weight on signal V_3 respect to V_2 , we may conclude that a sale in a context where S is selling must reveal a higher price respect to the situation where S is buy herding.

This justify as the spread increases within the occurrence of herding respect to the situation in which the informed types do not switch their behaviour.

Obviously, the above result holds even in the situation of sell herding.

Actually, not of the authors are prone to affirm that in the presence of herding behaviour the liquidity of the market decreases, but it exists a not so huge literature on the topic.

Part 4. Investor behaviour

In line with the CoBuild's dictionary definition, "sentiment" is an attitude that people have and it is based on a miscellaneous of thoughts and feelings.

Shiller (1984) identifies investors' sentiments as market trends of what is "in fashion" among traders. In fact, trading on famous models and trading on noise, rather than on news, are phenomena that have been connected with investor sentiments [Lee *et al.* (1991), De Long *et al.* (1990), Black (1986) and Shiller (1984)].

4.1. Sentiment investor and relation between sentiment and herding effect

In accordance with the psychology literature, individuals' sentiments influence their judgments about future events, affecting their decision-making process. Generally, evidence from psychology reveals that people with positive feelings make optimistic choices and people with negative feelings make pessimistic choices [Arkes, Herren & Isen (1988), Bower (1981), Wright & Bower (1992)].

Market sentiment is the main prevailing behaviour of investors as to anticipated price development in a market. It is represented by the accumulation of many different fundamental and technical factors, among which we may observe price history, economic reports, seasonal factors and national and world events.

As the sentiment accounts for the emotional state of the capital market, we might suppose that it is able to affect herd behaviour.

We see that exist many proxies for sentiment. Among the most famous proxies are those suggested by Baker and Wurgler (2006), who built a sentiment proxy depended on several factors. Their measures included closed-end fund discounts, NYSE share turnover, the number of IPOs, the equity share in new issues, the dividend premium and the Consumer Confidence Index from the University of Michigan. Many researchers, such as Schmelling (2009), have made use of these proxies.

In recent times, Ben-Rephael, Kandel and Wohl (2012) have used two tools to assess investor sentiment in mutual fund flows.

The first was the survey-based Consumer Sentiment Index from the University of Michigan Survey Centre, employed even by Lemmon and Portniaguina (2006). The second was the Baker and Wurgler's (2006) measure, which depends on six indirect measures of investor sentiment i.e. the trading volume revealed by NYSE turnover, the closed-end fund discount, the dividend premium, the number of IPO and first-day returns on IPOs and, finally, the equity share presented in new issues. On the other hand, Baker, Wurgler and Yuan (2012) developed an investor sentiment index relative to six major stock markets (Canada, France, Germany, Japan, UK and the US), employing three different approaches.

Long, Shleifer, and Waldmann (1990) asserted that traders are affected by sentiment, and in their opinion, this is related to the confidence they feel in relation to future cash flows. According to Shleifer and Vishny (1997), it may be expensive and risky to compete with sentimental investors because their choices have an impact on the market price of securities. Furthermore, Eichengreen and Mody (1998) stated that a variation in a set of asset prices could transform investor sentiment and terminate in a contagion effect, above all in the short-term. Relatively to the timeframe, Baek and Bandopadhyaya (2005) established that changes in sentiment could justify short-term fluctuations in asset prices, in a better way than any other set of fundamental factors.

Many empirical studies have revealed an important relationship between investor sentiment and market returns [Baker & Wurgler (2006), (2007); Brown & Cliff (2005); Lee, Jiang & Indro (2002)]. The outcome shows that individual investors are easily affected by sentiment, and that sentiment affects the traders' decision-making process.

Moreover, the outcomes observed by Lee *et al.* (2002), based on the Investors' Intelligence Sentiment index, have shown that changes in sentiment are negatively correlated with market volatility. Volatility rises (drops) when investors become more optimistic (pessimistic).

Brown and Cliff (2005) found evidence that sentiment affects asset valuation, given their studies based on a sample of 456 observations between January 1963 and December 2000. As a group, investors are prone to overvalue (undervalue) assets during times of extreme optimism (pessimism) or high (low) sentiment. When investors are optimistic (pessimistic), the market estimation is higher (lower) respect to the intrinsic value. Hence, the authors assume that asset-pricing models should take into account the role of investor sentiment.

We have also reported that there exists empirical evidence about the fact that investor sentiment has a significant influence in the stocks market returns e.g. Baker & Wurgler (2006), (2007) and that the capital market is positively linked to investor sentiment [Lee *et al.* (2002), Wang, Keswani & Taylor (2006)].

Despite the growing interest in this promulgation and the huge number of researches that is interested in the analysis of the relationship between investor sentiment and market returns, there exist not many works studying the effects of sentiment on herd behaviour.

Thus, extra studies are necessary to acquire more information on the relationship between herding intensity and investor sentiment. We guess to find that if sentiment is low (high), many (few) investors will mimic other traders whom they think that own more reliable information in relation to the market.

For measuring investor sentiment, Vieira and Simões (2015), inspired by Schmeling (2009) and Vieira (2011), make use of the European Economic Sentiment Indicator (ESI), published by the European Commission and acquired from the DG ECFIN database. The ESI index is a compound measure, made up of five confidence indicators characterized by divergent weights.

These five elements are:

- industrial confidence indicator;
- services confidence indicator;
- consumer confidence indicator;
- construction confidence indicator;
- retail trade confidence indicator.

The confidence indicators depend on surveys, whose recipient is each member state involved in the European Union, and it consists of fifteen sentiment components, including industrial production, commercial activity, consumption and savings.

Moreover, ESI is computed as an index characterized by a mean value of 100 and a standard deviation of 10. Ergo, we may affirm that we usually wait for ESI values higher (lower) than 100 in bull markets (bear markets).

So, given the hypothesis that sentiment may affect the synchronised behaviour of traders' groups, the authors decide to detect its impact on herding behaviour taking into account only significant dimensions groups. In fact, in order to analyse this relationship, they developed the following regression, based on the ordinary least squares model:

$$H_{i,t} = \alpha + \beta_1 H_{i,j,t-1} + \beta_2 ESI_t + \varepsilon_t \quad \text{Eq. 41}$$

where α and β embody the model parameters, ESI_t is a proxy for lagged investor sentiment, $H_{i,j,t-1}$ is the herding intensity statistic at the time $t - 1$ and ε_t is the regression residuals.

We analyse the lagged herding variable to take into account the influence of former period herding on the herding behaviour in the subsequent period. For the model shown in the Eq.41, we run three different regressions, computing the three types of i sequences (up, down and

zero). Our expectations is to find a negative value of β_2 , resulting a negative relationship between sentiment and herd behaviour.

Consequently, in order to determine the nature of causality, we employ the Granger causality test: we want to understand if the sentiment causes herding or viceversa, making use of the following regressions:

$$H_{i,t} = \beta_1 H_{i,j,t-1} + \beta_2 ESI_t + \varepsilon_t \quad \text{Eq. 42}$$

$$ESI = \beta_1 H_{i,j,t-1} + \beta_2 ESI_t + \varepsilon_t \quad \text{Eq. 43}$$

where Eq.42 shows that current herding is linked both to their past values and to the value of sentiment, while the Eq.43 observe the relation between sentiment and sentiment in previous times.

Anyway, sentiments like optimism, pessimism, hope and fear might affect traders' financial decision-making. In fact, on the one hand Lakonishok *et al.* (1992) and Liao, Huang and Wu (2010) stated that sentiment could have a main role to play in investor decisions, and on the other hand, psychological studies have confirmed its importance. From Schwarz (2002), for instance, we infer that the individuals making decision process will be affected by emotional and sentiment factors.

The authors, as expected, find a negative relationship in all of the three series, concluding that the higher the sentiment, the lower will be the herding. This conclusion looks like consistent, because it exhibits that if sentiment is high, investors will not feel the necessity to mimic other investors and it will be more reasonable to make independent choices. Conversely, if sentiment is low, there will be a higher probability that investors decide to follow the choices of other traders.

As regard to the relationship between current and previous herding, we observe that the herding coefficient is positive and statistically significant for each type of sequence, so that we expect to find that the higher is the herding in a given period, the higher the sheeple behaviour will be in the following period.

The outcomes imply that the direction of causality is from sentiment to herding and not viceversa, and only in the neutral (i.e. positions where prices do not change) positions, as it is the only case in which the estimated F-value is statistically significant⁹³.

⁹³ There is no other causality relation, because all the other F-values are statistically insignificant.

4.2. Bubbles – history of contagion

*“Men, it has been well said, think in herds; it will be seen that they go mad in herds, while they only recover their senses slowly, and one by one”.*⁹⁴

“Were all these people stupid? It can’t be. We have to consider the possibility that perfectly rational people can get caught up in a bubble.

*In this connection, it is helpful to refer to an important bit of economic theory about herd behaviour.”*⁹⁵

In the development of dissertation about the relation between the occurrence of the sheeple behaviour and the rise of a bubble, we want to start from a list of some data.

Indeed, we can observe that the total world market capitalization increased from \$3.38 trillion (thousand billions) in 1983 to \$26.5 trillion in 1998 and to \$38.7 trillion in 1999. In order to understand the importance of these numbers, we may state, that, in perspective, the 1999 U.S. budget was \$1.7 trillion, whereas its 1983 budget was \$800 billion. However, market capitalization and trading volumes tripled during the 1990s, while the volume of securities issuance was, even, multiplied by six.

Obviously, privatization has played a key role in the stock market growth [Megginson (2000)]; *De facto*, stock market investment represents the best game to play.

Nevertheless, when a market crash takes place, at the same time, on most of the world stock markets, as we have seen in October 1987, it would lead to the quasi-instantaneous evaporation of trillions of dollars.

Another example is the one that we have attended in January 2001: a stock market crash of 30%, which would be turned into an absolute loss of about 13 trillion dollars! In fact, market crashes are able to gulp down years of pensions and savings in a moment.

Stock market crashes are even interesting since they embody the category of phenomena known as “extreme events”. Extreme events, in fact, are an element of many natural and social systems, often called to by scientists as “complex systems”.

The years since the early 1970s reveal some data in terms of the volatility in the prices of commodities, currencies, real estate and stocks, and the frequency and severity of financial crises not seen before. In the second half of the 1980s, moreover, Japan saw a heavy bubble in

⁹⁴ Mackay, C. (2012). *Extraordinary popular delusions and the madness of crowds*. Start Publishing LLC.

⁹⁵ Shiller, R. (2008). How a bubble stayed under the radar. *New York Times*, 2.

its real estate and in its stock markets. During the same period, the prices of real estate and of stocks in Finland, Norway, and Sweden rose even more rapidly than in Japan. In the early 1990s, furthermore, there was a sudden rush in real estate prices and in stock prices in Thailand, Malaysia, Indonesia, and in most of the neighbouring Asian countries; then, in 1993, stock prices augmented by about 100 percent in each of these countries. In the second half of the 1990s, finally, the United States were involved in a bubble in the stock market: it was represented by a mania in the stocks prices of firms working in the new industries like information technology and the dotcoms.

Besides, bubbles always implode; in fact, by definition a bubble is related to a non-sustainable pattern of price changes or cash flows. The implosion of the asset price bubble in Japan drove to the massive collapse of a large number of banks and other types of financial firms and more than a decade of weak economic growth. The implosion of the asset price bubble in Thailand, on the other hand, provoked the contagion effect and drove to sharp declines in stock prices everywhere in the region. An exception to these events is represented by the implosion of the bubble in U.S. stock prices in 2000, which made stock prices decreased for the next several years, while the following recession in 2001 was rapid and not deep.

In the aftermath of several famous global crises, herd behaviour in financial markets is well known in financial literature. Scholars emphasize the idea that herd behaviour adopted by market traders worsens market volatility, ruins market stability, so that exacerbating financial markets instability⁹⁶ [Eichengreen *et al.* (1998), Falkerts-Landau & Garber (1999), Furman & Stiglitz (1998), Morris & Shin (1999), Persaud (2000) and Shiller (1990)].

Philippas *et al.* (2013) examine the problem of the effects of a decreasing in the dispersion of REIT cross-sectional returns, inquiring whether they are more pronounced during the recent financial crisis. Even the prior literature [see, for instance, Economou *et al.* (2011), Tan *et al.* (2008)] and reports in the financial press imply that herding effects should be much stronger during the periods of market distress; the authors, to achieve their purpose, introduced a slope dummy variable for the squared market returns, as in the following equation:

$$CSAD_t = \alpha + \gamma_1 |R_{m,t}| + \gamma_2 (R_{m,t})^2 + \gamma_3 D^{CRISIS} (R_{m,t})^2 + \varepsilon_t \quad Eq. 44$$

⁹⁶ The herding behaviour is more marked during periods of turmoil respect to the periods of stability. Christie and Huang (1995) underline in their paper that a “herd” is more likely to occur under conditions of market stress, where individual investors are prone to overcome their own beliefs (cascades) and follow the market consensus.

where D^{CRISIS} takes the value 1 on the trading days during the crisis period and 0 otherwise.

There are many known case of herding. One of the most dramatic and popular in recent times is the observation [Huberman and Regev (2001)] of a contagious speculation linked to a non-event in the following sense. A Sunday New York Times article on a possible development of a new cancer-curing drugs led the biotech company Entremed's stock to rise from 12.063 at the Friday May 1, 1998 close to open at 85 on Monday May 4, close near 52 on the same day and remain above 39 in the three succeeding weeks. The enthusiasm reflected on to other biotechnology stocks. It results that the potential major discovery in cancer research had already been included in one of the leading scientific journal – Nature – and in several famous newspapers (including the Times) more than five months earlier but, at that time, market reactions were essentially negligible.

Hence, the exuberant public attention drove to a long-term increasing in share prices, although no officially new information had been presented. The very noticeable and extremely optimistic Sunday New York Times article of May 3, 1998 drove to a rush on Entremed's stock and other biotechnology companies' stocks, which is suggestive of similar excitements leading to bubbles in historical times previously treated. In fact, a plausible assumption is that information technology, the internet and biotechnology are among the foremost new frontiers, on which sensational stories will be prone to enthusiasm, contagion, herding and speculative bubbles.

