HERD BEHAVIOUR AND MARKET EFFICIENCY: EVIDENCE FROM THE PORTUGUESE STOCK EXCHANGE

André Barreto das Neves de Almeida Braga

Dissertation submitted as partial requirement for the conferral of

Master in Management

Supervisor:
Prof. Pedro Fontes Falcão, ISCTE Business School
Invited Assistant Professor
Department of Marketing, Operations and Management

Co-supervisor:
Prof. José Dias Curto, ISCTE Business School
Associate Professor
Department of Quantitative Methods

September 2016

Abstract

This study examines herd behaviour in the Portuguese stock market by analyzing daily data from 2000 to 2016. To test for the existence of herding we use the cross sectional standard deviation and the cross sectional absolute deviation of returns as a measure of dispersion. According to rational asset pricing models equity return dispersion increases with market return but, if investors adopt an imitative behaviour the increasing linear relation between dispersion and market return will not be observable and, as a consequence, risk diversification becomes more difficult to accomplish. We find statistically significant evidence of herd behaviour during asymmetric market conditions, particularly during periods associated with positive returns. Furthermore we find supportive evidence for increased herding formation after the outbreak of the sovereign debt crisis. The findings also suggest that there is a contagion effect between the Spanish stock market and the Portuguese stock market regarding herding behaviour.

Keywords: Herding behaviour, volatility, risk diversification, stock market efficiency

JEL Classification System: G02, G11, G12, G14

Resumo

Este estudo examina o comportamento de manada no mercado acionista português através da análise de dados diários entre 2000 e 2016. Para testar a existência de comportamento de manada são utilizadas as medidas "*cross sectional standard deviation*" e "*cross sectional absolute deviation*" das rendibilidades para medição da sua dispersão. De acordo com os modelos tradicionais de avaliação de ativos a dispersão das rendibilidades aumenta com a rendibilidade do mercado mas, se os investidores adotarem um comportamento imitativo, a relação linear entre dispersão e a rendibilidade do mercado não será observável, tornando a diversificação de risco um objectivo mais difícil de alcançar. Encontramos evidência estatisticamente significativa de comportamento de manada durante condições assimétricas de mercado, particularmente durante períodos associados com rendibilidades positivas. Além disso encontramos evidência para o aumento da formação de comportamento de manada após o início da crise da dívida soberana. Os resultados sugerem também que existe um efeito de contágio entre o mercado acionista espanhol e o mercado acionista português no que diz respeito ao comportamento de manada.

Palavras-chave: Comportamento de manada, volatilidade, diversificação de risco, eficiência do mercado accionista

Classificação JEL: G02, G11, G12, G14

Dedication

To my parents.

Acknowledgments

I would like to thank both my supervisors, Prof. Pedro Fontes Falcão and Prof. José Dias Curto for their comments and suggestions throughout this endeavour and particularly for their enthusiasm, commitment and availability during the EMBA programme. I would also like to thank the other professors of the EMBA programme. I am grateful to have had the opportunity to attend their classes, which were a truly enriching experience.

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Abbreviations

BS Black-Scholes model

CAPM Capital Asset Pricing Model

CMVM Portuguese Securities Market Commission

CSAD Cross sectional absolute deviation

CSSD Cross sectional standard deviation

DCF Discounted Cash Flow

E.g. For example, Latin: *exempli gratia*

EMH Efficient Market Hypothesis

GARCH Generalized autoregressive conditional heteroscedasticity

IBEX35 Spanish Exchange Index

I.e. That is, Latin: *id est*

KF Kalman Filter

OLS Ordinary Least Squares

PSI20 Portuguese Stock Index

1. Introduction

The last few years witnessed several financial crisis. The Lehman Brothers collapse was paradigmatic and marked the beginning of a process characterized by significant volatility and economic instability. Additionally, the European sovereign debt crisis, followed by the emerging markets economic downturn, are proof that the damage caused by this kind of financial turmoil is very difficult to overcome and the shockwaves triggered by these events are impossible to predict.

When the global economic scenario was giving some indications that the crisis was entering a new less volatile chapter, suddenly in July 2015 China was the main stage of a stock market crash, with enormous proportions, which wiped out nearly USD 4 trillion from the market, causing countless stockholders to flee after suffering heavy losses. The real reasons behind this particular market crash are not totally clear but, nevertheless, the fear took over investors and the consequences were severe for those involved. These types of events are just a demonstration of our inability to predict some trends caused by sudden shifts in investor perceptions of future market performance and the consequences of those shifts.

Given this scenario investor behaviour is a subject increasingly studied. A question posed in current research is if investor behaviour, and particularly biased behaviour, is being overlooked in traditional financial models and if such biased behaviour can be a trigger to market volatility. If so, the critical objective must be to determine how these biases can be incorporated in the existing models in order to accurately explain and predict market patterns.

But this problem is not exactly a new one since it is well known that investors in financial markets are always facing a dilemma: if the market is trending in a given direction how sure can they be of their own private information to be able to ignore the market trend? At that particular point investors have two choices: they may ignore their own convictions and beliefs and “follow the herd” or they can maintain the confidence in their analysis expecting that market efficiency, as predicted by modern finance, will shift asset prices closer to their fundamental value. In the first situation we are in the presence of the so called “herd behaviour”, the main topic of the present thesis, which is an issue that is attracting increasing attention, mainly due to the recent financial crisis (Mobarek *et al*., 2014).

Herd behaviour is characterized by market movements in which market participants adopt an imitative behaviour of the actions of other investors, despite the fact that their own private information may suggest a different action. However it is relevant to point out that in some instances this type of behaviour can be seen as “normal”, because imitative patterns are a feature of human behaviour and in fact we are influenced by the actions of others since birth (Hirshleifer and Teoh, 2003). Therefore we can conclude that investor behaviour is, obviously, influenced by external factors. The main question to be discussed is not if this type of influence occurs but what is the extension, and consequences, of that influence.

One of the most recurrent assumption in the studies carried out on the financial markets’ activity is that market agents behave in a rational fashion, and that their main goal is profit maximization while, simultaneously, trying to keep risk exposure as low as possible. But, intuitively, one can assume that financial agents don’t always take the most rational action in every single situation, and this can be observed when financial bubbles form and eventually burst.

During the last two decades several studies were conducted regarding behavioural finance that demonstrated that, in given conditions, investors act based in cognitive biases. Biases in the decision process in the presence of risk, uncertainty or lack of relevant information, lead to increasing market volatility and the disruption of the expected association between the market value of an asset and its fundamental value (Schiller, 1999). It is also important to consider that a relevant feature of human behaviour is imitation and such characteristic may have relevant consequences in market stability, given the fact that imitation can lead to unexplained market volatility. And if, as stated, imitative behaviour can be considered a normal feature in individuals, because the learning process is mostly based in mimicking behaviours of others, we must consider the necessity of reflecting this specific behaviour in asset valuation. Therefore we should expect to see, in forthcoming models for evaluating assets, the incorporation of investor behaviour patterns, specifically imitative behaviour.

An important issue is that imitation can have either positive or negative consequences, according to the behaviour being mimicked. Bikhchandani & Sharma (2001) argue that when investors are influenced by decisions of other individuals (perceived by their actions) they can enter a herding movement that may subsequently reveal itself as the wrong decision for everyone involved: this is a feature of market bubbles formation. Another relevant issue is that some market strategies are solely based on voluntary imitation of the actions, inferred largely from market trends, of other market players. According to Devenow & Welch (1996) there is consensus among market agents about the vast influence that imitative behaviour has on investor strategy, and that we can assume that investors are severely influenced by the behaviour of the other participants in financial markets. But the main question relating to imitative behaviour in financial markets that should be posed is why do investors take an imitative course of action, and Bikhchandani & Sharma (2001) propose that this happens because each investor can observe the actions of others but are unable of knowing their intrinsic motivation and are also incapable of accessing their private information, i.e. the private information that motivated the action in the first place.

1.1 Scope of the research

Investor behaviour is, understandably, a broad subject, rooted both in finance and investor psychology, and therefore this thesis will narrow the scope of the analysis and focus only on the previously mentioned imitative behaviour in financial markets, particularly herd behaviour, which is, as stated before, a behaviour where an investor suppresses his/her own information and convictions and essentially does what everyone else in the market is doing. The starting point is market efficiency: a market is considered efficient if it has the ability to adapt quickly and without biases to new relevant information, not giving enough time to investors to profit from any type of mispricing. In that case a price of a stock should reflect, at any given time, all available information, and therefore the price of a stock should reflect the intrinsic value of a company. The cornerstone of market efficiency is thus the extreme competition among investors to profit from new information, but what happens if investors stop making investment decisions based on new information but based only on signals they deduce from other investors' actions? In that situation market efficiency, as we perceive it, is at risk and herd behaviour will introduce new challenges to the process of investment decision.

1.2 Relevance of the analysis

Our view is that the study of imitative behaviour in stock markets is vital mainly because this type of behaviour increases the correlations among stocks. A significant consequence of this outcome is that in a market where investors herd in a systematic way an investor has to include more stocks in the portfolio to achieve the same degree of risk diversification that could otherwise be achieved in a market where herding is not widespread. Therefore the correct understanding of this process is relevant for all kinds of market participants: investment bankers, financial advisors, fund managers and also for any individual investor.

Some of the more sophisticated investors have been using the intuition behind this line of research, basing their strategies in models that follow market trends. By being more agile they enter the market when the herding movement is forming, exacerbating the process, and they exit before the movement starts to reverse. A direct consequence of this type of strategy is, eventually, the formation of bubbles. These situations represent a major concern for supervisors and policy makers who can also significantly benefit from an enhanced comprehension of these movements.