Making a deeper analysis, in computational terms, Sornette and Johansen (1999) have analysed the stock market bubbles and crashes at the macroeconomic and microeconomic levels, making use of LPPL (Log-periodic Power Law) approach. From a macroeconomic perspective, the model postulates that we are examining rational markets, which show incomplete information. In this environment, the trade price reveals not only the fundamental value but also the future expectations relative to profitability and risk. Conversely, from a microeconomic perspective, the Sornette-Johansen model exhibits that traders (rational investors and noisy traders) are linked locally through certain networks that regulate their anticipations in relation to market earnings. Furthermore, along with this mimicking behaviour showed on a horizontal level, each trader acquires information on a vertical level from other public or private sources. Moreover, trading choices depend on the decisions of other members of the network, but may even include external influences.

According to these features, traders develop mimicking behaviour, forcing the market to a speculative bubble regime, which may turn into a drastic crash, or may reveal a smooth evolution around a declined local trend. Hence, a stock market bubble may be seen as a market

regime where trading prices show a super exponential behaviour, i.e. the price changes are characterized by an exponential evolution.

In order to explain better this mechanism, we report even Sornette (2003), who recalls the idea that all the traders in the world are organized into a network of family, friends, colleagues, contacts, and so on, which represent a source of opinions, so that they influence each other locally through this network [Boissevain and Mitchell (1973)]. We call “neighbours” of the individual Susan on this worldwide graph, the group of people directly linked with Susan. Other sources of influence are also represented by newspapers, web sites, TV stations, and so on. Precisely, if Susan is directly linked with k “neighbours” in the worldwide graph of connections, there will occur only two forces that affect Susan’s opinion:

- the opinions of the above-mentioned k people along with the impact of the media;
- an idiosyncratic signal, which Susan only holds (either received or created);

According to the concept of herding and imitation, the hypothesis is that investors are prone to imitate the opinions of their “neighbours”, not contradict them. It is not difficult to see that the first force will tend to generate order, while the second force will tend to generate disorder, or alternatively, heterogeneity. The idea is that there is a fight between order and disorder and what we are interested in is, which behaviour may result from this fight? Is the system able to cross unstable regimes, such as crashes? Are these crashes predictable?

In order to reply to our questions, we formalize the situation starting from considering a network of investors: each one can be identified by an integer $i = 1, \dots, I$ and $N(i)$ shows the group of the traders, who are directly linked to agent i according to the world-wide graph of acquaintances.

If we isolate one investor, Susan, $N(Susan)$ will represent the number of investors directly linked with her and who are able to exchange information with her, and affect directly her choices. For simplicity, we postulate that each trader, included Susan, can adopt only one of several possible states. In the easiest version, we are taking into account only two possible states: $s_{susan} = -1$ or $s_{susan} = +1$. We could think at these states as “buy” and “sell”, “bullish” and “bearish”, “optimistic” and “pessimistic”, and so on.

Furthermore, we will prove that, gaining only the information about the investment choices made by $N(Susan)$ “neighbours” at time $t - 1$, i.e. yesterday, Susan is able to maximize her return by having made yesterday the choice $s_{susan}(t - 1)$, given by the signed sum of the choices of each of her “neighbours”. Alternatively, the optimal Susan’s choice, focusing on the local polling of her “neighbours”, is based on the idea that it represents a sufficiently faithful image of the market mood, and it is direct to mimic the behaviour adopted by the most of her neighbours.

Indeed, we may take into account some possible deviations, i.e., Susan can choose to follow her own idiosyncratic “intuition” rather than being affected by her “neighbours”. This idiosyncratic choice can be involved in the model setting a stochastic element independent from the decisions of the neighbours or of any other investor.

We can state that, the reason why it is normally optimal for Susan to act according to the opinion of the majority, is due to the movement of prices, which normally move in that direction, forced by the law of supply and demand.

Traders, in fact, are always exchange information, “calling each other to take the temperature” [Sornette (2003)], definitely polling each other before making their choices. Ergo, the strategy that maximizes Susan’s expected profit is the one that identify her position with the sign derived by the sum of the actions of all her “neighbours”. This assumption is revealed in the following equation:

$$s_i(t - 1) = \text{sign}(K \sum_{j \in N_i} s_j + \varepsilon_i) \quad \text{Eq. 45}$$

Where the position $s_i(t - 1)$ offers to Susan the maximum payoff and it depends on her best prediction of the price variation $p(t) - p(t - 1)$ from yesterday to today. The function $\text{sign}(x)$ can be equal to +1 or -1 for positive or negative argument of x and, finally, K is a positive constant of proportionality between the price change and the aggregate buy-sell orders and it is inversely proportional to the market depth; in fact, the larger is the market, the smaller is the relative impact of a given unbalance between buy and sell orders, so that the smaller is the price variation. ε_i is the noise and N_i is the number of neighbours with whom the investor i is in touch in a relevant way. In a nutshell, the Eq.45 remarks that the best investment choice for a given trader is to make the same of the majority of her neighbours, always considering the uncertainly (noise), which take into account the possibility that most of her neighbours might achieve a non-correct prediction of the behaviour of the total market.

We can look at Eq.45 as a mathematical formulation of Keynes’ beauty contest. In fact, Keynes (1936) stated that stock prices are not only defined by the firm’s fundamental value, but also by mass psychology and investors’ expectations. According to his opinion, professional investors are more prone to direct their energy, not to estimating fundamental values but rather, to analysing how the crowd of investors is likely to behave in the future.

Additionally, Orlèan (1984, 1986, 1989a-b, 1991, 1995) has studied the paradox of the mixture between rational and imitative behaviour, calling it “mimetic rationality” (*rationalité mimétique*). He has even elaborated models of mimetic contagion among investors in the stock markets, which are focused on irreversible processes of opinion creating.

The mimicking behaviour above-mentioned and identified by the previous equation, might be included in a more general set of stochastic dynamical models used to represent interacting elements, particles, agents in several different contexts, especially in physics and biology [Liggett (1985), (1997)].

The tendency that push agents towards imitation is based on the coupling strength K^{97} , while the force towards idiosyncratic (or noisy) behaviour depends on the extent σ of the noise term. Thus, the value of K relative to σ defines the result of the battle between order and disorder, and eventually the structure of the market prices.

Ergo, we are able to state that models that mix the following characteristics would show the same features, especially apparent coordinate buying and selling periods, driving eventually to many financial crashes.

The system has to involve the following features:

- A system of agents who are affected by their “neighbours”.
- Local imitation spreads spontaneously into global cooperation.
- Global cooperation among noise traders leads to collective behaviour.
- Prices have to be linked to the properties of this system.

System parameters develop slowly through time.

What we understand, is that it is more likely that a crash occurs when the locally imitative system is headed for a critical point. Indeed, a system is directed to a critical point when local influences spread out over long distances and the average state of the system becomes flawlessly sensitive to a small perturbation, or, in other words, different parts of the system become highly correlated. Another feature is that critical systems are self-similar across scales: in fact, at the critical point, an ocean of traders who are largely bearish may surround different continents of traders, who are largely bullish, each of which, consequently, encloses seas of bearish traders with islands of bullish traders; this progression is even applicable on a smaller scale, i.e.: a single trader [Wilson (1979)]. As a matter of fact, the critically self-similarity is what drive the local imitation cascades to the global coordination (thanks to the scale effect). In the previous analysis Sornette (2003) using the so-called Ising model because this is one of the easiest possible description of cooperative behaviours coming from repetitive interactions

⁹⁷ In the Ising model, we can observe a critical point K_c , which identifies the properties of the system. When $K < K_c$, disorder prevails: the sensitivity to a small global impact is small, the clusters of traders, who are in agreement, keep on being of small dimension, and imitation only irradiates among close neighbours. According to this situation, the susceptibility χ of the system to external news is small since many clusters characterized by different opinions behave incoherently, so that more or less they counteract their response.

On the other hand, when the imitation strength K increases and gets close to K_c , we observe that order starts to spread: the system, in fact, becomes extremely sensitive to a small global perturbation, traders agree with each other form large clusters, and imitation irradiates over long distances.

among traders; Obviously, several other models have recently been realized in order to consider more realistic properties of people and of their economic interactions.

Part 5. Empirical evidence of herding on Chinese stock market

The aim of the empirical analysis is to make an effort to provide evidence of the presence of herding behaviour in Chinese stock markets. The founding hypothesis is that herding may be found thanks to the examination of equity returns dispersion because whether agents come to a decision of suppressing their own belief in favour of market consensus, they will make individual stock returns clustered around the overall market return.

As we reported in the previous paragraphs, Christie and Huang (1995) used the cross sectional deviation of returns (CSSD)⁹⁸ as a measure of return dispersion⁹⁹, we decide to apply a development of their measure, proposed by Chang Cheng and Khorana (2000), as a better identification of dispersion since it is less affected by the existence of outliers. In fact, in their model, they use the cross sectional absolute deviation of returns (CSAD)¹⁰⁰ and they suggest a non-linear regression specification for recognizing sheeple behaviour.

5.1. Institutional background

The Chinese stock market is made up of two official exchanges, the Shanghai Stock Exchange and the Shenzhen Stock Exchange. Both exchanges were founded in December 1990, and they are regulated by the China Securities Regulatory Commission (CSRC).

Since their foundation both markets have been grown at a conspicuous speed; furthermore the total number of listed companies on the two exchanges increased from 14 in 1991 to 2.613 in 2014 and the total market capitalization, conversely, rose from RMB 11 billion in 1991 to RMB 36 billion in 2014¹⁰¹.

Two different types of shares are traded: A-shares and B-shares.

⁹⁸ See Eq.23 at 56.

⁹⁹ They isolate the levels of dispersion in the extreme tails of the market return distribution to test if it diverges relevantly from the average levels of dispersion that relaxed the outermost market return.

¹⁰⁰ See Eq.24 at 57.

¹⁰¹ The data are extracted from the official website of the two stock exchanges. Data are updated to December, 2014 because it represents the last certain data published from Shanghai Stock Exchange.

The first ones can be purchased and sold only by Chinese investors¹⁰² and are RMB-denominated while the B-shares were limited to foreign investors before February 2001 and only later B-shares market became tradable by both domestic and foreign investors. Moreover, B-shares are US-dollar denominated on the Shanghai Stock Exchange (SHSE) and HK-dollar denominated on the Shenzhen Stock Exchange (SZSE).

Hence, the A-share markets is controlled by domestic retail investors, whereas foreign institutional traders played a more important role in the B-share markets. In fact, for instance, in 2008 individual investors in the Shanghai A-share market owned over the 99% of the account with less than 0,08% owned by institutional investors.¹⁰³

The Chinese stock market is a fully order driven and automated market and both exchanges are suited to handling high volume of trading activity. Other features characterizing these two markets are a daily price limit of 10% applied to each common stock and a settlement of T+1 for securities traded in local currencies while a T+3 settlement is applied on the B-shares.

Furthermore, in the past years, Chinese financial markets have been famous for their lack of transparency. As Demirer and Kutan (2006) underlined, the reporting requirements for listed companies in China were neither well-developed nor extensive, and, most of all, significantly less stringent than the regulation applied to the developed countries. Many researches, actually, have evidenced that the ownership structure of state-owned enterprises, where managers are often selected by the government, badly affects the information environment of these firms [Haw, Hu, Hwang & Wu (2004)]. Thus, in this context, we expect that retail investors could base their decision on the actions of other traders, who seem to be more informed about market developments, following the market consensus.

Even though the Chinese financial market was a fast-growing leader, it may not be identified as a deep and mature stock exchange similar to those of a developed country. Evidence of this sentence is the fact that China's market capitalization in 2001 was about 45% of GDP, while the corresponding figure for the US was over 300% [Green (2003)]. Moreover:

- The legal framework and the rule of law are weak and only few alternatives for investors exist;
- Interest rates are controlled and kept low in favour of government enterprises in order to give them the benefits of borrowing loans at a rate below the market ones;

¹⁰² Since November 2002, even QFII (Qualified Foreign Institutional Investors) are admitted to the trading activity in the A-shares with some limits (for instance quota available for the QFII Program was USD 10 billion in total initially, rising until to USD 50 billion in 2012).

¹⁰³ Shanghai stock Exchange Statistical Annual, 2008

- The central government is greatly concerned in the ability of the stock market to finance state-owned enterprises because of the existence of a thin corporate bond market;
- Investors have not the same options of their neighbours in the world, because of the heavy government interference (such as regulation and central bank intervention), so that they are prone to speculate in the stock market, giving rise to a significant market volatility;
- Two thirds of outstanding shares are not publicly tradable.

Hence, trading behaviour in China's financial markets may be different from what we observe in other markets. Traders, in fact, may be affected on their activity by others' choices, which may be more informed about market developments, by following the market consensus. Given the growing significance of China's stock market, along with its unique microstructure features, where traders have to handle a Communist (but increasingly market oriented) government, it is necessary to observe how agents in Chinese markets, especially during transition, behave.

On the other hand, we also have to underline that recently, the Chinese government has issued several measures in order to reform the stock market. For instance, the CSRC has given the possibility to shareholders to purchase stocks in the open market and to companies to start stock repurchase programme with the aim of making prices more stable. It has even decided to convert the non-tradable shares (most of all state-owned because only the A and B shares belonged to the category of tradable products) into tradable ones, conveying to investors the signal that the Chinese market has no longer the intention to control the listed companies [Yao, Ma & Peng He (2014)]. Furthermore, the regulation has been developed in order to "encourage" the corporate governance, thanks to a compulsory information disclosure and strict auditing procedures. Even the limits set on the trading of A-shares are slightly diminished in favour of a limited allowance of foreign investors in the A-share market since November 2002 [Chan, Fung & Liu (2007)].

More recently the Xi Jinping has shared the draft of the 13th five year plan: the most important points reveal the will of the government of transform China in a total developed economy. In fact, this plan includes the disposal of the "zombie enterprises", i.e. the state owned ones, the will of transforming the country from one focused only on industrialization and exports to a market with a booming internal demand, a stronger environmental attention and the building of new infrastructures¹⁰⁴.