As discussed above some tactics undertaken by market participants intensify the process of herding and, additionally, some trading strategies developed by institutional investors have a relevant impact on prices (Lobão and Serra, 2006). This conclusion allows the introduction of an important issue because investors may also profit from movements exacerbated by imitative behaviour, and therefore some biased behaviours act as facilitators for the successful implementation of rational strategies broadly based on the analysis of trends, e.g. "momentum" or "market timing" strategies. From this point onward we shall use the term "technical analysis" to encompass all types of strategies solely based on the analysis of past market performance, trends and chart patterns. As we shall discuss in following chapters there is some empirical evidence that strategies based on "technical analysis" may turn out to be lucrative in the short-term until asymmetries are corrected. Briefly this type of strategy consists in buying winners and sell losers in short term scenarios. It is possible to infer that herd behaviour creates opportunities for those who implement this type of strategy, although it is obvious that the practical problem rely on the exact moment when one should enter or exit a given stock. Bikhchandani and Sharma (2001) argue that these strategies can be seen as rational, while they actively try to explore the short term persistence of some trends and the respective returns, and this is the same as stating that these strategies can gain from the formation of herding movements.

Therefore we can conclude that strategies based on the analysis of past performances are motivated by objective and logical reasoning and consequently we are in the presence of "rational herding". On the other hand it is also important to highlight the fact that according to the Efficient Market Hypothesis (Fama, 1998) prices reflect all available information, and therefore it is not possible to implement such market strategies successfully.

Rational herding assumes that investors may be influenced by external issues or by difficulties accessing critical information, costs related with accessing that information or even agency costs. Rational herding can also be associated with informational cascades which means that rational herding is linked to the process of observational learning. This learning process is entirely rational in spite the fact it may be erroneous, therefore leading to a negative outcome.

In the case of agency costs the prospect of comparisons among investor's performance leads to imitation given the fear of comparative under performance. In these situations the question arises because it is easier for an investor to explain underperformance when the market shows downward tendencies, while explaining losses when the rest of the market is reaping benefits of an upward movement is obviously harder. The reasoning that leads to this attitude is understandable: when in doubt an investor just does what others are doing in order to avoid being criticized for not achieving, at least, an average performance.

But according to Cipriani and Guarino (2014) a cautious approach to the study of herding is required because it is impossible to infer from the data freely available if we are facing spurious herding - when there is a reason that propels the market as a whole in a given direction, e.g. a change in interest rates - or intentional herd behaviour.
Conversely non-rational herding relates to a behaviour where investors adopt, blindly, actions of others, engaging in an imitative process without consideration for any available, even if not relevant, information.
As a note we should acknowledge the fact that as a consequence of extreme market volatility, and due to high pay-offs earned by some portfolio managers that systematically are unable to beat the benchmarks, the media are increasingly dedicating their attention to the herding phenomena.
Summing up, the subject is not just a theoretical and ambiguous problem, but a critical issue that can result in severe consequences for financial markets stability.
Concluding this introductory section we can define the main goals of this study:

i) empirically validate the existence of herd behaviour among investors in Euronext Lisbon;
ii) measure the intensity of such behaviour in different conditions;
iii) determine the influence of an exogenous variable, the returns in the Spanish stock market, on the intensity of herding in the Portuguese market.

The main assumption in the present study is that even though theories based on the Efficient Market Hypothesis are extremely valuable in order to understand, and model, market behaviour, being also invaluable tools in the construction of investment and pricing models, it seems critical to acknowledge that financial markets face increasingly complex variables that are dependent on the way individuals perceive the multiple choices they face.
Academic research, and industry as well, must try to incorporate these variables into the existing financial models. Since we face bubbles and crashes cyclically it is imperative to study and understand the mechanics of the market that causes those destructive phenomena.

As stated by Lobão and Serra (2006) new evidence on the consequences of herding-like behaviour on asset valuation will help to shed some light on current debates over market efficiency and will also help to clarify and support the arguments in favor, or against, the formulation of existing asset pricing models.

1.3 Structure of the thesis

The present study is structured as follows: Section 2 presents a review of relevant literature on behavioural finance and, in particular, on the subject of herd behaviour. In this section it is also possible to find an overview of some of the most common biases investors display followed by the discussion of the most relevant empirical studies relating to herd behaviour. To understand some of the criticisms made to traditional models we will also introduce the subject, focusing in the Efficient Market Hypothesis and valuation models based on the assumptions of the EMH. This section will also present a description of some of the financial assumptions of modern finance challenged by phenomena like herding movements. The chapter ends with a discussion of the most widely used econometric models employed to demonstrate the existence of herding. These models are mostly based in volatility estimation and the use of this estimation as an input to Ordinary Least Squares (OLS) method. Section 3 proposes the hypotheses to be tested and explains the methodology to be applied and section 4 presents the results of the empirical study. As last, section 5, presents the major conclusions of the study.

2. Literature review

Behavioural finance is increasingly being used to explain investor idiosyncrasies and market anomalies when rational, or traditional, models seem unable to provide enough explanation to observed events (Ritter, 2003). Therefore, the first undertaking of the present study is to review some of the assumptions of traditional finance recalling that in some cases these assumptions may not hold given the biases of the "normal" investor.

2.1 Efficient Market Hypothesis

The cornerstone of modern, or traditional, finance is understood to be the Efficient Market Hypothesis (EMH) proposed by Fama (1965), although this theory and some of its alleged shortcomings are increasingly being questioned by behavioural economists, based on new empiric evidence gathered over the last few years (Yao *et al*, 2014), and this issue will be the starting point of the following discussion.

The EMH is built on the assumption that market participants behave rationally and that the price of a stock should reflect all available information, which means that price should reflect the fundamental value of an asset, and that such value can be estimated by using a traditional model like DCF with a cost of opportunity that correctly reflects the implied risk.

According to Fama (1965:90) an efficient market is "*a market where, given the available information, actual prices at every point in time represent very good estimates of intrinsic values*". It is also assumed that investors are capable of processing all available information, and that is the reason why the price of an asset is a reflex of that information. As a consequence of these assumptions the theory predicts that it is not possible to implement a strategy that provides a return above what can be expected given the implicit risk. In other words an active participant cannot expect to "beat the market", and if an investor intends to achieve higher returns the only choice is to choose assets with higher risk.

According to Fama (1970) there are three forms of the theory: weak, strong and semi-strong.

The least rigorous form of EMH, the weak form, suggests that the price of a stock reflects all available information, past and present. The weak form only considers one set of information, which is historical information about the security price itself. In this situation movements in stock prices are a consequence of new information, and if the information is new obviously it cannot be predicted from previous information or by recent movements in prices. These assumptions must invalidate technical analysis, simply because it is assumed that markets follow a random walk and so such unpredictable movements make it impossible to obtain higher returns by analyzing past returns. The semi-strong form of market efficiency suggests that current prices reflect all publicly available information. In this form public information includes not only historical prices but also information reported by the company like financial statements or dividend announcements, or exogenous information like releases of macroeconomic data, political environment news, etc. The strong form of EMH assumes that current stock prices fully reflect all public and private information, including inside information.

As noted by Shleifer (2000) the models developed in the framework of traditional finance are built on the assumptions of the EMH.

Although the EMH remains to date as the widespread foundation of the tools developed to investigate and understand how financial markets work, providing a framework for the study of human behaviour under uncertainty, it has failed over and over again in anticipating behaviours in several circumstances (Shiller, 1999).

Hirshleifer (2015) also argues that markets witnessed several violations of the EMH over the years, and that, contrary to the predictions of the EMH, investor's sentiment affect financial markets.

Yao *et al.* (2014) note that the EMH is being disputed empirically and theoretically, and its apparent flaws in modelling returns have been described by several studies, concluding that the EMH fails to recognize that financial markets mechanics are imperfect due to cognitive biases and complex human responses.

These arguments provide a key motivation for the academia to start including new dimensions in asset pricing models that should be able to explain (or even predict) anomalies that cannot be explained by models based on pure rationality (some critics refer to these models as “bias free models”). In other words research should focus on improving models that, at the present time, lack the dimension of human behaviour in the face of uncertainty and risk.

Nevertheless we can assume, in the EMH framework, that there are markets where investors can overreact when receiving new information or when facing unexpected market movements. However the general assumption in this particular situation is that these movements cannot be foreseen and that they offset each other. The expectation is that the market, as a whole, is always correct in a fundamental value point of view. But the question that immediately emerges is: if these assumptions hold in every situation how can we explain market bubbles or crashes?

Other relevant issue is that industry’s practice does not fully support EMH assumptions and institutional investors often employ technical analysis as a tool on their daily work. It is important to note that even in the presence of a highly efficient market, where investors have little to gain from active management strategies and buy-and-hold strategies are recommendable and where transactions costs will consume eventual gains, portfolio management and financial analysis maintain a great deal of importance. Financial analysis, in every scenario, allows for the optimization of factors like diversification goals, risk profile adequacy, investment horizon and tax management.

Lo (2004) proposes a new approach to this debate, between EMH proponents and those on the other side of the barricade, trying to reconcile EMH with behavioural finance concepts, in a model where both approaches may coexist, but there is a long road ahead before a common ground can be reached.

2.2 Behavioural finance

2.2.1 Investor behaviour and asset valuation

As previously discussed behavioural finance is an approach to financial markets that strives to answer questions that cannot be fully explained solely by using traditional finance models. The starting point of such approach is to recognize that investors are not always rational, despite the fact that they may all pursue the same goal: wealth maximization.

According to Barberis & Thaler (2013) behavioural finance, applied to stock markets, is based on two pillars: one regards limits to arbitrage and the other is related to investor psychology. In the first situation it is impossible for rational traders to undo the trading errors of less rational investors. The second, based on psychology, describes the biases that one can expect to observe in investment activity. The authors also argue that rationality is observable when an investor updates his/her beliefs in face of new information, and, besides that, is capable of acting according to those beliefs. The update of beliefs can be analyzed by Bayes' theorem, according to which each new data is used to update the present beliefs or, strictly speaking, probabilities change according to new evidence.