¹⁰⁴ Il piano quinquennale della Cina in dieci punti, Il Sole 24 Ore, 5/03/2016

5.2. Data and methodology

The dataset used in this study is obtained from Thomson Datastream database and it deals with daily and monthly firm-specific data. To calculate the individual stock returns, daily data for all firms listed on the Shanghai Stock Exchange (SHSSE) and Shenzhen Stock Exchange (SZSE) over the period from February 17, 2006 to February 15, 2016 and belonging to A and B shares categories are collected. In fact, our analysis is based on:

- Shanghai Stock Exchange A-share price index (CHSASHR)
- Shanghai Stock Exchange B-share price index (CHSBSHR)
- Shenzhen Stock Exchange A-share price index (CHSZASHR)
- Shenzhen Stock Exchange B-share price index (CHSZBSHR)

Log returns are computed to measure the stock performance for shares in the following way:

$$R_{it} = 100 \times (\log(P_{it}) - \log(P_{it-1})) \quad \text{Eq. 46}$$

Where R_{it} is the observed stock return of firm i at time t , P_{it} is the observed price of firm i observed at time t and P_{it-1} is the observed price of firm i observed at the time $t - 1$. Moreover, B shares are adjusted for exchange rate effects¹⁰⁵.

The chosen methodology depends on the computation of $R_{m,t}$, which stands for the cross-sectional portfolio return at time t and it is computed as the equally weighted average stock returns in the portfolio. Note that both $|R_{m,t}|$ and $R_{m,t}^2$ will appear in the following equations. In fact, CCK¹⁰⁶ remarks that the rational asset pricing models imply an increasing linear relation between the dispersion in individual asset returns and the return on the market portfolio. Conversely, during periods of relatively large market price fluctuations, traders could react in a more uniform way, revealing herding behaviour. If it happens, the correlation among asset returns will rise, so that the corresponding dispersion among returns will drop or, at least, will grow at a less-than-proportional rate with the market return. The research for the herding phenomenon through the study of the returns' dispersion behaviour is the reason for including a non-linear term (the squared market return, $R_{m,t}^2$) in the test equation, and if the results of the analysis will show that the coefficient of $R_{m,t}^2$ (γ_2) is significantly negative, it will be consistent with the presence of sheeple behaviour.

¹⁰⁵ RMB-USD and RMB-HKD exchange rate are used to convert USD- and HKD-denominated share prices into RMB-denominated prices, so that the returns obtained can be compared each other's.

¹⁰⁶ Acronym that stands for Chang, E. C., Cheng, J. W., & Khorana, A. (2000). An examination of herd behaviour in equity markets: An international perspective. *Journal of Banking & Finance*, 24(10), 1651-1679.

The base model, or more precisely, the model theorized by the literature, consider an OLS estimation only with two regressor i.e. $|R_{m,t}|$ and $R_{m,t}^2$, but the high frequency time series market data (daily returns in our case) usually reveal a high level of serial correlation, so that we need to handle the implications of this feature in order to avoid to obtain a biased estimation of the parameters. Thus, we add a 2-day lag of the independent variables as well as of the dependent variable ($CSAD_t$) to our equation, in order to further improve the power of the model. We also evaluate the possibility of using the heteroskedasticity consistent standard errors to compute the estimated regression OLS coefficients, or, alternatively, to abandon the OLS estimation in favour of a Garch specification, which models even the variance.

Hence, the three specification models considered in this introductory analysis are the following:

$$1. \quad CSAD_t = \alpha + \gamma_1 |R_{m,t}| + \gamma_2 R_{m,t}^2 + \varepsilon_t \quad \text{Eq. 47}$$

$$2. \quad CSAD_t = \alpha + \gamma_1 |R_{m,t}| + \gamma_2 R_{m,t}^2 + \gamma_3 |R_{m,t}|L1 + \gamma_4 |R_{m,t}|L2 + \gamma_5 R_{m,t}^2 L1 + \gamma_6 R_{m,t}^2 L2 + \gamma_7 CSAD_t L1 + \gamma_8 CSAD_t L2 + \varepsilon_t \quad \text{Eq. 48}$$

$$3. \quad CSAD_t = \alpha + \gamma_1 |R_{m,t}| + \gamma_2 R_{m,t}^2 + \gamma_3 |R_{m,t}|L1 + \gamma_4 |R_{m,t}|L2 + \gamma_5 R_{m,t}^2 L1 + \gamma_6 R_{m,t}^2 L2 + \gamma_7 CSAD_t L1 + \gamma_8 CSAD_t L2 + \varepsilon_t$$

$$\sigma_t^2 = \alpha_0 + \alpha_1 u_{t-j}^2 + \theta_1 \sigma_{t-1}^2 \quad \text{Eq. 49}$$

The Eq.48 includes even the first two lags of the variables involved in the model in order to take into account the high autocorrelation of the residuals and the heteroskedasticity-consistent standard errors in order to guarantee the significance of the regression coefficients. As we may observe in the Fig.5 and Fig.6, making use of these instruments, the autocorrelation is highly decreased with respect to the simplest model and, furthermore, even the value of the adjusted R^2 increased.

If on one hand the OLS estimation with heteroskedasticity-consistent standard errors solves the problems of the occurrence of autocorrelation in the residuals, the Breush-Pagan Test still reveals the presence of heteroscedasticity in all markets, and the reset test suggests that the specification chosen is not the adequate one¹⁰⁷.

Hence, we decide to abandon an OLS specification in favour of a GARCH(1,1) model as we expect it is able to model the variance. The use of a GARCH(1,1) is justified by the fact

¹⁰⁷ The p-values of these two test lead us to refuse the null hypotheses of homoskedasticity and of the model fitness.

that the autocorrelation functions of standardized residuals and of the squared residuals do not show significant levels of autocorrelation.

In Appendix A, we report the table, which consists of the coefficients values, including the test for the autocorrelation concerning the three different specifications.

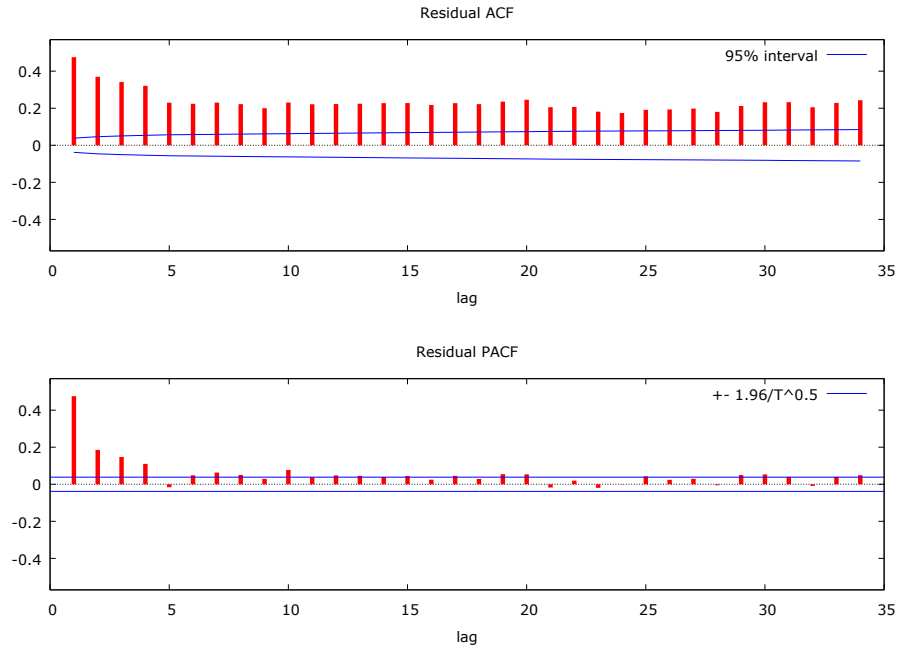


Fig. 6 Shanghai A shares - Residual ACF - PACF of $CSAD_t = \alpha + \gamma_1 |R_{m,t}| + \gamma_2 R_{m,t}^2 + \varepsilon_t$. Adjusted R squared=0,3164

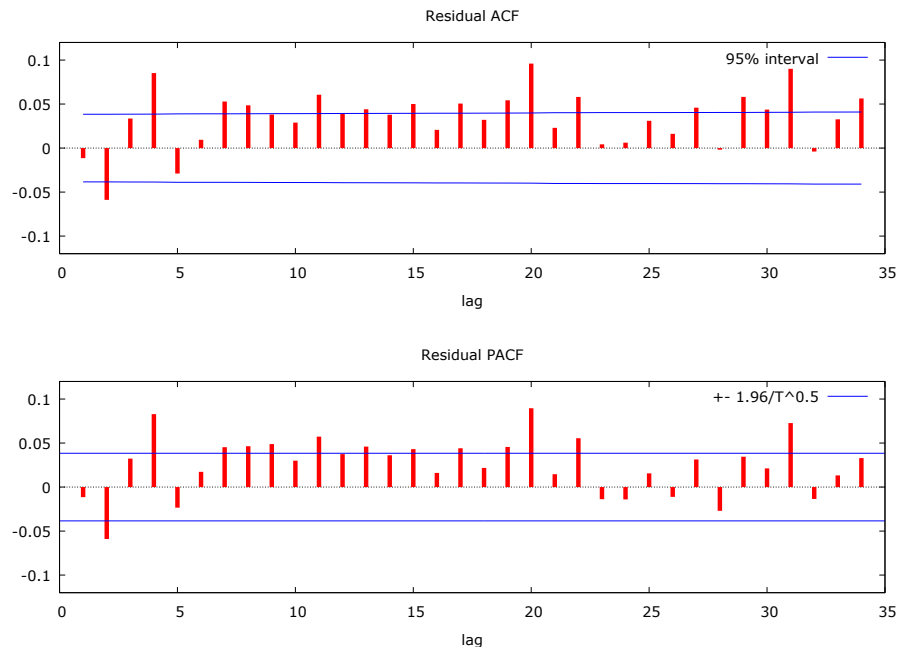


Fig. 5 Shanghai A shares - Residual ACF - PACF of $CSAD_t = \alpha + \gamma_1 |R_{m,t}| + \gamma_2 R_{m,t}^2 + \gamma_3 |R_{m,t}|L1 + \gamma_4 |R_{m,t}|L2 + \gamma_5 R_{m,t}^2 L1 + \gamma_6 R_{m,t}^2 L2 + \gamma_7 CSAD_t L1 + \gamma_8 CSAD_t L2 + \varepsilon_t$. Adjusted-R squared=0,5910. The coefficients are estimates through an OLS model with standard HCO errors

5.3. Main outcomes

In the following paragraphs we discuss the results concerning the data used and the model selected, with the aim of combining the outcomes with some macro and microeconomic explanations.

5.3.1. Descriptive statistics

| Market/ variables | | Mean | Std.dev. | Skewness | Kurtosis | Serial correlation at lag | | | | |
|----------------------|-----------|---------|----------|----------|----------|---------------------------|---------|--------|---------|--------|
| | | | | | | 1 | 2 | 3 | 5 | 20 |
| SHA | CSAD | 0,01675 | 0,00742 | 0,35273 | 2,3714 | 0,6895 | 0,5616 | 0,4876 | 0,3679 | 0,3293 |
| | $R_{m,t}$ | 0,00062 | 0,01996 | -0,83552 | 2,9788 | 0,0862 | 0,0016 | 0,0513 | -0,0011 | 0,0262 |
| SHB | CSAD | 0,10859 | 0,94856 | 2,22710 | 6,1098 | 0,5230 | 0,4561 | 0,4067 | 0,3448 | 0,2547 |
| | $R_{m,t}$ | 0,00053 | 0,02053 | -0,53766 | 5,3695 | 0,1032 | -0,0092 | 0,0270 | 0,0183 | 0,0401 |
| SZA | CSAD | 0,01679 | 0,00751 | 0,44752 | 2,5460 | 0,6776 | 0,5460 | 0,4715 | 0,3647 | 0,3087 |
| | $R_{m,t}$ | 0,00072 | 0,01995 | -0,86114 | 2,7304 | 0,1056 | 0,0041 | 0,0541 | -0,0099 | 0,0183 |
| SZB | CSAD | 0,01108 | 0,00593 | 0,94429 | 2,5731 | 0,6988 | 0,5876 | 0,5012 | 0,3985 | 0,3371 |
| | $R_{m,t}$ | 0,00043 | 0,01736 | -0,48483 | 4,6283 | 0,0983 | -0,0091 | 0,0381 | 0,0153 | 0,0490 |

Table 2 Descriptive statistics.

The table reports the daily mean, standard deviation, skewness, kurtosis of the cross-sectional absolute deviation (CSAD) and the market return ($R_{m,t}$) over the sample period for the Shanghai A (SHA), Shanghai B (SHB), Shenzhen A (SZA) and Shenzhen B (SZB) share market. In addition, the autocorrelation function of the CSAD and $R_{m,t}$ is shown for lags 1, 2, 3, 5 and 20, along with the test statistics of the Jarque-Bera test for normality.

Table 2 reports the univariate statistics for the daily cross-sectional absolute deviation (CSAD) and the market returns ($R_{m,t}$) in relation to the four Chinese stock markets (SHA, SHB, SZA, SZB) over the sample period (17/02/2006 – 15/02/2016).