In the paper "The end of Behavioural Finance", Thaler (1999:16) concludes his summary of the activity developed until that moment in the research on behavioural finance, with the following observation:

"I predict that in the not-too-distant future, the term "behavioural finance" will be correctly viewed as a redundant phrase. What other kind of finance is there? In their enlightenment, economists will routinely incorporate as much "behaviour" into their models as they observe in the real world. After all, to do otherwise would be irrational."

But regardless of all the work being developed in this field, the painful truth is that practical applications are still very limited, and researchers, and investors alike, still have a long way until we can have practical tools that can be applied to valuation models widely recognized by investors, like the CAPM. For example, Muradoglu *et al*. (2005) try to integrate subjective outlooks by professional analysts in order to create a portfolio, suggesting that this method can achieve superior results compared to standard models that use historical quotes.

2.2.2 Prospect theory

In the previous chapter we have argued that the models used to evaluate assets are based on the EMH assumptions, starting from a framework where rational interpretation and treatment of all the available information is the norm.
We now further refer to the notion that the basis of EMH is related to the expected utility hypothesis, a theory of choice under uncertainty, which states how an individual undertakes a rational decision when the outcome is uncertain. Basically the theory claims that an individual chooses the action with the highest expected utility, and the expected utility of an action is a weighted average of the utilities of each of its possible outcomes.
But despite the fact the use of traditional financial models is currently common practice that does not imply that the expected utility theory is able to explain every decision undertaken in financial markets with its ever evolving complexity.
In the late 70's of the last century several theories emerged, trying to fill in the gaps left unexplained by expected utility theory. In that particular field of study the most frequently cited paper is Prospect Theory (Kahneman & Tversky, 1979). The authors propose that the existing theories are unable to explain the process of individual decision and, moreover, individuals systematically make choices that violate the assumptions of expected utility hypothesis. Several experiences expose the apparent fragility of the theory in explaining the process of decision as a whole and to the matters at hand these findings are of the utmost relevance because in financial markets a decision process must be, by all accounts, efficient. To illustrate this point it is useful to ponder over the conclusions attained from a widely discussed experience (based on one of the many conducted by the cited authors) where the participants face the following choice: receive EUR 1.000 with a probability of 50% or receive EUR 500 with a probability of 100%. The second answer is the choice of most participants. Next is presented the alternative of losing EUR 1.000 with a probability of 50% or losing EUR 500 with a probability of 100%. In this case the majority opted for the first choice. Since both problems have obviously the same probability we must be facing a violation of the expected utility hypothesis.

The implications for financial decision makers are obvious, given the fact that when facing complex situations the investors may not make the most efficient decision, in a mathematical, and thus financial, sense. And this occurs although the investor has, in those situations, the information needed to make a valid decision.

Kahneman & Tversky (1979) also argue that people usually behave as if improbable events are impossible and face highly probable events as a certainty. That is where prospect theory comes in, proposing a mathematically formulated alternative to the expected utility hypothesis.

A practical example of the workings of this theory in financial markets is given by Schiller (1999), who argues that this theory can explain the excessive price attributed to out-of-the money or in-the-money options when compared to prices obtained with the Black-Scholes model (likewise near-the-money options present prices consistent with the BS model). The justification results directly from the previously mentioned function since people tend to overestimate the low probability of the underlying reaching the strike price (Schiller, 1999).

2.2.3 Cognitive dissonance and behavioural biases

Another recurring subject studied by behavioural finance is related to cognitive dissonance.

Cognitive dissonance is a mental conflict that arises when an individual is confronted with some evidence that his/her beliefs are incorrect. When facing this type of situation individuals tend to make decisions not entirely rational since their goal is to mitigate that dissonance.

Schiller (1999) suggests that an individual can choose to ignore the new information he/she came in contact with or, in alternative, develop new arguments that can allow him/her to keep, and cope with, previous beliefs. A demonstration of this situation is the fact that investments in funds with a positive recent performance are higher than divestments in funds with recent weak performances. Apparently the motive that drives investors to be fast coming in and slow exiting these funds is the difficulty to face the fact that a bad investment was chosen, and losses will be incurred. That is the catalyst to make the decision process lengthier until arriving at a final divestment decision. This is also related with remorse (Schiller, 1999), a negative feeling that drives investors to postpone decisions that they know will bring them negative feelings.

Coval and Shumway (2001) studied the behaviour of traders at the Chicago Board of Trade and conclude that they exhibit high degrees of loss aversion, and that such characteristic has a severe impact on their behaviour while facing decisions that encompass risk. In this particular environment, traders that suffer losses during the morning trading period display a higher probability to take on more risk in the afternoon. On the other hand, traders with positive returns in the morning show the tendency to trade less, and in smaller amounts, in the afternoon.

Ritter (2003) argues that cognitive psychology and limits to arbitrage are the foundation stones of the study of behavioural finance, offering a summary of the most common cognitive biases showed by investors, e.g., overconfidence, mental accounting or framing. The author further argues that heuristics, which are usually described as mental rules of thumb that allow individuals to make decisions in a simplified, and generally more effective way, can also lead to cognitive biases.

Some of the more prominent biases addressed in literature relating to investment decision, e.g. Hirshleifer (2015), Barberis and Huang (2001), Ritter (2003), Schiller (1999), are described below, although the list does not pretend to be exhaustive in the enumeration nor description of cognitive biases. The list serves only the purpose of showing that these biases appear in a myriad of forms and may be present in every aspect of life[1]:

a. <u>Overconfidence</u> occurs when a person overstates his/her own abilities. In financial markets this translates, for example, in excessive trading with usually weaker performance (Barber and Odean, 2001). But, at the same time an individual may believe that his/her performance was better than the average.

[1] For more on this subject we suggest the book by Montier (2010), "The Little Book of Behavioral Investing: How not to be your own worst enemy", that gives a concise, light and practical insight to these questions.

b. Framing relates to the way individuals perceive different situations depending how those situations are presented. The way the situation is presented, or presents itself, makes a significant difference, i.e., the same facts framed in a different context can be perceived in different ways.

c. Mental accounting is a compartmentalization of thoughts or attitudes regarding a set of subjects. The classical example is the attitude towards personal finance management where a person makes compartmentalized economic decisions assuming different investment levels when in principle they should combine them.

d. Anchoring can be described as a focus on a particular piece of information, resulting in an individual getting attached to that "anchor" and eventually overlooking other relevant information.

e. Confirmation Bias is the tendency that individuals show when trying to validate individual preconceptions relating to a subject. Intuitively individuals try to find evidence to support previous ideas. E.g., if we dislike someone for no apparent reason it is expected that we will focus on negative characteristics that can confirm our predisposition to dislike that individual.

f. Gambler's Fallacy occurs when we make predictions based on past events. In this situation people think that future probabilities are altered by past events, when in fact they are not. We can throw a dice ten times and get a six every single time, but that obviously does not imply that we will get a six at the eleventh throw. The probability (1/6) is unchanged from throw to throw. This is a common statistical misconception.

g. Hindsight bias occurs when someone reflects over past events and assume that those events were predictable in the first place. The expression usually associated with this situation is "I knew it all along". The individual places himself in a situation where, after the occurrence, he believes he was able to predict it.

h. Loss aversion is the tendency for an individual to prefer avoiding losses in comparison to acquiring gains.

i. Disposition effect is a tendency of individual investors to sell stocks showing a positive performance instead of those decreasing in value. Investors showing this biased behaviour are keener to recognize gains than losses, a behaviour related to loss aversion. Barberis and Xiong (2012) derive a model in order to try to explain the motivations of these investors.

2.2.4 Informational cascades

Bikhchandani *et al.* (1992) argue that an informational cascade occurs when an individual, after observing the actions of other investors ignores his/her own information and follows the behaviour of those individuals. Four main mechanisms which lead to standardization of social behaviour are identified: external rewards, punishment for those that don't follow the trend, preference for conformity and communication. The authors propose an explanation to the reason why behaviour can be idiosyncratic and fragile, presenting a model where individuals converge rapidly towards the same action, supported by very little information, which leads to the formation of herding movements. The model comprises the observation of a given number of individuals, who make decisions in a sequential manner, about the adoption or rejection of an event. The cost of taking an action is equal to everyone involved. The winnings, *V*, are equal for all participants and can assume values between 0 and 1, with identical probability. A signal *Xi*, received by the individual *i* can be either positive *(H)* or negative *(L)*, and *H* is observed with a probability p_i>0.5 if the true value is 1 and (1- p_i) if the true value is 0. Therefore the first individual in a sequence adopts the behaviour if the signal is *H* and rejects the behaviour if the signal is *L*. The second individual in the sequence infers the signal from the action of the first individual, adopting the behaviour if the signal is *H*. If the signal is *L* the individual can either accept or reject that signal with a p_i=0.5. The third individual in the sequence, or cascade, adopts the behaviour if the signals he/she is presented with from the predecessors are both *H*, starting a positive cascade, or rejects if both signals are

L, starting a negative cascade. This process is understood to be the origin of herding movements.

Welch (1992) notes that in Initial Public Offers is possible to observe these situations, with an increase in the number of individuals that subscribe stocks when, after the initial phase, several investors showed interest in the subscription of the new securities.

According to Bikhchandani *et al*. (1992), the problem that arises from informational cascades is that they prevent the information from being included in a cumulative process. If that information was treated in a cumulative way subsequent decisions would be informed and not just imitative. That would prevent the formation of negative cascades and all the actions would converge to the correct decision.

After the formation of a cascade there is not any incorporation of new valid information and, therefore, the decisional process does not improve for the individuals that make decisions after observing their predecessors.

Mendel and Shleifer (2012) show that in the presence of noise traders it is possible that some investors follow sentiment, suppressing valid information, trusting that prices are reflecting information, when in fact those price movements are being influenced by noise.

Cascades form rapidly, with increasing standardization of actions as the number of individuals who adopt the behaviour increases. But cascades are also fragile, given the fact that new information, even with low significance, can easily interrupt a cascade. This delicacy allows for some of the lost information to be recaptured again into the decisional process.