The statistics show that the mean daily equity market return ($R_{m,t}$) ranged from 0.0429% for the Shenzhen B market, to 0.0719% for Shenzhen A market, and A-shares have consistently higher mean values of $R_{m,t}$ than B-shares, whereas the standard deviation of B-shares are, respectively, the highest and the lowest value (Shenzhen and Shanghai). Our findings, which reveal higher returns' values for the A-shares market, are in antithesis with the results of CCK (2000), but we may corroborate our point of view, underlying that we are handling a different period (more recent, and, hence, characterized by a more reformed Chinese market) and mentioning Chang *et al.* (2008), who justified the discount values of B market with an information power of Chinese investors,¹⁰⁸ which make the B market returns discounted. In

¹⁰⁸ The A shares market returns benefit even from liquidity effect, diversification effects, differential risk premiums or maybe to the restrictions to foreign investors.

fact, investors in A-shares markets are not only more informed than those in B-shares market, but also A-shares adjust to information faster than B-shares [Chiang *et al.* (2008), Yao (2013)]. This situation may be due to the fact that foreign investors involving in the relatively small and illiquid B-share markets own restricted and more common sources of public and private information, while the domestic investors trading in a wider and liquid A-share markets can reach a richer pool of primary and secondary sources of information¹⁰⁹. Another plausible explanation to the higher mean return of A-shares could be identified in the explosive growth experienced by the A-shares between 2005 and 2007 due, at most, to the elimination of some trading restrictions as regard to the citizenship of traders. Overall, we observe that the difference between the two types of markets is not so high since, after the 2002, the Chinese market became less segmented [Yao (2014)].

We observe, in addition, that the correlations at the first lag are quite high, but this is due, as above-mentioned, to the frequencies of financial returns. In fact, after a transformation of the data sample in monthly frequency the computation of residuals autocorrelation will almost completely disappear as the figure below exhibits.

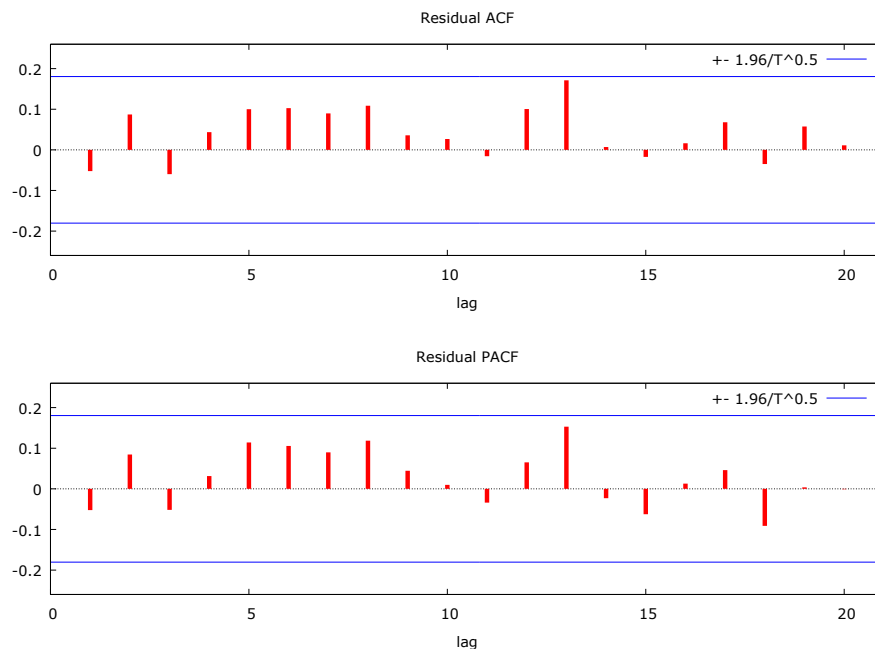


Fig. 7 ACF and PACF of residuals relative to the monthly data-set for Shenzhen B market

Nonetheless, even in the daily frequency data, the t-statistics for these coefficients are in general insignificant, and after 20-lags the level of serial correlation has largely decreased in each of the markets studied. The descriptive statistics on the dispersion measure (*CSAD*) are also

¹⁰⁹ For instance media coverage, analyst reports, and rumours.

reported in the Table 2. By definition, *CSAD* takes on a minimum value of zero when all agent stock returns move in perfect unison with the market, and increases when the returns deviate away from market return. The lowest value is again observed in the Shenzhen B-shares, while the highest is recorded in the Shanghai B-shares, so that if we expect that one of the market examined have revealed no herding phenomenon, we would likely refer to SHB. The high level of autocorrelation is evident in the *CSAD* series, which range from 0,4561 in Shanghai B market to 0,6988 in Shenzhen B market and it is significant even after 20 lags. This support the use of lagged variables in the equation regression in order to make the level of autocorrelation lower.

5.3.2. Evidence of herding

In this section, we report the results of the specification model chosen in order to detect the presence of the herding behaviour in the Chinese stock markets.

| | SHA | SHB | SZA | SZB |
|------------|---------------------------------------|---------------------------------------|---------------------------------------|--|
| α | 0,00438 (12,0710)*** | 0,01314 (11,2129)*** | 0,00451 (11,1828)*** | 0,00260 (11,0309)*** |
| γ_1 | 0,21899 (9,3236)*** | 4,14375 (44,8125)*** | 0,24786 (9,5933)*** | 0,29445 (13,4294)*** |
| γ_2 | -0,89482 (-2,1540)** | 12,27000 (7,1448)*** | -0,88222 (-2,0136)** | -2,36326 (-4,9485)*** |
| γ_3 | -0,04921 (-2,7754)*** | -1,40241 (-11,4801)*** | -0,04539 (-2,5796)*** | -0,08613 (-4,9263)*** |
| γ_4 | -0,01610 (-0,9068) | -0,63612 (-5,2023)*** | -0,01442 (-0,8455) | -0,05564 (-3,7573)*** |
| γ_5 | 1,00834 (2,6778)*** | -1,21389 (-0,7171) | 0,73553 (2,0455)** | 1,89594 (4,4016)**** |
| γ_6 | 0,22123 (0,6283) | -3,36523 (-2,4102)** | 0,10373 (0,3194) | 0,60003 (2,0041)** |
| γ_7 | 0,46062 (18,6035)*** | 0,38663 (16,8263)*** | 0,44801 (16,7766)*** | 0,39183 (15,2611)*** |
| γ_8 | 0,11692 (5,0301)*** | 0,18302 (7,9236)*** | 0,10070 (4,5887)*** | 0,18378 (7,8225)*** |
| α_0 | 7,49E-07 (2,0461)** | 1,12E-05 (2,5867)*** | 6,26E-07 (1,4351) | 3,74E-07 (2,0300)** |
| α_1 | 0,08265 (3,4627)*** | 0,11942 (4,3772)*** | 0,06823 (2,3127)** | 0,09445 (3,1959)*** |
| β_1 | 0,88553 (23,2494)*** | 0,86865 (30,7414)*** | 0,90436 (18,9600)*** | 0,87706 (21,7871)*** |

Table 3 Estimates of herding behaviour in Chinese markets.

The table reports the estimated coefficients of the model of Eq.49. The sample period is from 21/02/2006 to 15/02/2016 because of the inclusion of the first two lags for each variable. Number in parenthesis are t -statistics based on robust standard errors QML. ***, ** and * represent statistical significance at the 1%, 5% and 10% levels respectively.

Table 3 provides the regression results of Eq.49 using daily data. The coefficient of $R_{m,t}^2$, γ_2 , is statistically significant for each of the four markets and negative in each regression except for Shanghai B market (where we have just found a very high level of cross sectional absolute dispersion), proving that the linear relationship between $CSAD_t$ and $R_{m,t}$ does not hold neither for Shenzhen market nor for Shanghai A market. Actually, in light of the results, the hypothesis that we may advance as explanation for the absence of herding phenomenon in Shanghai B market is relative to the fact that this market could be considered the closest to the idea of a

developed one. Many studies, in fact, revealed that the sheeple behaviour is a phenomenon, which distinguishes, most of all, the non-developed markets¹¹⁰.

Moreover, if we take into account only the A-shares market, we observe that the Shanghai Stock Exchange exhibits little higher level of herding; the Shanghai A-shares, in fact, consist of some of the most important and famous companies listed in China, so that it is more likely that they are subjected to a bigger level of imitation with respect to the firms listed on Shenzhen Stock Exchange, because they are considered as the symbol of the economic and political power in China¹¹¹. Anyway, the highest level of herding is exhibited by the Shenzhen B-shares, a reliable result, as this market is limited to the small-medium firms, so that, we can deduce that it is characterized by the lack of information (a good environment for the occurrence of sheeple behaviour).

We analysed even the monthly data in order to understand if the herding phenomenon is a short-lived behaviour or, whether it lasts in time.

To examine the data, we were forced to partly modify the descriptive model used because with a monthly frequency, the matrix obtained is not positive definite in Shanghai A market and in Shenzhen A market. To overcome this drawback, we have decided to delete some variables in the model, which result even not significant in the other two markets because of the use of monthly data. Furthermore, these variables had been added to the base model (Eq.47) in order to reduce the correlation resulted from daily data, but, now, working with data characterized by lower frequency, we cannot use them as, by definition, they show less correlation in the residuals (in fact, we are not weaken the model deleting the lag variables necessary only for the study of daily data). In Table 4 we may observe the outcomes, that are consistent with the observation of Christie and Huang (1995), prone to define the sheeple behaviour as a short-lived phenomenon. In fact, in all markets analysed we observe that the coefficients are not even negative but they are significant.

| | SHA | SHB | SZA | SZB |
|------------|------------------------------|-------------------------------|-------------------------------|-----------------------------|
| α | 0,03370 (4,4287)*** | 0,14473 (5,8208)*** | 0,03847 (6,4052)*** | 0,01994 (4,3445)*** |
| γ_1 | 0,01327 (0,2686) | 3,40412 (11,1414)*** | -0,0179677 (-0,4165) | 0,15655 (3,0269)*** |
| γ_2 | 0,43836 (2,3205)** | 6,46733 (5,3956)*** | 0,63402 (4,2236)*** | 0,33350 (1,8070)* |
| γ_3 | 0,40489 | 0,25085 | 0,42472 | 0,32547 |

¹¹⁰ See Christie and Huang (1995), Chang *et al.* (2000) and Henker *et al.* (2006).

¹¹¹ Shenzhen market is considered the Stock Exchange for small and mid firms.

| | | | | |
|------------|-------------|--------------|-------------|--------------|
| | (4,1617) | (1,8126)* | (4,4134)*** | (2,1984)** |
| α_0 | 0,00001 | 0,00029 | 0,00009 | 0,00001 |
| | (1,2126) | (1,4726) | (1,6839)* | (1,0908) |
| α_1 | 0,07151 | 0,14353 | 0,26280 | 0,10259 |
| | (0,5456) | (2,1469)** | (0,8237) | (1,2741) |
| β_1 | 0,87008 | 0,81550 | 0,35286 | 0,85684 |
| | (7,8678)*** | (19,1450)*** | (1,0168) | (11,9208)*** |

Table 4 Estimates of herding behaviour in Chinese markets.

The table reports the estimated coefficients of the model of Eq.49. The sample period is from 03/2006 to 02/2016 and the data show monthly frequency. Number in parenthesis are *t*-statistics based on robust standard errors QML. ***,** and * represent statistical significance at the 1%, 5% and 10% levels respectively.

Moreover, if we focus on the idea behind the mimicking behaviour, we will note that in each market considered, except of the segment of Shanghai B-shares, the magnitude of the non-linearity in dispersion-market return relationship (captured by γ_2) is high. In fact, from the Fig. 8 below, it seems evident that this relationship is quite far from linear, and as the average market returns in absolute terms become larger, the return dispersion rises but at a decreasing rate. Furthermore, this result is consistent with Christie and Huang (1995), as from their work we can deduce that during periods of market stress, i.e. when the absolute value of $R_{m,t}$ surpasses a certain threshold, $CSAD_t$ is prone to be narrower.

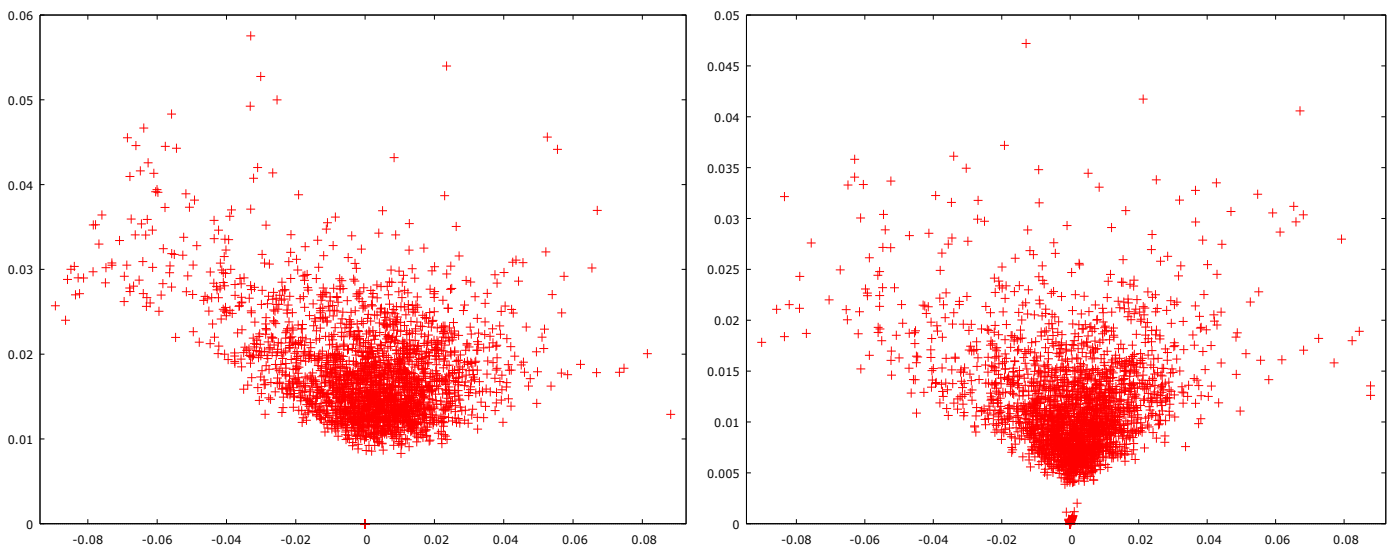


Fig. 8 Relation between $CSAD_t$ (Y axis) and $R_{m,t}$ (X axis). In the top left the Shenzhen A-shares, follow to the right Shenzhen B-shares.

With the purpose of analysing the phenomenon from different points of view, we divide the sample in five subsamples (each one of about two years), in order to examine the evolution of the herding behaviour across time. According to the aim of making use of the best specification model we analyse the possibility of carry on with the use of GARCH (1,1) in order to create

continuity with our previous choices. Unfortunately, this was not possible because, to reach the convergence, we were forced to delete some variables that are significant in the explanation of the phenomenon. This is the reason for a different choice with respect to the previous tests: while in the previous part we left an OLS with heteroskedasticity robust errors in favour of a GARCH specification, in this specific sub-analysis the outcomes force us to reject the superiority of a GARCH model.

Hence, we adopt the benchmark model of the Eq.48 for all markets within each period, even if in some circumstances not all variables appear significant; for instance, γ_5 is not significant across time in Shanghai B-shares, whereas it is useful in other markets. The aim, in fact, is the will of creating a reasonable comparison between four different markets, starting from the same specification model.

In Table 5 we can observe that the coefficients responsible for the herding behaviour (γ_2) are usually decreasing in magnitude and significance across time, revealing that as the Chinese markets become more and more developed, the necessity for mimicking behaviour decreases. This is true except for the last period (26/02/14-15/02/16) where, probably due to the crisis contingency, the herding phenomenon originated again.

According to the Shanghai B shares market, we have to make a clarification because the coefficient was always positive, make us likely to affirm that there are no difference across the different scenarios. However, it becomes higher and more significant across time, showing a trend that suggests us that Shanghai B-market is on the way to become an efficient market (anyway even the Shanghai B market exhibits less efficiency during the last sub period).

| Time-Period | α | γ_1 | γ_2 | γ_3 | γ_4 | γ_5 | γ_6 | γ_7 | γ_8 |
|-------------------|------------------------|------------------------|--|--------------------------|--------------------------|--------------------------|------------------------|------------------------|----------------------|
| SHA | | | | | | | | | |
| 21/02/06-18/02/08 | 0,00472 (5,4847)*** | 0,26944 (4,4048)*** | -1,98824 (-2,0403)** | -0,0121478 (-0,2410) | 0,07108 -1,42980 | 0,62753 -0,60490 | -0,934255 (-0,9715) | 0,47355 (9,5411)*** | 0,09541 (1,8780)* |
| 19/08/08-19/02/10 | 0,00665 (4,8960)*** | 0,23271 (4,0017)*** | -1,43645 (-1,6873)* | 0,01369 (0,3912) | 0,02819 (0,7115) | 0,23018 (0,4389) | -0,164823 (-0,2685) | 0,38341 (7,3419) | 0,03559 (0,7543) |
| 22/02/10-22/02/12 | 0,00504 (5,9940)*** | 0,24461 (4,3373)*** | 1,62888 (-1,3049) | -0,0177436 (-0,5606) | -0,0536614 (-1,7800)* | 0,44306 (0,6552) | 0,57690 (0,9185) | 0,42259 (6,3921)*** | 0,08008 (1,1475) |
| 23/02/12-25/02/14 | 0,00471 (5,7473)*** | 0,21064 (3,3637)*** | -0,619643 (-0,3910) | -0,0199158 (-0,5160) | 0,00440 (0,1209) | -0,00373343 (-0,0030) | -0,237888 (-0,2548) | 0,49393 (9,6076)*** | 0,01641 (0,2927) |
| 26/02/14-15/02/16 | 0,00483 (5,5512)*** | 0,37984 (5,3533)*** | -2,69771 (-3,2256)*** | -0,0726638 (-1,8524)* | 0,04264 (0,8334) | 1,60245 (2,4491)** | -0,312049 (-0,3880) | 0,37944 (6,0242)*** | 0,10604 (1,4834) |

| SHB | | | | | | | | | |
|-------------------|-------------|--------------|---------------------|--------------|--------------|-------------|--------------|-------------|-------------|
| 21/02/06-18/02/08 | 0,03008 | 5,09773 | 2,45475 | -1,43938 | -0,574012 | 0,96213 | 0,24003 | 0,37287 | 0,12386 |
| | (6,5591)*** | (15,6015)*** | (0,5499) | (-3,9378)*** | (-2,0038)** | (0,1500) | (0,0815) | (7,5314)*** | (2,9050)*** |
| 19/08/08-19/02/10 | 0,02259 | 4,40773 | 8,24115 | -1,12469 | -0,131153 | -0,857561 | -4,10858 | 0,30227 | 0,11190 |
| | (5,7940)*** | (24,1658)*** | (4,1935)*** | (-4,2154)*** | (-0,4905) | (-0,3767) | (-1,9181)* | (6,1288)*** | (2,4815)** |
| 22/02/10-22/02/12 | 0,02248 | 3,83644 | 19,52050 | -1,22854 | 0,14718 | -0,715851 | -2,84012 | 0,35535 | -0,00604796 |
| | (7,3229)*** | (17,1824)*** | (4,5080)*** | (-4,8688)*** | (0,6286) | (-0,2027) | (-1,1653) | (6,7444)*** | (-0,1289) |
| 23/02/12-25/02/14 | 0,01929 | 3,86512 | 19,06030 | -1,26277 | -0,163012 | 9,89559 | -7,46144 | 0,30065 | 0,08882 |
| | (7,9915)*** | (20,5140)*** | (4,7625)*** | (-4,1399)*** | (-0,7649) | (1,4399) | (-2,7164)*** | (6,4539)*** | (1,9622)* |
| 26/02/14-15/02/16 | 0,01751 | 3,89384 | 11,13380 | -0,61251 | 0,09374 | -2,5366 | -4,96326 | 0,23052 | 0,11244 |
| | (7,1904)*** | (15,5734)*** | (3,5241)*** | (-2,4778)** | (0,3605) | (-1,0175) | (-1,6473) | (5,4031)*** | (2,7485)*** |
| SZA | | | | | | | | | |
| 21/02/06-18/02/08 | 0,00463 | 0,28436 | -1,56802 | -0,0078373 | 0,04483 | 0,28598 | -0,789885 | 0,47227 | 0,09016 |
| | (5,3965)*** | (4,8992)*** | (-1,6908)* | (-0,1532) | (0,9952) | (0,2740) | (-1,0116) | (9,9732)*** | (1,9490) |
| 19/08/08-19/02/10 | 0,00666 | 0,25061 | -1,29548 | -0,0172845 | 0,04883 | 0,35849 | -0,476 | 0,36703 | 0,03965 |
| | (4,8788)*** | (4,7852)*** | (-1,7131)* | (-0,4915) | (1,3579) | (0,7197) | (-0,8989) | (6,9179)*** | (0,8532) |
| 22/02/10-22/02/12 | 0,00502 | 0,24416 | -1,19329 | 0,01134 | -0,05734 | -0,227007 | 0,77223 | 0,41619 | 0,06871 |
| | (6,5549)*** | (4,0371)*** | (-0,8318) | (0,2884) | (-1,8789)* | (-0,2334) | (0,9894) | (6,3870)*** | (1,0885) |
| 23/02/12-25/02/14 | 0,00502 | 0,28218 | -1,88882 | 0,00314 | 0,02435 | -0,558694 | -0,764439 | 0,45380 | -0,0210438 |
| | (5,8626)*** | (4,2002)*** | (-1,1529) | (0,0663) | (0,6783) | (-0,3684) | (-0,8973) | (8,9465)*** | (-0,4775) |
| 26/02/14-15/02/16 | 0,00443 | 0,40012 | -2,1031 | -0,0975277 | 0,04883 | 1,69672 | -0,617808 | 0,38321 | 0,12500 |
| | (5,0311)*** | (5,4137)*** | (-2,2037)** | (-2,0806)** | (0,9275) | (2,0352)** | (-0,7389) | (5,3516)*** | (1,8021)* |
| SZB | | | | | | | | | |
| 21/02/06-18/02/08 | 0,00370 | 0,29510 | -2,48382 | -0,0157946 | -0,0512585 | 0,92528 | 0,40204 | 0,47840 | 0,12299 |
| | (6,6247)*** | (5,4036)*** | (-3,1263)*** | (-0,4307) | (-1,4288) | (1,2724) | (0,8043) | (9,7823)*** | (2,0194)** |
| 19/08/08-19/02/10 | 0,00369 | 0,21555 | -1,73205 | -0,0273981 | -0,0168449 | 1,13594 | 0,13137 | 0,36990 | 0,12384 |
| | (5,2144)*** | (6,3372)*** | (-3,5166)*** | (-0,9916) | (-0,7266) | (2,5657)** | (0,3688) | (7,0022)*** | (2,6874)*** |
| 22/02/10-22/02/12 | 0,00298 | 0,26927 | -2,01101 | -0,00582458 | -0,0672414 | -0,216041 | 1,19863 | 0,39403 | 0,08569 |
| | (6,9256)*** | (6,0684)*** | (-1,7052)* | (-0,1989) | (-2,4526)** | (-0,2861) | (1,9463) | (7,8745)*** | (1,5057) |
| 23/02/12-25/02/14 | 0,00331 | 0,35875 | -2,38976 | -0,0792072 | -0,0908464 | 2,30908 | 2,07953 | 0,29993 | 0,09824 |
| | (6,8274)*** | (8,1720)*** | (-1,8838)* | (-2,2056)** | (-2,6401)*** | (2,3068)** | (2,7608)*** | (5,2797)*** | (2,1308)** |
| 26/02/14-15/02/16 | 0,00307 | 0,45268 | -3,50867 | -0,165512 | 0,04226 | 2,14833 | -0,0511902 | 0,33036 | 0,05843 |
| | (7,4343)*** | (12,3884)*** | (-5,9403)*** | (-4,8178)*** | (0,8856) | (4,1205)*** | (-0,0687) | (6,6614)*** | (1,0285) |

Table 5 Estimates through OLS of herding behaviour in Chinese markets among subsamples.

The table reports the estimated coefficients of the model of Eq.49. The sample period is from 21/02/2006 to 15/02/2016 because of the inclusion of the first two lags for each variable. Number in parenthesis are t-statistics based on robust standard errors HCO. ***, ** and * represent statistical significance at the 1%, 5% and 10% levels respectively

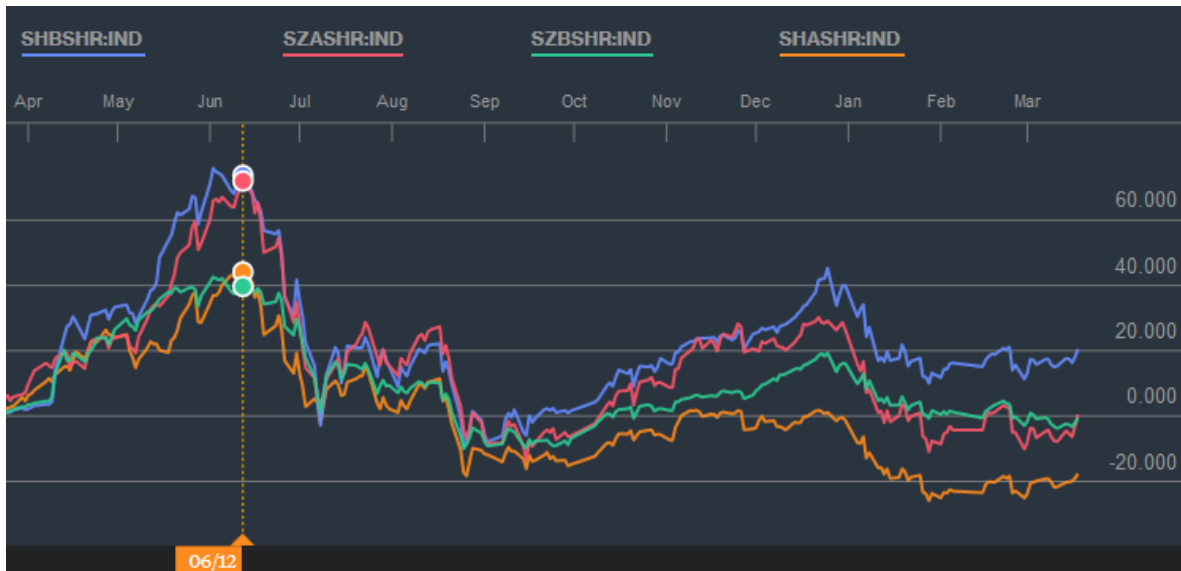


Fig. 9 Evolution of Chinese indexes during 2015
 Source: <http://www.bloomberg.com/quote/>

To validate our hypotheses, as a robustness test, we study the possible effect of the Chinese financial crisis that has taken place from 12 June 2015 (the Fig.10 shows as it is the exactly date of the collapse in the Chinese financial system) to 2 October 2015, on our results.

In fact, this crisis is considered by some analysts as the worst one after that of sub primes in 2008 and probably comparable to the crisis 1929 in the USA since in one month the Chinese markets burnt 3000 billion dollars, i.e. about the 20% of its value, which is more or less 10 times the Greek GDP in 2014.

Prior literature [see among others Economou *et al.* (2011) and Tan *et al.* (2008)] and reports in the financial press underline that herding phenomenon should be much more severe through periods of market distress, and according to the implications of the recent financial bubble, the recent crisis period provides a suitable framework to analyse this conjecture. In particular, we extend the benchmark model, shown in the Eq.49, by including a slope dummy variable for the squared market returns, as described in the following model:

$$\begin{aligned}
 CSAD_t &= \alpha + \gamma_1 |R_{m,t}| + \gamma_2 R_{m,t}^2 + \gamma_3 |R_{m,t}| L1 + \gamma_4 |R_{m,t}| L2 + \gamma_5 R_{m,t}^2 L1 + \gamma_6 R_{m,t}^2 L2 + \\
 &\gamma_7 CSAD_t L1 + \gamma_8 CSAD_t L2 + \gamma_9 D^{CRISIS} R_{m,t}^2 + \varepsilon_t \\
 \sigma_t^2 &= \alpha_0 + \alpha_1 u_{t-j}^2 + \theta_1 \sigma_{t-1}^2
 \end{aligned}
 \tag{Eq. 50}$$

Where D^{CRISIS} takes the value 1 on trading days during the crisis period and 0 otherwise.