In equity markets cascades are observable in several situations where investors infer information from the decisions of their predecessors and support their own actions in those previous decisions. These processes lead, in extreme situations, to the formation of bubbles or crashes. Bank runs are another classic case of this type of situation, because as soon as there is an indication that a bank can be facing difficulties, even though the indication is false, a process can begin where the first depositors try to retrieve their money, creating a cascade that translates into a bank run. This can occur even if the observers that imitate the behaviour of first movers hold information that the bank in question is in fact solvent.

Kim and Nofsinger (2005) argue that in markets with less information, or where information is less accessible, transparent or presents lower quality, investors will tend to follow trends and as a consequence cascades will have a higher probability of formation.

Following a study of the US stock market Sias (2004) suggests that small stocks, for which there is less information or the information asymmetries are more pronounced, are more susceptible to herd behaviour, because it is more likely for investors to ignore their private information. Consequently informational cascades will form in that particular scenario.

2.3 Herd behaviour

Hwang and Salmon (2004) define herding has an event that occurs in financial markets when some participants start to replicate the actions of others, inferred by movements in the market, largely gauged by returns or volumes, instead of making informed decisions based on their own beliefs.

Bikhchandani and Sharma (2001) argue that the term "herd" has a negative connotation in the markets. Some types of market participants are described as herds that enter the market with short term goals, few information and lack of knowledge of risk-return issues. In this situation the first investors to make a decision are very important because they will define the actions of the followers.

This type of behaviour is also described by Dhaene *et al*. (2012) as a high degree of co-movement of asset prices in financial markets, stating that herding is a leading indicator for systemic risk potential, and consequently data collection about its magnitude may give information on the degree of diversification attainable in portfolio investing.

2.3.1 Types of herding

As previously mentioned it is important to differentiate between a rational behaviour, which can appear to be simple imitation but is in fact based on an objective decisional process (spurious herding), and imitative behaviour undertaken without enough informational support regarding the decision being made (herd behaviour).

As discussed, Bikhchandani & Sharma (2001) suggest that herd behaviour is a result of the intention of investors to imitate each other in some scenarios (intention in imitating is the key). They also distinguish this from a type of behaviour, spurious herding, that results from several investors choosing the same action, while facing the same investment decisions, and accessing the same degree of information about the problem. This is an efficient behaviour because is a logical consequence of processing the information available.

On the contrary herd behaviour is not necessarily efficient because it is nothing more than a replication of actions of others. Spurious herding is illustrated with the movement created after an interest rate rise that drives the investor from the stock market to the bond market, in the search for yield. This decision is based on economic indicators, and relates to fundamental factors but may result in herding movements. The same situation can be seen when there are exchange rate fluctuations that drives investors to choose cross border investments. These decisions, made in an individual manner, and not by mere replication of the behaviour of others, are efficient in a perspective of own wealth maximization.

Nevertheless Bikhchandani & Sharma (2001) highlight the fact that these distinctions are not easily made in an empirical setting, at least with publicly available data. To conduct a deeper analysis of individual motivation we would need to access private information from a sample taken from a population of investors.

An example of a market where there is evidence of intentional herding is given by Graviilidis *et al*. (2013) after studying Spanish funds. These authors argue that even though it is impossible to understand in isolation the motivation behind an investor's actions it is possible to infer the existence of herding from the correlations between those actions and the arrival of new information with impact on fundamental analysis.

Based on this correlation it is argued that institutional herding in the Spanish market is intentional.

2.3.2 Herding in the Portuguese stock market

Economou *et al.* (2011) argue that there is evidence of herding in the Portuguese stock market, using a sample that comprises a period that stretches from 1998 to 2008, but only in periods of negative returns or when the volume of transactions is higher. It is also argued that herd behaviour is present in Italian and Greek stock markets.

There is a particularity in the study conducted by Economou *et al.* (2011) which is the study of herding during the global financial crisis (even though the period of the crisis is restricted to 2008) and they conclude that herding was present in Portugal during that period. Holmes *et al.* (2013) note that herding is persistent among mutual funds managers. There is a strong evidence that the imitative behaviour is intentional, and Holmes *et al*. (2013) suggest that the conclusions are consistent with the assumption that less skilled managers try to imitate the decisions of the managers they perceive as more skilled. The results are, to a certain extent, justified by the size of the market, where the fund managers are aware of the behaviours and relative strengths of other managers. In that sense it is much easier for someone to implement strategies that mimic the apparently more skilled managers. The authors go even further, suggesting that particular attention should be given to these managers, and the decision processes and the strategies implemented should be more scrutinized and consequently the rewards should be adjusted.

Lobão and Serra (2002) tested for the existence of herding among 32 mutual funds in Portugal. Using the methodology proposed by Lakonishok *et al.* (1992) they find evidence of herd behaviour particularly in bullish markets and when the market is less volatile. The justification, although not very intuitive, is that higher volatility is considered a proxy for the arrival of unexpected information to the market.

Mobarek *et al*. (2014) suggest that there is a direct influence of the German stock market over the markets of France, Norway, Sweden, Greece and Italy, but this influence is not present neither in Portugal or Ireland. It is also noted that herd behaviour in Portugal is not more intense during crises or asymmetric market conditions. Vieira and Pereira (2013) use the methods proposed by Patterson and Sharma (2006) and Christie and Huang (1995) and their findings suggest that these two different methodologies to analyze herding may lead to different conclusions: by adopting the method suggested by Patterson and Sharma (2005) they find evidence that investors imitate each other, however, using the model proposed by Christie and Huang (1995) there is not any evidence of herding.

In the last few years also a few master thesis have concentrated their focus on studying herd behaviour in the Portuguese stock market, with mixed results. To the best of our knowledge the most recent thesis on the subject were the ones conducted by Pereira (2012), Santos (2013) e Furtado (2012). The first, using Patterson and Sharma (2006) model, concludes for the existence of herding in PSI20 (Portuguese Stock Index), the other two, using Christie & Huang (1995) and Chang *et al.* (2000) models, suggest that there is not a clear evidence for herd behaviour.

2.3.3 Implications on technical analysis

Technical analysis is a tool used for investing in financial markets where the variables of interest are price movements and volumes. Technical analysts try to predict movements in the markets using statistical analysis of past trends. This technique differs from fundamental analysis, where the investment decisions are done according to the outcome of an examination of the economic and financial structure of a company and its prospects. Fundamental analysis prescribes a longer term approach, providing a foundation for more stable investments and, therefore, is less susceptible to sudden movements in the market. Everything else being equal in economic terms, a price movement in a given company does not have an immediate and direct impact in the intrinsic value of that company.

But with technical analysis the scenario is quite different: the intrinsic value of a company is not important, because all that is needed is market data. And since market movements are assumed to follow trends once one has been defined the price movement is predicted to follow the same direction as the trend. Therefore if one argues that the EMH is correct then we must assume that technical analysis has no validity as an investment decision tool.

Lo, Mamaysky and Wang (2000) note that technical analysis is viewed with skepticism among academics, in contrast with fundamental analysis which is commonly accepted, but the authors also argue that some techniques used may provide incremental information although that does not necessarily mean that technical analysis delivers any potential additional gains.

Brock, Lakonishok and LeBaron (1992) findings suggest that some strategies based on technical analysis outperform the market.

Regarding momentum strategies Kelsey, Kozhan and Pang (2011) state that there is already a substantial body of literature that confirms the existence of value adding momentum strategies in stock trading consisting in buying past winners and selling past losers and that the observed strategies produced noteworthy gains on average.

But despite the ongoing discussion about the validity of technical analysis we argue that movements in prices are amplified by this type of approach, like a self-fulfilled prophecy, with consequences in herding among market participants. The central argument here is that when studying herd behaviour and trying to include behavioural variables in investment models, it is necessary to keep in mind that technical analysis practitioners have a direct impact on the market by engaging voluntarily in herding movements. Supporting this reasoning Menkhoff (2010) argue that technical analysis practitioners consider that psychological factors that affect investors are important for their strategies and that herding is useful.

2.3.4 Implications on risk management and investment decisions

It is important for our overall goal, which in broad lines is to understand how herd behaviour can impact the way investors perceive financial markets, react to shifts in trends and above all manage their portfolios, to comprehend how risk affects the expected return of an investment. In light of the modern portfolio theory we need to understand the:

i. impact that herding can have on the risk of a given portfolio;

ii. implications of the phenomenon on the returns of a well balanced portfolio;

iii. intuition behind the econometric models presented in the following chapter.

The relationship between risk and the expected return of an individual asset, described by the Capital Asset Pricing Model, provides the necessary foundation for the understanding of the impact of behavioural biases on risk diversification.

As stated by Chiang and Zheng (2010:1) herd behaviour is "*often used to describe the correlation in trades resulting from interactions between investors*". So, if herding is present in any given market, investors require a larger number of stocks to achieve an inferior degree of correlation in the portfolio and, consequently to achieve the same degree of diversification.

A very common remark among investors and also widely used by the media is "that a given security is more risky than other". That type of ranking of securities' risk in an ordinal manner is clearly not enough for a complete understanding of the subject of this study. It is necessary to understand the quantitative mechanics of risk in order to understand how market factors, recalling that we will be restraining our focus on the issue of herd behaviour, are affected by individual behaviour.

The main idea, and the starting point of this discussion, is that an investor expects increasing returns with increasing risk. It is well beyond the scope of the present work to discuss the merits or demerits of the methods used by the market to define risk, so the focus will remain on the questions related to risk and diversification that directly affect the present study. In view of this statement it will be assumed that risk is measured by the standard deviation of the rates of return of an entire portfolio, which means to measure how much the observations stray away from the expected average value of the portfolio. The concept is reasonably easy to implement and the statistical tools associated with the calculations are simple to use and interpret. However a word of warning is needed at this point: Markowitz showed[2] that the validity of the standard deviation of returns as a measure of risk is only observed for an entire portfolio and

[2] Markowitz, H.M. (1952) 'Portfolio selection', Journal of Finance, 7 (March), 77–91.

not for an individual asset held within a portfolio. The reason for this is "diversification", and that means that part of the risk of an asset when held in a portfolio is diversified away and one of the most feared consequences of herding is that this behaviour has negative implications in portfolio diversification.