The estimated coefficients are reported in the Table 6 for each Chinese market. Surprisingly our results reject the hypothesis that the sheeple behaviour is more pronounced during a crisis period (the coefficients, γ_9 , are not significant and for the Shenzhen A-shares the coefficient is

even significantly positive). This outcome suggests that over the recent financial crisis period the return dispersion in the Shenzhen A market has increased, whereas the other three markets have not been significantly influenced by the contingency.

Hence, we find that investors in one of these markets behave differently in crisis period with respect to the period before, supporting the argument of rational asset pricing models (which state that periods of market stress show wider level of return dispersion as stocks exhibit different sensitivities to market movements). This finding seems to be consistent with those of Demirer and Kutan (2006) and Tan *et al.* (2008), whose results reveal that during the 1997 Asian financial crisis, traders did not adopt herding behaviour in the Chinese stock market.

Therefore, the question is: “why did the herding effect increased during the last sub period if the responsibility is not attributable to the crisis contingency?” It seems not possible to find an unique answer, but we can suppose that investors feel the sensation that the Chinese government is losing the power of controlling the economy (for example, People's Bank of China – PBOC - Governor Zhou Xiaochuan had announced that China would likely lift its controls on deposit rates in one or two years¹¹²) because of the economic opening that will drive to the end of a planned system. Conversely, another possible explanation could be represented by the scepticism of the investors in a real path toward reform of financial markets. In fact, as we may read on Wall Street Journal, on November 2015 China lift IPO ban, introduced to halt the summer selloff. However, as Shen Hong reports, to some investors this move appears only as another tempt to “steer the direction of trading”¹¹³

| | SHA | SHB | SZA | SZB |
|------------|--|---------------------------------------|---------------------------------------|--|
| α | 0,00439 (12,0873)*** | 0,01320 (11,2371)*** | 0,00455 (11,3438)*** | 0,00259 (11,1024)*** |
| γ_1 | 0,22107 (9,2687)*** | 4,12889 (43,6446)*** | 0,25503 (9,5449)*** | 0,29870 (13,1379)*** |
| γ_2 | -0,950558 (-2,2209)** | 12,72910 (6,9254)*** | -1,06215 (-2,2865)** | -2,51801 (-4,7458)*** |
| γ_3 | -0,0482398 (-2,7432)*** | -1,39227 (-11,474)*** | -0,043019 (-2,4442)** | -0,0865265 (-4,8922)*** |
| γ_4 | -0,0151454 (-0,8584) | -0,629008 (-5,0768)*** | -0,0135574 (-0,7919) | -0,0547813 (-3,6704)*** |
| γ_5 | 0,98733 (2,6639)*** | -1,1525 (-0,6768) | 0,68197 (1,8995)* | 1,90267 (4,3086)*** |
| γ_6 | 0,19645 (0,5644) | -3,3062 (-2,3621)** | 0,08426 (0,2584) | 0,57387 (1,8958)* |
| γ_7 | 0,45867 (18,5069)*** | 0,38506 (16,7909)*** | 0,44326 (16,5456)*** | 0,39150 (15,2035)*** |

¹¹² Michael Lelyveld , Conflicts in China economic goals, www.atimes.com, 11/03/2015

¹¹³ <http://blogs.wsj.com/chinarealtime/2015/11/09/some-investors-skeptical-of-chinas-move-to-lift-ipo-ban/>

| | | | | |
|------------|-----------------------------------|-------------------------------------|--------------------------------------|-----------------------------------|
| γ_8 | 0,11644 (5,0045)*** | 0,18219 (7,7984)*** | 0,09826 (4,4603)*** | 0,18302 (7,6895)*** |
| γ_9 | 0,49488 (0,7238) | -2,06329 (-0,7925) | 1,90429 (3,1349)*** | 0,54327 (1,3772) |
| α_0 | 7,45550E-07 (2,0532)** | 1,08491E-05 (2,4483)** | 5,45750E-07 (1,2860) | 3,77220E-07 (2,0023)** |
| α_1 | 0,08242 (3,4837)*** | 0,11699 (3,9777)*** | 0,06214 (2,1323)** | 0,09447 (3,1842)*** |
| β_1 | 0,88588 (23,4387)*** | 0,87159 (28,7382)*** | 0,91384 (19,3554)*** | 0,87665 (21,4692)*** |

Table 6 Herding and crisis period.

The table reports the coefficients of the augmented model shown in Eq.50. The sample period is from 21/02/2006 to 15/02/2016 because of the inclusion of the first two lags for each variable. Number in parenthesis are *t*-statistics based on robust standard errors QML. ***, ** and * represent statistical significance at the 1%, 5% and 10% levels respectively.

5.3.3. Asymmetry patterns in herding behaviour

This section presents an analysis of the possible asymmetric patterns, which describe the herding behaviour according to different scenarios:

- Direction of the market return
- Levels of trading volume
- Levels of volatility

5.3.3.1. Asymmetric effects of market return

Since the direction of the market return may alter investor behaviour, we examine the possible asymmetries in the mimicking behaviour conditional of whether the market is rising or falling. The herding regression is estimated separately for positive and negative market return; in more specific terms, the system can be specified as:

$$\begin{aligned}
 CSAD_t^{UP} &= \alpha + \gamma_1^{UP} |R_{m,t}^{UP}| + \gamma_2^{UP} (R_{m,t}^{UP})^2 + \gamma_3^{UP} |R_{m,t}^{UP}| L1 + \gamma_4^{UP} |R_{m,t}^{UP}| L2 + \gamma_5^{UP} (R_{m,t}^{UP})^2 L1 + \\
 &\gamma_6^{UP} (R_{m,t}^{UP})^2 L2 + \gamma_7^{UP} CSAD_t^{UP} L1 + \gamma_8^{UP} CSAD_t^{UP} L2 + \varepsilon_t \\
 \sigma_t^2 &= \alpha_0 + \alpha_1 u_{t-j}^2 + \theta_1 \sigma_{t-1}^2 \quad \text{if } R_{m,t} > 0
 \end{aligned} \tag{Eq. 51}$$

$$\begin{aligned}
 CSAD_t^{DOWN} &= \alpha + \gamma_1^{DOWN} |R_{m,t}^{DOWN}| + \gamma_2^{DOWN} (R_{m,t}^{DOWN})^2 + \gamma_3^{DOWN} |R_{m,t}^{DOWN}| L1 + \\
 &\gamma_4^{DOWN} |R_{m,t}^{DOWN}| L2 + \gamma_5^{DOWN} (R_{m,t}^{DOWN})^2 L1 + \gamma_6^{DOWN} (R_{m,t}^{DOWN})^2 L2 + \gamma_7^{DOWN} CSAD_t^{DOWN} L1 + \\
 &\gamma_8^{DOWN} CSAD_t^{DOWN} L2 + \varepsilon_t \\
 \sigma_t^2 &= \alpha_0 + \alpha_1 u_{t-j}^2 + \theta_1 \sigma_{t-1}^2 \quad \text{if } R_{m,t} < 0
 \end{aligned} \tag{Eq. 52}$$

Where $R_{m,t}^{UP}$ is the equal-weighted portfolio return at time t when the market rises and $(R_{m,t}^{UP})^2$ is the squared value of this term. $CSAD_t^{UP}$ is the $CSAD$ at time t corresponding to $R_{m,t}^{UP}$. On the other hand, the variables with superscript “down” involve the scenario where the market declines. The asymmetric patterns in sheeple behaviour have been proved by a numbers of previous literature contributes. In fact, Christie and Huang (1995) remark that increases in return dispersions during downside market movements are much lower than those for upside movements. Both CCK (2000) and Demirer and Kutan (2006) researches underline that return

dispersions are, on average, wider in up-markets with respect to the down-markets, reminding that this effect is produced by a “flight to safety” of the market consensus during “bad times”. In Table 7 and in Table 8 we summarize the results of herding regression under asymmetric conditions. Across declining market conditions herding is persistent whereas it does not occur during the rising scenario except in the case of Shenzhen B market (smaller and less informed). The absence of sheeple behaviour may be explained through the confidence of Chinese investors (and probably also of the institutional traders) in the economic reforms. For instance, we may mention a recent renewal: precisely, on 2014 November, the Shanghai Stock Exchange has made another step toward the future transformation in a real developed financial market thanks to the “Shanghai-Hong Kong Stock Connect” realizing for the foreign investors the possibility to invest directly in the A-shares through a local broker. This evolution should end in the future inclusion of the A-shares in the international indexes such as FTSE and MSCI. This element could support the evidence of lack of the herding phenomenon during the period of rising market as a proxy of the development in progress. Moreover, our findings reveal that the herding effect is more pronounced when market is falling (it may be attributable to a decreased investor confidence and heightened preference for risk aversion¹¹⁴) rather than when it is rising except for the Shenzhen B market. The coefficient γ_2 , in fact, is smaller and less significant in three of the four markets.

From a behavioural finance point of view, one of the possible explanations for this finding is that the idea of loss, which implies that human beings react to losses more extremely than to gains [Tversky and Kahneman (1986)]. In fact, for instance, individual investors hold more than 40% of the value of the Chinese stock market, and if they know to be inexperienced and uninformed with respect to their institutional counterparties, greater herding behaviour in down markets may occur in this traders’ group as they try to avoid loss and follow market consensus to sell in order to avoid the displeasure of losing [Paulo Lao and Harminder Singh (2011)].

Consistent with our previous analysis, Shanghai B-shares do not reveal the presence of herding behaviour, and in the rising market the coefficient is still higher with respect to the benchmark model (21,25840 vs 12,27000) strengthening the idea that there are no reasons to mimicking the market consensus during a period of market stability. This element supports, even in this scenario, the idea that herding is more prominent in non-developed market; finally, the data highlight that herding is more prominent in Shanghai A-shares than in Shenzhen A shares

¹¹⁴ Another interpretation for our outcome could be found in the directional asymmetry outlined by McQueen et al. (1996), whose results showed as stocks of each size in the US react more quickly to negative news and with delay to the positive one.

during a period of market stress, probably because, as above-mentioned, the former market is considered by the investors the gauge of the political and economic instability.

| | SHA | SHB | SZA | SZB |
|------------|-----------------------------------|---------------------------------------|------------------------------------|--|
| α | 0,00200 (6,1264)*** | 0,01119 (5,5762)*** | 0,00191 (5,5168)*** | 0,00238 (7,8435)*** |
| γ_1 | -0,0373445 (-2,5301)** | 3,38796 (27,1891)*** | -0,0158884 (-1,0801) | 0,25010 (9,8839)*** |
| γ_2 | 0,53049 (1,6236) | 21,25840 (8,9157)*** | 0,65031 (1,9393)* | -2,22653 (-3,2045)*** |
| γ_3 | 0,06607 (3,9708)*** | -1,08478 (-7,0118)*** | 0,05090 (2,9263)*** | -0,0637545 (-2,7078)*** |
| γ_4 | 0,07469 (5,2589)*** | -0,879016 (-5,2158)*** | 0,03469 (2,5345)** | -0,0282191 (-1,4655) |
| γ_5 | -0,0291522 (-0,0712) | -6,90713 (-2,9769)*** | -0,356601 (-0,7855) | 1,62258 (2,4892)** |
| γ_6 | -1,39372 (-4,5841)*** | -6,37149 (-2,5985)*** | -0,746663 (-2,2506)** | 0,11250 (0,2557) |
| γ_7 | 0,49743 (17,1387)*** | 0,37419 (12,8885)*** | 0,51189 (16,5690)*** | 0,36273 (11,5665)*** |
| γ_8 | 0,30699 (10,6574)*** | 0,30167 (7,3114)*** | 0,31168 (10,8920)*** | 0,24893 (7,4106)*** |
| α_0 | 1,32713E-07 (1,5947) | 8,45636E-06 (1,1003) | 7,61123E-08 (1,2533) | 1,58521E-07 (0,8931) |
| α_1 | 0,07460 (3,7462)*** | 0,13948 (1,8014)* | 0,06646 (3,0764)*** | 0,09049 (1,6040) |
| β_1 | 0,90907 (32,6200)*** | 0,85508 (10,6938)*** | 0,92660 (35,6132)*** | 0,89641 (13,0761)*** |

Table 7 Herding in rising markets.

The table reports the coefficients of the augmented model shown in Eq.51. The sample period is from 21/02/2006 to 15/02/2016 because of the inclusion of the first two lags for each variable. Number in parenthesis are t-statistics based on robust standard errors QML. ***, ** and * represent statistical significance at the 1%, 5% and 10% levels respectively.

| | SHA | SHB | SZA | SZB |
|------------|--|---------------------------------------|--|---------------------------------------|
| α | 0,00305 (6,9572)*** | 0,01351 (7,4922)*** | 0,00300 (6,8738)*** | 0,00314 (8,5638)*** |
| γ_1 | 0,25491 (14,6378)*** | 4,08177 (34,0023)*** | 0,27464 (17,1137)*** | 0,24281 (12,6239)*** |
| γ_2 | -1,36278 (-4,0156)*** | 12,11380 (5,8799)*** | -1,28816 (-4,1626)*** | -1,2689 (-3,8439)*** |
| γ_3 | -0,140516 (-6,7691)*** | -1,49639 (-8,5362)*** | -0,0971499 (-5,4117)*** | -0,0758837 (-3,2293)*** |
| γ_4 | -0,0714026 (-3,5141)*** | -0,947237 (-5,8857)*** | -0,0975914 (-6,1625)*** | -0,0899976 (-4,4872)*** |
| γ_5 | 1,93862 (5,3067)*** | -2,27505 (-1,1414) | 1,03179 (3,2179)*** | 1,32421 (2,8137)*** |
| γ_6 | 0,35110 | -3,10611 | 0,54632 | 1,00657 |

| | | | | |
|------------|--------------|--------------|--------------|---------------|
| | (0,9859) | (-2,0348)** | (2,1639)** | (2,8483)*** |
| γ_7 | 0,51142 | 0,40866 | 0,45424 | 0,36633 |
| | (14,0969)*** | (12,3682)*** | (2,1639)*** | (9,9884)*** |
| γ_8 | 0,25526 | 0,23677 | 0,30810 | 0,23053 |
| | (8,0134)*** | (7,3499)*** | (10,2961)*** | (6,6934)*** |
| α_0 | 3,87052E-07 | 3,08279E-06 | 1,59841E-07 | 7,77333E-08 |
| | (1,3026) | (1,1397) | (1,5738) | (1,1774) |
| α_1 | 0,12239 | 0,06793 | 0,08096 | 0,02939 |
| | (1,9852)** | (2,7008)*** | (3,0782)*** | (3,2149)*** |
| β_1 | 0,84591 | 0,93095 | 0,90473 | 0,96471 |
| | (10,6294)*** | (42,2935)*** | (28,3818)*** | (103,8095)*** |

Table 8 Herding in declining markets.