Therefore the question that must be addressed is how diversification works and how herd behaviour can hinder that process.

Assuming a given number of securities, held in a single portfolio, with equal weighting, one would be tempted to say that the risk of that portfolio would be the average standard deviation of the securities. But that would be incorrect, and the reason is that part of the risk of each individual security is diversified away when held in a portfolio, because we must account for the interaction of the different returns. That interaction is represented by a joint probability distribution, so the risk of the securities held in a portfolio will, to some measure, cancel each other out, if, and only if, those securities are not perfectly correlated. In that situation a portfolio has less risk than the average risk of the securities and the reason is diversification. In this situation is used the simple correlation coefficient which is a measure of the strength and the direction of a linear relationship between two variables. If two securities i and j have a strong positive linear correlation, ρ is close to +1 and a ρ value of exactly +1 indicates a perfect positive relation. Positive values indicate a relationship between i and j such that as values for i increases, values for j tend also to increase.

For an investor the only risk that is relevant is the risk that cannot be diversified away ("undiversifiable" or "systematic risk"). But there is a limit to diversification and an investor can add more and more assets to a portfolio, but at some point there is not any additional gain in diversification. Without going into extensive considerations we can assume that there is a common element to all the stocks included in the portfolio that results from a shared economic environment, which inhibits further diversification. When an economy is thriving it is expected that, to some extent, all the companies will benefit from those positive settings. The inverse must be true if an economy is declining. But not all companies will feel the same effects at the same time nor with same intensity, and it is that situation which allows for diversification.

It is also important to introduce the *beta* of a security, because the models used in the present study are based on the concept of the increasing dispersion of returns when the market rises/declines since each stock has a different sensibility to market fluctuations. The *beta* of a security gives a quantitative measure for how much we can expect a security to react to a change in the market as a whole, e.g., a stock with a β equal to 1.2 implies that an increase of *y%* in the market will correspond to an expected increase of 1.2 * *y%* in the return of the security.

Concluding, it is possible to say that, when held in a diversified portfolio, the unsystematic risk of a security is diversified away, leaving only the impact of the security's market-based risk on the return of the portfolio.

The above overview of risk and diversification serves the purpose of demonstrating the fact that when the returns of the securities within a portfolio are more positively correlated it will be increasingly difficult to reduce risk trough diversification.

The main conclusion obtained from this discussion is that in the presence of significant herd behaviour the returns are more correlated and more stocks will be needed to achieve risk diversification, and as we indicated before that is one of the main problems arising from herding in stock markets. Guillaume and Linders (2014:1) summarize this understanding by stating that "*in order to obtain an equity portfolio with the desired risk-return profile, an investor invests in different stocks, because it is well-documented that one of the benefits of owning a stock portfolio is diversification. However, it is well-known that this diversification benefit is changing over time. Furthermore, if there is a strong co-movement between the different stocks, the diversification benefit is reduced because the stock prices will tend to move almost in unison*".

2.4 Empirical studies and econometric methodologies

Christie & Huang (1995) argue that asset pricing models assume that return's dispersion increases in conjunction with the absolute value of market return but American market data is used to conclude that the assumptions of rational valuations models do not hold in every situation after being found evidence of herd behaviour.

The analysis of cross sectional standard deviation of returns is proposed as a method to detect herding[3]:

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

where:

$R_{i,t}$ represents the observed return of security i on day t

$R_{m,t}$ represents the average of returns of N securities included in market portfolio on day t

As previously seen herding occurs when investors ignore their own information and convictions and initiate an imitative process of the collective actions of the market, which is more likely to occur during extreme market movements. So, in the presence of herd behaviour in a given market we should expect the assets returns to converge to the average return of the market, or, in other words, that the increase in dispersion decreases with market performance as a whole. In extreme situations we can even expect to observe a decrease in dispersion.

Given these assumptions Christie & Huang (1995) estimate the following model:

$$CSSD_t = \alpha + \beta^L D_t^L + \beta^U D_t^U + \varepsilon_t \quad (2)$$

where:

$D_t^L = 1$, if the market return on day t lies in the extreme lower tail of the return distribution, or zero otherwise

$D_t^U = 1$, if the market return on day t lies in the extreme upper tail of the return distribution, or zero otherwise

These variables are intended to determine the existence of asymmetric investor behaviour in extreme upward or downward market situations. Although one could

[3] For further information on the use of cross sectional studies in active portfolio management refer to Gorman *et al.* (2010)

always discuss what “extreme market movements” are in this particular situation these movements are defined as the 1 or 5 percent of the upper and lower tails of the returns distribution.

If the estimates for the coefficients β^L e β^U are negative, and statistically significant, we can assume the presence of herd behaviour. On the other hand, if the estimates for β^L e β^U are positive, and statistically significant, the dispersion of stock returns tends to increase with extreme market movements, and this is consistent with traditional asset valuation models, and inconsistent with the existence of herding towards market consensus.

Economou *et al.* (2010) argue that cross-sectional standard deviation of returns is an intuitive method to investigate the existence and intensity of herding in stock market contexts, but it is also a measure that is not very robust in the presence of outliers. In order to overcome the problems raised by the existence of outliers Chang *et al*. (2000) propose the use of cross-sectional absolute deviation of returns as the starting point for the model. The authors build on the original model by Christie & Huang (1995), suggesting a non-linear regression that aims to determine the relationship between equity returns’ dispersion, measured by the absolute deviation of returns, and the return of the market.

By proposing the use of the absolute deviation of returns Chang *et al*. (2000) argue that if market participants engage in a behaviour where they suppress their own beliefs, during extreme market movements, the relationship that should occur between dispersion and market return won’t be observable (recalling that a linear relationship is in the genesis of the traditional and rational asset pricing models, which also predict that return dispersion is a growing function of market return). Furthermore it is argued that such relation can become nonlinear. Investor behaviour was studied in several markets with the goal of determining the existence of herd behaviour in those markets. In developed markets (USA, Hong Kong and, to some extent, Japan) evidence of herding was not found. During extreme market movements the dispersion of returns in the USA and Hong Kong continued to increase linearly, this being evidence that herding is not present in those markets. In South Korea and Taiwan evidence was found for the existence of herding, given the fact that dispersion of returns is not linear in those markets, where stock returns dispersion decreases while the absolute return of market, as a whole, increases. A relevant fact of the cited study is that, in every country analyzed, the dispersion of returns increases at a higher rate while the market is showing an upward trend, therefore one can conclude that there is asymmetry in investor behaviour.

In conclusion, in the presence of herd behaviour, during extreme market movements, we should expect a less than proportional increase, or even a decrease, of the standard deviation of returns which is determined by the equation:

$$CSAD_t = \frac{\sum_{i=1}^{N} |R_{i,t} - R_{m,t}|}{N} \quad (3)$$

Using the Capital Asset Pricing Model (CAPM) as a starting point to illustrate the relationship between market return and the dispersion of returns Chang *et al.* (2000) suggest the following regressions depending on the behaviour of the market (ascending or descending):

$$CSAD_t^{UP} = \alpha + \gamma_1^{UP} |R_{m,t}^{UP}| + \gamma_2^{UP} (R_{m,t}^{UP})^2 + \varepsilon_t \quad (4)$$

$$CSAD_t^{DW} = \alpha + \gamma_1^{DW} |R_{m,t}^{DW}| + \gamma_2^{DW} (R_{m,t}^{DW})^2 + \varepsilon_t \quad (5)$$

where,

$|R_{m,t}^{UP}|$ represents the absolute value of the average return of the upward market

$|R_{m,t}^{DW}|$ represents the absolute value of the average return of the downward market

In the presence of herd behaviour it is argued that the coefficient γ_2 should be negative and statistically significant.

If the coefficient is found to be positive then the assumptions of the traditional, or rational, asset pricing models hold, and the hypothesis of the prevalence of imitative behaviour should be set aside.

Chiang and Zheng (2010) suggest a modification in the Chang *et al.* (2000) model, where the regression has the following formulation:

$$CSAD_t = \gamma_0 + \gamma_1 R_{m,t} + \gamma_2 |R_{m,t}| + \gamma_3 R_{m,t}^2 + \varepsilon_t \qquad (6)$$

where,

$R_{m,t}$ represents the average return of the market on day t

$|R_{m,t}|$ represents the absolute value of the market return

Including $R_{m,t}$ in the above equation permits us to evaluate, or at least account for, the asymmetry in behaviour when the market is up or down.

The non-linear element $R_{m,t}^2$ is included in the equation since it is assumed that the correlation between returns increases at a rate that is not proportional to the increase of the chosen benchmark.

A result for the regression where the estimated coefficient γ_3 is negative, and statistically significant, will be consistent with the existence of herding.

Chiang and Zheng (2010) also suggest that less sophisticated investors show a rational behaviour if they imitate other investors they regard as successful, and that explains some situations where we observe groups of investors embarking in the same trades for periods of time. But as in previous studies it is concluded that these situations drive stock prices away from their fundamental value and make risk management a more difficult task. To arrive to these conclusions trade correlations in eighteen countries were analyzed. Latin American and Asian economies (like Argentine, Brazil, China, Singapore or Thailand) were among the subjects of the study, as more robust markets, like US, UK or France. The conclusions suggest that there is evidence of herding in all the markets, except in the US and Latin America. According to this paper empirical research has been following two different paths: one is based on dynamic correlations, with market movements being explained by contagion while the other path examines dispersion of returns in extreme market situations, e.g. Christie & Huang (1995).

Chiang and Zheng (2010) argue that the model by Chang *et al.* (2000) is appropriate for analyzing individual markets but does not consider influences from external markets. Nevertheless, isolation does not exist in a currently globalized world and financial markets are the best example of that. In these markets information and misinformation flow in a way that events in external markets may have direct impact on the behaviour of the market being studied.

This study is very significant because it shifts the focus from an individual analysis to a wider approach where spillover effects among countries are also considered. It is suggested that a crisis in a given a country's stock market may create a situation of herding that tends to affect other countries by contagion (in this paper the US market is the reference after which the behaviour of the other markets is hypothesized and compared). Therefore Chiang and Zheng (2010) propose the introduction of variables that proxy the impact of external markets movements, particularly the US stock market performance, which is recognized has having considerable influence in the financial markets globally:

$$CSAD_t = \gamma_0 + \gamma_1 R_{m,t} + \gamma_2 |R_{m,t}| + \gamma_3 R_{m,t}^2 + \gamma_4 CSAD_{us,t} + \gamma_5 R_{us,t}^2 + \varepsilon_t \quad (7)$$

where $R_{us,t}^2$ and $\mathrm{CSAD}_{\mathrm{us,t}}$ refer to the US market variables.

The introduction of these variables should increase the explanation power of the regression, indicating that herd behaviour can be triggered by the performance of external markets, particularly the ones with greater economic impact on the markets under examination (given geographic proximity, commercial trades, cultural similarity, etc.).

A positive, and statistically significant estimated coefficient for the variable $CSAD_{us,t}$ suggests a significant influence of the external market over the market under analysis. A negative and statistically significant estimated coefficient for the variable $R_{us,t}^2$ suggests that domestic herding is strongly influenced by the American market.

But herd behaviour should also be studied as a phenomenon that may depend on market direction. As seen previously Christie and Huang (1995), Chang *et al*. (2000) and Chiang and Zheng (2010) argue that herd behaviour is more common during periods when market returns are declining.

Also, as noted by Tan *et al*. (2008), we must be aware of asymmetrical characteristics of average returns depending if we are facing an upward trend or a downward one.
To test for the asymmetry effects Chiang and Zheng (2010) propose the following equation, where D is a dummy variable that assumes a value of 1 if $R_{m,t}$<0.

$$CSAD_t = \gamma_0 + \gamma_1(1-D)R_{m,t} + \gamma_2 DR_{m,t} + \gamma_3(1-D)R_{m,t}^2 + \gamma_4 DR_{m,t}^2 + \gamma_5 CSAD_{us,t} + \gamma_6 R_{us,m,t}^2 + \varepsilon_t \tag{8}$$

We must recall that it is also possible to examine herding intensity in extreme market conditions by using Eq. (2) as proposed by Christie & Huang (1995).
Mobarek *et al.* (2014) conducted a large study concerning the occurrence of herding in several stock markets, spanning a period from 2001 to 2012, concluding that herding is stronger during crisis and extremely asymmetric market conditions. They observe that the conclusions don't apply to Portugal during the considered period of analysis. Furthermore they argue that European stock markets suffer a strong influence of the German stock market, demonstrating that there is a herding connection between the considered markets and the German market.
Caporale *et al.* (2008) found evidence of herd behaviour in the Greek stock market, particularly in periods of rising returns. But they argue that investors in that particular stock market, in some ways comparable with the Portuguese stock market, have become more rational since 2002, a situation they attribute to regulatory and institutional reforms.
Some studies have been conducted recently in the Chinese stock market. For example, Yao *et al*. (2014) suggest that the presence of herd behaviour is very strong in the Chinese stock market, particularly in the *B*-share market.
Demirer *et al*. (2010) also found that herding severely affects the stock market in Taiwan, giving support to the argument that herd behaviour is a pattern observed in the emergent or less sophisticated markets.
Chiang et al (2013) argue that the prevailing methodologies to determine the existence of herding fail to recognize the fact that this kind of behaviour can be a time-varying

occurrence. The usual specification of regression models employed to estimate herding does not address the issue that the process can experience changes during the periods analysed. Therefore, assuming that we possibly face an inconstant and random process, the estimation of fixed coefficients may not be the best methodology to investigate the subject.

Mergner and Bulla (2005) implement and compare several techniques in order to estimate systematic risk in eighteen industry sectors in Europe. After comparing the results of a constant coefficient model (OLS) to the estimates of time-varying betas of four different methodologies (GARCH, a Kalman Filter approach, a Stochastic Volatility model and Markov switching model) they conclude that sector betas are best described by a random walk process, estimated via Kalman filtering.

According to Mergner (2009) a dynamic process can be represented in a state space form, and that includes regression models, both linear and non-linear, with varying coefficients. A model in state space form is represented by a system of equations where one, the state or transition equation, presents the stochastic behaviour and dynamics of the state variables. The other equation, referred to as the observation or measurement equation, relates the observed variables to the state variables, which are unobservable. The Kalman Filter is a basic tool for estimating models in state space form, and it consists of a set of two recursive equations: a prediction equation and an updating equation. The calculations of this system of equations rely on a recursive algorithm which computes estimates for the unobserved state variables at time t, based on the available information and, once new information is available the algorithm updates the estimates.

Hwang and Salmon (2004) suggest a model in space state form, estimated via Kalman Filter, where herding follows a dynamic progression. Using the Capital Asset Pricing Model (CAPM) in equilibrium as the starting point for the investigation on herding patterns it is assumed that, in fact, CAPM's betas evolve over time as a result of shifts in investor sentiment.

Chiang et al. (2013) also use this methodology to conduct a study on 11 countries, and the results confirm previous conclusions obtained by OLS estimation. The notable exception is the US market, where the new evidence obtained by considering time-varying coefficients points towards the absence of herd behaviour, contrary to the conclusion obtained by using multiple regression estimation. It is significant for the present study that the use of different methodologies highlights the fact that herding can indeed be a time changing event. Another noteworthy feature of the cited study is the inclusion of VIX (CBOE Volatility Index), a measure of volatility of the S&P500, as an explanatory variable for the occurrence of herding. The VIX is commonly referred to as the fear index because represents the expected implied volatility in a short-term horizon and is used as a measure of market risk. By using VIX as independent variable Chiang et al (2013) argue that a rise in volatility, with VIX as proxy for market risk, leads to a decrease in herding.

A different methodology from those used in the present study is proposed by Patterson and Sharma (2006). Using their model to analyze the stocks of the NYSE they find evidence of market efficiency and consequently rule out the hypothesis of herding.

Despite the importance of the presented models for the estimation of herd behaviour in stock markets Dhaene *et al*. (2012) suggest that the degree of herding may be changing randomly over time making the task of capturing information on this type of behaviour from past data a very difficult endeavour.

Also, new models are being proposed to predict herding, e.g. the HIX, the Herd Behaviour Index, which is a tool created to assess the level of diversification between stock prices for the immediate, short term, future.

The HIX assumes values between 0 and 1, where a value of 1 specifies that is not possible to achieve diversification in that particular moment in a given market.

Guillaume and Linders (2015) propose that the HIX should be modelled by a stochastic process in order to identify the changing trends of information given by the index. By using the process to predict trends in herding the investors will be in a better position to make informed decisions on portfolio strategy, specifically concerning diversification. This is just an example of the pathways investigation can follow in the forthcoming years when trying to create models to capture the intensity of herding and its consequences.

3. Hypothesis, sample and methodology

3.1 Hypothesis

As previously discussed the existing studies on herding are unable to present a definitive conclusion about this type of behaviour in the Portuguese stock market.
So, the first hypothesis to be tested intends to determine the existence of herding in PSI20. The test is conducted resorting to a sample with a longer time frame than the samples used in the cited studies, considering daily observations from 14 January 2000 until 15 June 2016.

H_1: Herd behaviour is observable in the Portuguese stock market.

Our second hypothesis assumes that the intensity of herding is dependent on market asymmetries. The purpose of testing this hypothesis is to capture and evaluate those different intensities according to market direction, i.e., if the market is trending upward or downward.

H_2: Herding intensity is dependent on return asymmetry.

The third hypothesis, broadly based on the paper by Mobarek *et al*. (2014), is proposed with the aim of determining if herd behaviour is more pronounced in Portugal during the period when European sovereign debt crisis was at its height. This period witnessed a rise in volatility and market instability, creating shockwaves throughout the financial markets with direct impact on investors' perception of risk and, as result, on portfolio management decisions. Given this scenario the following hypothesis is proposed:

H_3: Herd behaviour increased during the sovereign debt crisis.

A test will also be conducted on herd behaviour under market stress situations. Market stress will be treated as extreme market movements using the same approach of Christie & Huang (1995), and the fourth hypothesis is stated as:

H_4: There is evidence of herd behaviour in the index PSI 20 during periods of market stress.

Mobarek *et al.* (2014) argue that markets exhibiting returns co-movements may have synchronous herding. Economou *et al*. (2011) suggest the inclusion of CSADs from markets that might explain herd behaviour among investors in the Portuguese stock market. In their study they included Italy, Greece and Spain CSADs as the independent variables.

The cross border effects are the main driver for the fifth hypothesis, where we will study the influence of the Spanish market on the Portuguese one. We must recall that Spain is Portugal's most important economic partner and, as such, represents a major influence in the Portuguese economy as a whole.

It is also relevant to note that, from a financial industry perspective, is not unusual for research analysts to treat the Iberian market as an entity when they produce research notes on Portuguese or Spanish stocks or, even more relevant, it is possible to find several funds that invest exclusively in the Iberian market (the portfolio consists only in shares from these two markets). Therefore the dependence of the Portuguese economy towards Spain is quite obvious and we suggest that the performance of the Spanish stock market is a major influence on the behaviour of the investors in Euronext Lisbon.

So our last hypothesis relates to the expected cross country effect of the Spanish market over the Portuguese stock market:

H_5: There is cross-country herd behaviour between the two Iberian markets.

3.2 Sample

The scope of the present study focuses on the Portuguese stock market index PSI20 and, concerning the last hypothesis, on the IBEX as well.