The table reports the coefficients of the augmented model shown in Eq.52. The sample period is from 21/02/2006 to 15/02/2016 because of the inclusion of the first two lags for each variable. Number in parenthesis are t -statistics based on robust standard errors QML. ***, ** and * represent statistical significance at the 1%, 5% and 10% levels respectively.

5.3.3.2. Asymmetric effects of trading volume

The level of herding behaviour may be linked even to the pattern of trading volume. We then analyse the possible asymmetric effects during periods of high or low volumes traded. We define the trading volume (V_t) as “high” if on day t , it is greater than the previous 30-day moving average; conversely, the trading volume is considered “low” if it is smaller than the previous 30-day moving average. The possible asymmetric effects are studied by using the following empirical specifications:

$$\begin{aligned}
 CSAD_t^{V-HIGH} = & \alpha + \gamma_1^{V-HIGH} |R_{m,t}^{V-HIGH}| + \gamma_2^{V-HIGH} (R_{m,t}^{V-HIGH})^2 + \gamma_3^{V-HIGH} |R_{m,t}^{V-HIGH}| L1 \\
 & + \gamma_4^{V-HIGH} |R_{m,t}^{V-HIGH}| L2 + \gamma_5^{V-HIGH} (R_{m,t}^{V-HIGH})^2 L1 + \gamma_6^{V-HIGH} (R_{m,t}^{V-HIGH})^2 L2 \\
 & + \gamma_7^{V-HIGH} CSAD_t^{V-HIGH} L1 + \gamma_7^{V-HIGH} CSAD_t^{V-HIGH} L2 + \varepsilon_t
 \end{aligned}$$

$$\sigma_t^2 = \alpha_0 + \alpha_1 u_{t-j}^2 + \theta_1 \sigma_{t-1}^2 \quad \text{Eq. 53}$$

$$\begin{aligned}
 CSAD_t^{V-LOW} = & \alpha + \gamma_1^{V-LOW} |R_{m,t}^{V-LOW}| + \gamma_2^{V-LOW} (R_{m,t}^{V-LOW})^2 + \gamma_3^{V-LOW} |R_{m,t}^{V-LOW}| L1 \\
 & + \gamma_4^{V-LOW} |R_{m,t}^{V-LOW}| L2 + \gamma_5^{V-LOW} (R_{m,t}^{V-LOW})^2 L1 + \gamma_6^{V-LOW} (R_{m,t}^{V-LOW})^2 L2 \\
 & + \gamma_7^{V-LOW} CSAD_t^{V-LOW} L1 + \gamma_7^{V-LOW} CSAD_t^{V-LOW} L2 + \varepsilon_t
 \end{aligned}$$

$$\sigma_t^2 = \alpha_0 + \alpha_1 u_{t-j}^2 + \theta_1 \sigma_{t-1}^2 \quad \text{Eq. 54}$$

Where the superscripts $V - HIGH$ and $V - LOW$ refer to high and low trading volume in order to create two different scenarios.

In Table 9 and in Table 10 we can observe the results of the asymmetric volume herding regression: the findings reveal that in a high volume state, the coefficient γ_2 is not significant in both of the A-shares market. However, herding in Shenzhen B-shares occurs in both states of volumes (the coefficient of the non linear term is negative and significant both when the trading volume is high and low): this outcome indicates that the sheeple behaviour is unrelated to trading volume in this segment and probably this is due to the fact that Shenzhen B-shares tend to be dominated by foreign institutions and perhaps they typically rely on common sources of information regardless of the level of market activity. In contrast, the tendency of herding by A-share investors to occur only in the low volume state suggests that the information driving their behaviour may be more different during relatively “quiet” periods of low volume.

An opposite behaviour could be observed in Shanghai B-shares: in fact, in both scenarios the mimicking behaviour is absent and, as we expect, we have a stronger efficiency in the periods of high volume trading. This pattern strengthens our previous findings since Shanghai B market is particularly efficient over our whole analysis.

| | SHA | SHB | SZA | SZB |
|------------|-----------------------------------|---------------------------------------|-----------------------------------|--|
| α | 0,00466 (8,4052)*** | 0,01487 (7,7295)*** | 0,00500 (9,0486)*** | 0,00317 (8,8735)*** |
| γ_1 | 0,06927 (1,7078)* | 387508,00000 (28,1464)*** | 0,10709 (2,9053)*** | 0,27362 (10,4315)*** |
| γ_2 | 0,95944 (1,0943) | 14,02060 (6,8488)*** | 0,88336 (1,1297) | -2,21603 (-4,8920)*** |
| γ_3 | -0,00871455 (-0,3267) | -1,18079 (-6,2978)*** | -0,0375813 (-1,3312) | -0,0994703 (-4,4273)*** |
| γ_4 | -0,00605 (-0,2309) | -0,589009 (-3,4515)*** | -0,00914062 (-0,3722) | -0,0732955 (-3,4982)*** |
| γ_5 | -0,0541994 (-0,0892) | 0,84115 (0,3476) | 0,06026 (0,0917) | 2,00099 (4,5352)*** |
| γ_6 | 0,06451 (0,11370) | -5,32563 (-2,5916)*** | 0,26002 (0,4721) | 0,95894 (2,6665)*** |
| γ_7 | 0,42105 (11,2357)*** | 0,32310 (8,6189)*** | 0,41602 (11,5122)*** | 0,36831 (9,4522)*** |
| γ_8 | 0,21551 (6,4234)*** | 0,22519 (6,8590)*** | 0,19045 (5,4823)*** | 0,19386 (5,2518)*** |
| α_0 | 0,00571 (1,5351) | 0,72746 (0,9806) | 0,05460 (0,7607) | 0,03427 (1,1726) |
| α_1 | 0,10277 | 0,07833 | 0,08827 | 0,11375 |

| | | | | |
|-----------|--------------|--------------|-------------|--------------|
| | (2,50940)** | (1,8162) | (1,0550) | (1,9114)* |
| β_1 | 0,87908 | 0,91541 | 0,88960 | 0,86864 |
| | (17,6533)*** | (19,3889)*** | (8,1845)*** | (12,2353)*** |

Table 9 Herding during periods of high trading volume in Chinese stock markets.

The table reports the coefficients of the augmented model shown in the Eq.53. The sample period is from 04/04/2006 to 15/02/2016 because of the inclusion of the first two lags for each variable and the use of a rolling window of 30 days for the computation of the moving average. Number in parenthesis are t-statistics based on robust standard errors QML. ***, ** and * represent statistical significance at the 1%, 5% and 10% levels respectively.

| | SHA | SHB | SZA | SZB |
|------------|--|---------------------------------------|---------------------------------------|--|
| α | 0,00382 (8,7563)*** | 0,01119 (8,1586)*** | 0,00442 (5,2710)*** | 0,00185 (6,0476)*** |
| γ_1 | 0,33361 (11,2817)*** | 4,24017 (29,9342)*** | 0,35442 (7,3465)*** | 0,29658 (6,5882)*** |
| γ_2 | -1,95562 (-4,2855)*** | 11,21580 (3,3723)*** | -1,9477 (-2,9493)*** | -2,13072 (-2,6993)*** |
| γ_3 | -0,0496432 (-2,1630)** | -1,26549 (-7,5873)*** | -0,0318419 (-1,2274) | -0,0748099 (-3,0408)*** |
| γ_4 | 0,01148 (0,4772) | -0,659246 (-4,0799)*** | -0,0341533 (-1,4118) | -0,0205158 (-0,7317) |
| γ_5 | 0,78954 (2,0457)** | -5,36973 (-2,5526)** | 0,49596 (1,2670) | 1,67176 (2,5022)** |
| γ_6 | -0,455043 (-1,1123) | -4,80319 (-2,91190)*** | 0,25959 (0,7059) | -0,314967 (-0,3866) |
| γ_7 | 0,43055 (12,5565)*** | 0,38588 (12,9196)*** | 0,39301 (7,3420)*** | 0,46268 (13,1314)*** |
| γ_8 | 0,10782 (3,4470)*** | 0,20092 (6,7930)*** | 0,10147 (3,3293)*** | 0,17138 (2,5570)** |
| α_0 | 0,04234 (0,8798) | 0,19686 (1,1981) | 0,09205 (0,5138) | 0,04043 (0,2099) |
| α_1 | 0,04847 (1,8038)* | 0,04066 (2,6882)*** | 0,06752 (0,8163) | 0,07578 (2,2152)** |
| β_1 | 0,93211 (19,3409)*** | 0,95505 (55,1226)*** | 0,89311 (5,6303)*** | 0,88464 (2,0436)** |

Table 10 Herding during periods of low trading volume in Chinese stock markets.

The table reports the coefficients of the augmented model shown in the Eq.54. The sample period is from 04/04/2006 to 15/02/2016 because of the inclusion of the first two lags for each variable and the use of a rolling window of 30 days for the computation of the moving average. Number in parenthesis are t-statistics based on robust standard errors QML. ***, ** and * represent statistical significance at the 1%, 5% and 10% levels respectively.

5.3.3.3. Asymmetric effects of volatility

We further examine the potential asymmetric effects of herding behaviour according to the market volatility. Following the previous methodology, we define volatility to be “high” when the observed volatility exceeds the moving average of volatility over the previous 30 days;

conversely, the volatility is characterized as “low” when it is below the 30-day moving average. To compute the two different scenarios, we analyse the resulting empirical specifications:

$$\begin{aligned} CSAD_t^{\sigma^2-HIGH} &= \alpha + \gamma_1^{\sigma^2-HIGH} |R_{m,t}^{\sigma^2-HIGH}| + \gamma_2^{\sigma^2-HIGH} (R_{m,t}^{\sigma^2-HIGH})^2 \\ &+ \gamma_3^{\sigma^2-HIGH} |R_{m,t}^{\sigma^2-HIGH}| L1 + \gamma_4^{\sigma^2-HIGH} |R_{m,t}^{\sigma^2-HIGH}| L2 \\ &+ \gamma_5^{\sigma^2-HIGH} (R_{m,t}^{\sigma^2-HIGH})^2 L1 + \gamma_6^{\sigma^2-HIGH} (R_{m,t}^{\sigma^2-HIGH})^2 L2 \\ &+ \gamma_7^{\sigma^2-HIGH} CSAD_t^{\sigma^2-HIGH} L1 + \gamma_7^{\sigma^2-HIGH} CSAD_t^{\sigma^2-HIGH} L2 + \varepsilon_t \end{aligned}$$

$$\sigma_t^2 = \alpha_0 + \alpha_1 u_{t-j}^2 + \theta_1 \sigma_{t-1}^2 \quad \text{Eq. 55}$$

$$\begin{aligned} CSAD_t^{\sigma^2-LOW} &= \alpha + \gamma_1^{\sigma^2-LOW} |R_{m,t}^{\sigma^2-LOW}| + \gamma_2^{\sigma^2-LOW} (R_{m,t}^{\sigma^2-LOW})^2 + \gamma_3^{\sigma^2-LOW} |R_{m,t}^{\sigma^2-LOW}| L1 \\ &+ \gamma_4^{\sigma^2-LOW} |R_{m,t}^{\sigma^2-LOW}| L2 + \gamma_5^{\sigma^2-LOW} (R_{m,t}^{\sigma^2-LOW})^2 L1 + \gamma_6^{\sigma^2-LOW} (R_{m,t}^{\sigma^2-LOW})^2 L2 \\ &+ \gamma_7^{\sigma^2-LOW} CSAD_t^{\sigma^2-LOW} L1 + \gamma_7^{\sigma^2-LOW} CSAD_t^{\sigma^2-LOW} L2 + \varepsilon_t \end{aligned}$$

$$\sigma_t^2 = \alpha_0 + \alpha_1 u_{t-j}^2 + \theta_1 \sigma_{t-1}^2 \quad \text{Eq. 56}$$

Where the superscripts $\sigma^2 - HIGH$ and $\sigma^2 - LOW$ refer to the high return volatility and low return and the volatility time series is computed as the deviation standard of a 30-day rolling window multiplied for the squared root of 252 (i.e. the number of trading days considered in the sample).

In Table 11 and in Table 12 are shown the estimation results of the asymmetric volatility model. We observe that the herding behaviour is smaller and less significant during periods of high volatility. This is consistent with our previous analysis, since we have found that during crisis period (suitable to be considered more volatile) the mimicking behaviour appears less emphasized. Moreover, even in this situation, we have to underline the absence of herding behaviour in Shanghai B-shares where the efficiency, according to the behaviour of other markets, rises with the decreasing of volatility.

| | SHA | SHB | SZA | SZB |
|------------|--------------------------------------|---------------------------------------|--------------------------------------|--|
| α | 0,00458 (7,5935)*** | 0,01489 (7,9082)*** | 0,00493 (8,1192)*** | 0,00266 (6,6721)*** |
| γ_1 | 0,19529 (5,5131)*** | 4,18141 (32,2204)*** | 0,23841 (7,7728)*** | 0,29417 (12,4952)*** |
| γ_2 | -0,608754 (-1,0353) | 12,11190 (5,2594)*** | -0,749229 (-1,4023) | -2,38976 (-5,7284)*** |
| γ_3 | -0,0553249 (-2,1094)** | -1,40028 (-7,7707)*** | -0,0519687 (-2,1497)** | -0,0825769 (-3,7863)*** |
| γ_4 | -0,0152884 (-0,6046) | -0,53866 (-3,1803)*** | -0,0211329 (-0,9048) | -0,0561435 (-2,7048)*** |
| γ_5 | 1,34955 (2,6805)*** | 1,64192 (0,7251) | 1,07810 (2,2851)** | 1,88526 (4,3204)*** |

| | | | | |
|------------|-------------------------|-------------------------|-------------------------|--------------------------|
| γ_6 | 0,20191 (0,4227) | -3,32267 (-1,7797)* | 0,22300 (0,5210) | 0,73081 (1,9094)* |
| γ_7 | 0,40198 (11,2060)*** | 0,36007 (10,1350)*** | 0,39397 (11,4459)*** | 0,35292 (9,0307)*** |
| γ_8 | 0,17577 (5,5865)*** | 0,15875 (4,8390)*** | 0,13160 (4,2589)*** | 0,20570 (6,3307)*** |
| α_0 | 0,05718 (0,8574) | 1,02788 (1,3029) | 0,04152 (1,6871)* | 0,01071 (1,0586) |
| α_1 | 0,06965 (1,5405) | 0,09486 (2,0709)** | 0,05986 (3,3135)*** | 0,04691 (1,7261)* |
| β_1 | 0,90944 (13,1353)*** | 0,89300 (17,7329)*** | 0,92442 (36,2638)*** | 0,94600 (30,31640)*** |

Table 11 Herding during periods of high volatility periods in Chinese stock markets.

The table reports the coefficients of the augmented model shown in the Eq.55. The sample period is from 04/04/2006 to 15/02/2016 because of the inclusion of the first two lags for each variable and the use of a rolling window of 30 days for the computation of the moving average. Number in parenthesis are t-statistics based on robust standard errors QML. ***, ** and * represent statistical significance at the 1%, 5% and 10% levels respectively.

| | SHA | SHB | SZA | SZB |
|------------|--------------------------------------|---------------------------------------|--------------------------------------|--|
| α | 0,00418 (9,1361)*** | 0,01191 (7,6133)*** | 0,00418 (9,2278)*** | 0,00232 (8,4880)*** |
| γ_1 | 0,25598 (7,6881)*** | 4,05278 (33,7986)*** | 0,28084 (8,0895)*** | 0,31595 (6,6288)*** |
| γ_2 | -0,980032 (-1,4866) | 14,76510 (7,0514)*** | -1,09717 (-1,6876)* | -2,55387 (-3,3180)*** |
| γ_3 | -0,00812497 (-0,2970) | -1,28325 (-7,8471)*** | -0,0136666 (-0,5261) | -0,0929915 (-3,3349)*** |
| γ_4 | -0,01703 (-0,6241) | -0,682048 (-4,0029)*** | -0,00218962 (-0,0781) | -0,0158425 (-0,5080) |
| γ_5 | -0,478116 (-0,7272) | -7,04228 (-3,5314)*** | -0,143409 (-0,2616) | 1,33189 (1,7969)* |
| γ_6 | 0,36685 (0,6217) | -3,05381 (-1,5720) | -0,253596 (-0,3925) | 0,06157 (0,0867) |
| γ_7 | 0,50326 (15,5523)*** | 0,39323 (12,4702)*** | 0,47520 (13,5731)*** | 0,48585 (12,9183)*** |
| γ_8 | 0,05437 (1,6463)* | 0,20805 (6,6402)*** | 0,06648 (2,1675)** | 0,10127 (2,5663)** |
| α_0 | 0,06603 (0,9723) | 0,08329 (1,4796) | 0,05587 (1,3651) | 0,07931 (0,2817) |
| α_1 | 0,06230 (1,9675)** | 0,07961 (2,3040)** | 0,05756 (2,4573)** | 0,10645 (1,97360)** |
| β_1 | 0,90552 (14,13290)*** | 0,90508 (22,1507)*** | 0,91551 (23,1432)*** | 0,81979 (1,8115)* |

Table 12 Herding during periods of low volatility periods in Chinese stock markets.

The table reports the coefficients of the augmented model shown in the Eq.56. The sample period is from 04/04/2006 to 15/02/2016 because of the inclusion of the first two lags for each variable and the use of a rolling window of 30 days for the computation of the moving average. Number in parenthesis are t-statistics based on robust standard errors QML. ***, ** and * represent statistical significance at the 1%, 5% and 10% levels respectively.

Conclusions

In this work we examined the investment behaviour of market agents within the Chinese stock market, in particular in relation to their tendency to conform towards the market consensus, called by the scholars “herding behaviour”.

The testing methodology selected in this study is based on the approach of Chang, Cheng and Khorana (2000), where equity return dispersions, measured by the cross-sectional absolute deviation of returns, is adopted to observe herding behaviour among investors. In fact, if agents form their trading decisions following the market consensus, the dispersion of returns will decrease or, at least, it increases at a less than proportional rate. The model employed in our research, is built on the assumption that herd behaviour is identified in the market by a non-linear relationship between the cross sectional absolute return dispersion (CSAD) and the corresponding equally weighted portfolio return. In our empirical tests, however, we adopt a modified version of the base model in order to take into account the occurrence of autocorrelation and heteroskedasticity displayed by the daily data. In fact, where the data enable us, we decide on a GARCH (1, 1) specification as Bollerslev *et al.* suggest and we also add two lagged variables of each variable included in the model with the aim of increasing its power.

Our findings allow to explain the investor behaviour in the Chinese stock market, analysing the trend of A-shares and B-shares (the only tradable shares listed in the two different Chinese stock exchanges) about the period between 2006 and 2016. As a matter of fact, we found evidences of the herding phenomenon in both Shanghai and Shenzhen markets except for Shanghai B-shares, where the data revealed a tendency for efficiency.

We also transformed the data changing their frequency, and we observed that with a lower (we choose the monthly one) frequency the herding effect did not occur in our sample; hence, this outcome proved as the sheeple behaviour is characterized by short horizons as Christie and Huang (1995) have proposed.

In addition, we have broken up the sample into five sub-periods, and the result of our analysis revealed that, while all markets (other than Shanghai B-shares) show significant herding behaviour at the beginning of the decade examined, such phenomenon has diminished over time except for the last sub-period, where something unknown happened and produced a trend reversal.

In order to inquire the causes of this change, we supposed that it was due to the recent financial crisis that hit China, but the data were not consistent with this explanation as the dummy

variable, which controls for the crisis, appeared not significant or significantly positive; hence, we suggested that further researches could come up with the answer to this question.

There is a host of empirical literature on herding denoting that an asymmetry between up- and down-going market days exists [see, for instance, Tan *et al.* (2008)]. According to this field of researches, we found out evidence of asymmetric patterns relative to the market return: in fact, our results showed that the herding phenomenon was more pronounced during days of negative market returns apart from Shenzhen B-shares. Similar results, furthermore, were obtained evaluating the existing relation between herding and the trading volume asymmetry. In both cases, in fact, we observed that the asymmetry makes the efficiency of Shanghai B market less prominent in the low state condition (we studied the asymmetric problem creating two opposite scenarios).

A particular digression, in the end, is necessary for the volatility asymmetry because the Shenzhen B-shares are still showing “contrarian behaviour”: in fact, the herding is stronger when the market return is positive, the trading volume is high and the volatility is low. This trend is interesting because what we expected is that herding phenomenon would be more relevant in periods of market instability characterized, for instance, by negative market return and high volatility.

In addition, Shanghai A market did not exhibit asymmetric patterns in relation to the volatility, whereas the Shanghai B-shares show less efficiency if the volatility is high, as we presumed. However, Shenzhen A-shares, according to the other Shenzhen market exhibited a stronger mimicking behaviour in the low volatility scenario. Unfortunately, we were not able to explain these particular reactions to the asymmetric conditions because there was not enough macroeconomic information on the Chinese socio-economic situation useful to explain such divergent features of the four markets.

The main purpose of this work was to contribute in providing additional research on herding in the Chinese stock market. No previous studies have focused on a so recent period or used the specification model that we adopt. Furthermore, the evidence and the conflicting results compared to Yao *et al.* (2014) are an additional proof that studies about herding in financial market, sometimes, offer a conflicting outcome especially if we change the time frame of the data sample.

Suggestions for further researches may be related to the study of the relation between the herding phenomenon and the measures adopted by Chinese policymakers because it may be a good starting point to reform the Chinese stock market with the aim of transforming it into a developed one. Another food for thought could be represented by the comparison with the

influences of other countries: for instance, if the USA government releases new information, how could react Chinese investors on Chinese market?

Appendix A

| | Eq. 47 | | | | Eq 48 | | | | Eq 49 | | | |
|------------|---------------------------|--------------------------|---------------------------|----------------------------|----------------------------|---------------------------|----------------------------|----------------------------|--------------------------|---------------------------|--------------------------|--------------------------|
| | SHA | SHB | SZA | SZB | SHA | SHB | SZA | SZB | SHA | SHB | SZA | SZB |
| α | 0,0118779 (30,5050)*** | 0,040215 (24,0989)*** | 0,0115421 (29,8016)*** | 0,00704853 (27,5331)*** | 0,00419213 (11,7880)*** | 0,0119202 (10,7796)*** | 0,00411185 (10,7388)*** | 0,00223186 (11,3970)*** | 0,00438 (12,0710)*** | 0,01314 (11,2129)*** | 0,00451 (11,1828)*** | 0,00260 (11,0309)*** |
| γ_1 | 0,422076 (12,9384)*** | 5,21511 (32,4300)*** | 0,438824 (12,7928)*** | 0,438828 (16,0950)*** | 0,25549 (9,9288)*** | 4,2685 (36,1984)*** | 0,269423 (910,8117)*** | 0,2967 (14,9824)*** | 0,21899 (9,3236)*** | 4,14375 (44,8125)*** | 0,24786 (9,5933)*** | 0,29445 (13,4294)*** |
| γ_2 | -2,46112 (-4,9217)*** | 4,04672 (1,7586)* | -2,29688 (-4,5488)*** | -3,2241 (-6,8957)*** | -1,52911 (-3,8195)*** | 9,65162 (5,2487)*** | -1,13271 (-2,8871)*** | -2,37882 (-7,3001)*** | -0,89482 (-2,1540)** | 12,27000 (7,1448)*** | -0,88222 (-2,0136)** | -2,36326 (-4,9485)*** |
| γ_3 | - | - | - | - | -0,0415823 (-2,2639)** | -1,72989 (-10,8253)*** | -0,0456556 (-2,3389)** | -0,0922482 (-5,9048)*** | -0,04921 (-2,7754)*** | -1,40241 (-11,4801)*** | -0,04539 (-2,5796)*** | -0,08613 (-4,9263)*** |
| γ_4 | - | - | - | - | -0,00527817 (-0,2607) | -0,797012 (-6,5436)*** | -0,00552038 (-0,2916) | -0,0646128 (-4,1211)*** | -0,01610 (-0,9068) | -0,63612 (-5,2023)*** | -0,01442 (-0,8455) | -0,05564 (-3,7573)*** |
| γ_5 | - | - | - | - | 1,01698 (2,7278)*** | -1,69555 (-0,7431) | 0,761701 (1,9124)* | 1,80756 (5,7258)*** | 1,00834 (2,6778)*** | -1,21389 (-0,7171) | 0,73553 (2,0455)** | 1,89594 (4,4016)**** |
| γ_6 | - | - | - | - | 0,168143 (0,4525) | -2,9977 (-2,2362)** | 0,0394265 (0,1177) | 0,624312 (2,4451)** | 0,22123 (0,6283) | -3,36523 (-2,4102)** | 0,10373 (0,3194) | 0,60003 (2,0041)** |
| γ_7 | - | - | - | - | 0,465345 (17,6379)*** | 0,451256 (18,6554)*** | 0,461505 (17,0101)*** | 0,457319 (17,9997)*** | 0,46062 (18,6035)*** | 0,38663 (16,8263)*** | 0,44801 (16,7766)*** | 0,39183 (15,2611)*** |
| γ_8 | - | - | - | - | 0,11978 (4,1070)*** | 0,214302 (8,7666)*** | 0,11885 (4,2363)*** | 0,195766 (6,7727)*** | 0,11692 (5,0301)*** | 0,18302 (7,9236)*** | 0,10070 (4,5887)*** | 0,18378 (7,8225)*** |
| α_0 | - | - | - | - | - | - | - | - | 7,49E-07 (2,0461)** | 1,12E-05 (2,5867)*** | 6,26E-07 (1,4351) | 3,74E-07 (2,0300)** |
| α_1 | - | - | - | - | - | - | - | - | 0,08265 (3,4627)*** | 0,11942 (4,3772)*** | 0,06823 (2,3127)** | 0,09445 (3,1959)*** |
| β_1 | - | - | - | - | - | - | - | - | 0,88553 | 0,86865 | 0,90436 | 0,87706 |

| | - | - | - | - | - | - | - | - | (23,2494)*** | (30,7414)*** | (18,9600)*** | (21,7871)*** |
|-----------|--------|--------|--------|--------|---------|---------|---------|---------|--------------|--------------|--------------|--------------|
| ACF lag 1 | 0.4753 | 0.5193 | 0.4702 | 0.5006 | -0.0114 | -0.0314 | -0.0129 | -0.0222 | 0.0013 | -0.0032 | 0.0052 | 0.0156 |
| ACF lag 2 | 0.3695 | 0.4487 | 0.3647 | 0.4492 | -0.0589 | -0.0873 | -0.0648 | -0.0677 | -0.0398 | -0.0519 | -0.0384 | -0.0524 |

Table 13 Herding coefficients in Chinese stock markets.

*The table reports the coefficients of the three different models shown in the Eq.47, Eq.48 and in the Eq.49. Number in parenthesis are t-statistics based on robust standard errors QML in the GARCH specification and on HCO errors in the OLS estimation. .***, ** and * represent statistical significance at the 1%, 5% and 10% levels respectively. The first two lag of the autocorrelation function are reported for each model.*

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