PSI-20 is the benchmark stock market index of Euronext Lisbon, and tracks the prices of the listed companies with the largest market capitalization in PSI Geral, which is the general stock market of the Lisbon exchange. The PSI-20 was started on the 31st of December of 1992 with a base value of 3,000 index points, having reached 4.453 in June of 2016. Euronext Lisbon is a part of the stock exchange group Euronext to which the indexes BEL20, CAC 40 and AEX also belong.

Despite the reference to 20 in its designation currently only 18 companies are listed in PSI 20:

Table 3.1
Companies listed in PSI 20 in June 2016

Euro million

Designação	Ticker	Market Cap
Corticeira Amorim SGPS SA	COR PL	958
CTT-Correios de Portugal SA	CTT PL	1,067
Sonae Capital SGPS SA	SONC PL	136
Altri SGPS SA	ALTR PL	596
Semapa-Sociedade de Investimento e Gesta	SEM PL	808
Jeronimo Martins SGPS SA	JMT PL	8,910
Sonae SGPS SA	SON PL	1,410
REN - Redes Energeticas Nacionais SGPS	RENE PL	1,352
NOS SGPS SA	NOS PL	2,807
EDP - Energias de Portugal SA	EDP PL	10,070
Banco Comercial Portugues SA	BCP PL	1,073
Galp Energia SGPS SA	GALP PL	10,365
Banco BPI SA	BPI PL	1,614
Pharol SGPS SA	PHR PL	93
Mota-Engil SGPS SA	EGL PL	353
EDP Renovaveis SA	EDPR PL	5,914
Navigator Co	NVG PL	1,803
Caixa Economica Montepio Geral	MPIO PL	202

The sample used in this study refers to PSI 20 returns calculated from daily closing prices from all the stocks in the index during the period analyzed.

We ignore the index PSI Geral given its lack of liquidity. Any conclusion based on this index could be biased because it would result from observations on illiquid stocks and, even more important is the fact that analysis of stocks not currently being traded is probably irrelevant to investors concerned with the problem of herding.

Of particular interest for the analysis of herding is the prevalence of day trading in a given market. According to CMVM[4] day trading represented 4.2% of the transactions in PSI 20 during 1Q2016, with 82.1% of the day-trading being made by non-institutional investors and 17.9% by institutional investors.

Table 3.2
PSI 20's Day-Trading Volume per Reception Channel and Type of Investor (except for own portfolio)

				Euro million
	1Q 2016		1Q 2015	
Internet	200.6	73.3%	319.5	83.4%
Institutional	1.2	0.4%	3.8	1.0%
Asset Management	0.0	0.0%	0.0	0.0%
Insurance and Pension Funds	0.0	0.0%	-	-
Other Investors	1.1	0.4%	3.7	1.0%
Retail	199.5	72.9%	315.7	82.5%
Other Electronic Means	9.1	3.3%	21.8	5.7%
Institutional	0.2	0.1%	0.1	0.0%
Asset Management	0.1	0.0%	0.0	0.0%
Insurance and Pension Funds	0.0	0.0%	-	-
Other Investors	0.1	0.0%	0.1	0.0%
Retail	8.9	3.3%	21.7	5.7%
Others	64.0	23.4%	41.6	10.9%
Institutional	47.7	17.4%	11.6	3.0%
Asset Management	39.1	14.3%	6.4	1.7%
Insurance and Pension Funds	0.3	0.1%	0.9	0.2%
Other Investors	8.4	3.1%	4.2	1.1%
Retail	16.3	5.9%	30.1	7.8%
TOTAL	273.7	100.0%	382.9	100.0%

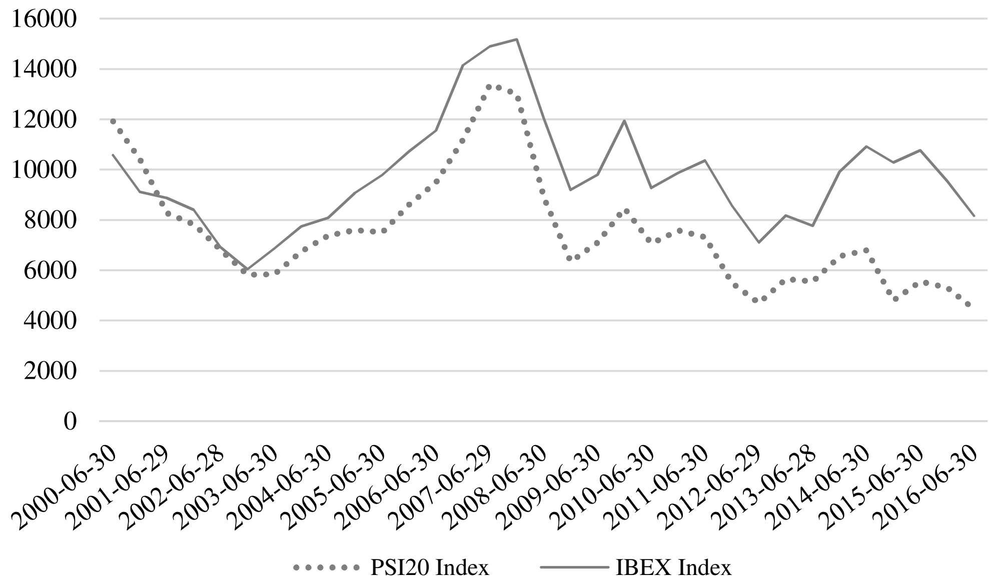
Source: *CMVM, Portuguese Securities Market Commission, 2016*

[4] CMVM's periodic statistics, consulted on July 2016: http://www.cmvm.pt/pt/Estatisticas/EstatisticasPeriodicas/

IBEX35 is the Spanish Exchange Index and comprises the 35 most liquid Spanish stocks traded in the Madrid Stock Exchange. As such it is the benchmark index of Bolsa de Madrid, Spain's main stock exchange. IBEX 35 started in 1992, and is calculated by Bolsas y Mercados Españoles (BME), the company that runs Spain's securities markets. It is a market capitalization weighted index and its composition is reviewed twice annually.

Figure 3.1 depicts graphically the correlation between PSI20 and IBEX35 indexes' performances during the period under analysis.

Figure 3.1
PSI20 and IBEX35 performance from January 2000 to June 2016, in index points (both indexes started from a base value of 3000 points in 1992)



3.3 Methodology

As proposed by Chiang and Zheng (2010) the daily return of the stocks is calculated by natural log differences of daily prices:

$$R_t = 100 \text{ X } (log(P_t) - log(P_{t-1}))$$

3.3.1 Incidence and intensity of herding

From the previously discussed studies we can conclude that the most widely used method to examine the intensity of herding is the cross sectional standard deviation of stock returns using the OLS method. Consequently we will begin the empirical analysis of the herding phenomena by using one of the presented models. As stated above the common assumption in these models is that the linear relationship between stocks return dispersion and market return is challenged when the market faces large price variations. The general assumptions of the more common asset pricing models is challenged if individual returns are concentrated around the market return. The same is to say that when market return increases the return's dispersion of the stocks that constitute that market should also increase since the sensitivity of each stock relating to the evolution of the benchmark is different.

Given the previous discussions we use the methodology proposed by Chang *et al.* (2000) to test the first hypothesis ("Herd behaviour is observable in the Portuguese stock market") and we follow Economou *et al.* (2011) and Mobarek *et al.* (2014), employing an equation, derived from Eq. (4) and Eq. (5), formulated as:

$$CSAD_t = \alpha + \gamma_1 |R_{m,t}| + \gamma_2 R_{m,t}^2 + \varepsilon_t \tag{9}$$

where $R_{m,t}$ represents the average return of the market on day t

The presence of a coefficient γ_2 negative and statistically significant would be consistent with the existence of herd behaviour during the examined time frame. Eq. (6) is used, as well, to test this hypothesis, also following Mobarek *et al*. (2014), which is, as explained before, an adaptation of the Chang *et al*. (2000) model as proposed by Chiang and Zheng (2010).

To address the previously discussed issue that herd behaviour can be understood as a time varying process, and following Chiang *et al.* (2013), we also estimate a model in state space form using the Kalman Filter. As discussed above this methodology permits the investigation of the potential time-varying nature of herd behaviour in the Portuguese market. Chiang *et al.* (2013) suggest the following system of equations:

$$CSAD_t = \beta_0 + \beta_1 |R_{m,t}| + \beta_2 R_{m,t}^2 + \varepsilon_t \quad (10)$$

$$\beta_{i,t} = \beta_{i,t-1} + \upsilon_{i,t} \quad (11)$$

$$\text{where } i = 1{,}2 \text{ and with } \upsilon_{i,t} \sim \mathrm{N}\left(0, \sigma_{\upsilon,i}^2\right)$$

The observation equation is analogous to Eq. (9), while the state equation assumes that the variables evolve according to a random walk process. Consequently the state variables $\beta_{i,t}$ are modelled as a random walk and estimated by the use of a Kalman Filter procedure.

3.3.2 Intensity of herding in asymmetric conditions

To test for the relationship between the dispersion and market returns, that can be asymmetric, Caporale *et al.* (2008) use the Chang *et al.* (2000) model represented by Eq. (4) and Eq. (5). As Economou et al. (2011), to perform a test on the second hypothesis, regarding herding asymmetry (herding dependent on market direction), the equation proposed by Chiang and Zheng (2010) is adapted, dismissing the cross border dependence of the US market. In this model *D* is a dummy variable that assumes the value 1 if $R_{m,t}$<0. Therefore the factors $\gamma_5 CSAD_{us,t} + \gamma_6 R_{us,m,t}^2$ are ignored in this particular situation and the resulting equation is:

$$CSAD_t = \gamma_0 + \gamma_1 (1-D)|R_{m,t}| + \gamma_2 D|R_{m,t}| + \gamma_3 (1-D) R_{m,t}^2 + \gamma_4 D R_{m,t}^2 \quad (12)$$

where:

$R_{m,t}$ represents the average market return on day *t*

$|R_{m,t}|$ represents the absolute value of the market return

D assumes the value 1 on the days where $R_{m,t}$<0, and 0 otherwise

3.3.3 Portuguese sovereign debt crisis

The third hypothesis is built on the assumption that imitative behaviour has intensified after the escalation of the European financial crisis and particularly after the eruption of the sovereign debt crisis. Additionally it is assumed that the financial bailout and the presence of the Troika, formed by the European Commission, the International Monetary Fund and the European Central Bank, exacerbated this type of behaviour in Portugal.

At the height of the global financial crisis Greece was forced, on 23 April 2010, to request a financial bailout from the EU, the ECB and the IMF and we will consider that the limit that determines the beginning of the European sovereign debt crisis. Following a period of severe stress, in a scenery of continuous widening of spreads and increasing yield levels, Portugal followed the same path and filled for bailout on 6 April 2011.

Our main objective is to assess if the financial crisis contributed to the developing of behaviours that stray away from those predicted by modern finance. The analysis focus on answering the question if investors flee when facing a potential crisis, abandoning their own models and retreating into the subjective feeling of safety they gain by mimicking the behaviour of the herd. Despite several different outcomes that resulted from this crisis, particularly during its most acute phase, our purpose is to gauge the effect that an event as significant as an international bailout has on a stock market in terms of herding patterns.

We will follow the model proposed by Mobarek *et al.* (2014), with the inclusion of a dummy variable D^C in the factor $R_{m,t}^2$, which is used to capture the non-linearity of the model. The variable will assume a value equal to 1 for the period after the bailout request and until the date when the Troika officially left Portugal.

$$CSAD_{\mathrm{t}} = \alpha + \gamma_1 |R_{m,t}| + \gamma_2 R_{m,t}^2 + \gamma_3 D^C R_{m,t}^2 + \varepsilon_t \qquad (13)$$

We expect the estimate for γ_3 to be negative and statistically significant if the herding effect is more pronounced during the acute crisis period.

3.3.4 Market stress and cross-country herd behaviour

To test the fourth hypothesis the already discussed methodology proposed by Christie & Huang (1995) will be used, considering two different scenarios of extreme market movements.

To determine these movements we will use a dummy variable to identify the observations that lay on the extremes of the distribution. The sample comprises the 5% or 1% of observations situated on the left and right tails of the distribution.

Regarding cross-country herd behaviour Economou *et al.* (2011) argue that there is an effect of contagion between similar markets who share some macroeconomic characteristics.

We further argue that economic dependence may lead to a cross country effect where herd behaviour in the dominant market may spread to the economically dependent market. In that situation widespread herd behaviour in the IBEX would exacerbate market movements in the PSI20. With the scenario of potential contagion between countries in mind we adapt the equation by Economou et al. (2011) proposing the following formulation, including only the Iberian markets:

$$CSAD_t = \gamma_0 + \gamma_1 R_{m,t} + \gamma_2 |R_{m,t}| + \gamma_3 R_{m,t}^2 + \gamma_4 CSAD_{sp,t} + \gamma_5 R_{sp,t}^2 + \varepsilon_t \qquad (14)$$

where:

$R_{m,t}$ represents the average market return on day *t*

$|R_{m,t}|$ represents the absolute value of the market return

$R_{sp,t}^2$ *and* $CSAD_{sp,t}$ refer to the Spanish market variables

4. Descriptive statistics and empirical results

This section presents the descriptive statistics and discusses the empirical results obtained using the methodologies described in section 3.

The first part of the chapter begins with the analysis of market returns and also of the results obtained by applying Eq. (3) and Eq. (1), which are used to compute the values for CSAD and CSSD.

4.1 Descriptive statistics

Descriptive statistics for the returns of the securities of the Portuguese stock market are presented in table 4.1. The table also presents descriptive statistics for CSAD and CSSD, the dependent variables in the models employed throughout the subsequent analysis.

Table 4.1
Descriptive statistics for returns, CSAD and CSSD for the Portuguese stock market, from January 2000 to June 2016

	$R_{m,t}$	CSAD	CSSD
Mean	-0.0242	1.2308	1.7432
Standard Error	0.0180	0.0082	0.0135
Median	0.0353	1.1384	1.5719
Standard Deviation	1.1625	0.5303	0.8704
Sample Variance	1.3514	0.2812	0.7576
Kurtosis	5.8927	6.6091	21.0171
Skewness	-0.3018	1.7387	3.0749
Range	18.6970	5.8485	12.2936
Minimum	-8.4540	0.2567	0.3899
Maximum	10.2430	6.1052	12.6834
Sum	-101.27	5141.18	7281.48
Count	4177	4177	4177

The daily data extends from the 14 January 2000 to 15 June 2016. A total of 4177 observations is considered, corresponding to daily closing prices, although not every stock is present for the total period (some were replaced and others were removed and then returned to the index during the time period under scope).

Beginning the analysis by the variable related to the market return ($R_{m,t}$) we observe that the average return is negative, presenting a value of -0.024.

The standard deviation of returns, a measure of volatility, presents a value of 1.16. Furthermore, the skewness is negative for returns, and by analyzing kurtosis we conclude the distribution is leptokurtic, a common stylized fact in empirical finance. Leptokurtic distributions are characterized by fatter tails than a normal distribution and a greater concentration around the mean. Hence, we can reject the null hypothesis of normal distributed stock returns.

The maximum observed return occurred on the 13^{th} of October 2008, and was 10.24%, bouncing back from the lowest value which was observed on 6 October 2008. This volatility is explained by the concerns around the credit crisis, and throughout this period there were constant news about systemic financial institutions going bankrupt or being intervened by governments (as in the case of Fortis, Dexia or Hypo Real Estate).

The variables CSAD and CSSD show positive skewness and high kurtosis (CSSD shows a value for kurtosis of 21, which indicates clearly that the distribution is highly leptokurtic) indicating that the data is not normally distributed. Standard deviation of CSAD and CSSD values indicates fairly high cross-sectional variations.

Descriptive statistics for stock returns from the IBEX are presented in table 4.2, along with descriptive statistics for CSAD.

For the Spanish stock market, which is used as an explanatory variable for the behaviour of the Portuguese stock market, we have considered 4148 daily observations, from the period ranging from 14 June 2000 to 15 June 2016.

Table 4.2
Descriptive statistics for returns and CSAD for the Spanish stock market, from January 2000 to June 2016

	$R_{m,t}$	CSAD
Mean	0.0060	1.1071
Standard Error	0.0210	0.0077
Median	0.0878	1.0022
Standard Deviation	1.3537	0.4937
Sample Variance	1.8326	0.2437
Kurtosis	4.4811	8.9021
Skewness	-0.1253	1.9794
Range	17.7761	6.3147
Minimum	-7.7190	0.3027
Maximum	10.0571	6.6174
Sum	24.92	4592.32
Count	4148	4148

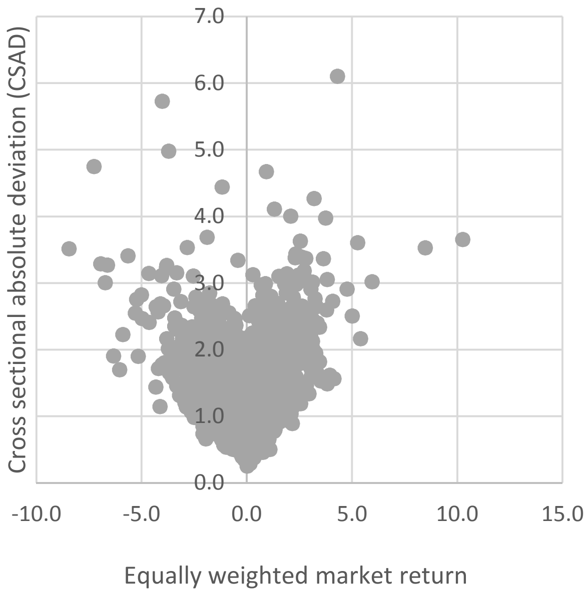
The observed average return for this period is virtually null and the standard deviation presents a value of 1.35. As expected, and discussed above, the distribution of the returns is also leptokurtic, with kurtosis presenting a value of 4.48.

The variable CSAD shows positive skewness and a high value for kurtosis, which indicates undoubtedly that the distribution is extremely leptokurtic, therefore indicating that the data is not normally distributed. The maximum observed return occurred on 13 October 2008.

Figure 4.1, presented below, displays the relationship between the daily cross-sectional absolute deviation (CSAD) and the corresponding market return ($R_{m,t}$) for the Portuguese equity market.

Following the discussion of the models used to test for the presence of herding it should be expected that if herd behaviour exists in the Portuguese equity market during the observed period the situation will be highlighted by the presence of a nonlinear relationship between the dispersion of the returns and the market return as a whole. So, when observing figure 4.1 we would assume that herding exists if dispersions decrease with market returns.

Figure 4.1
Relationship between the daily cross-sectional absolute deviation (CSAD) and the corresponding market return (Rmt) for the Portuguese stock market



The observation of figure 4.1 is not conclusive, even though the relationship between CSAD and $R_{m,t}$ appears to be linear, indicating that dispersions are an increasing function of the market return. That would indicate that herding is not widespread in the Portuguese market, but that intuition needs to be confirmed resorting to the models discussed.

4.2 Empirical results

This section presents the main results regarding the hypotheses set out in the previous chapter.

Chang *et al.* (2000) suggest that the standard errors of the estimated regressions should be adjusted for heteroscedasticity and autocorrelation using the method proposed by Newey and West (1987). Christie & Huang (1995) also report heteroscedasticity consistent *t*-statistics in their seminal paper.

Mobarek *et al.* (2014) also suggest the use of the Newey-West (1987) estimator to obtain heteroskedastic and autocorrelation consistent variances for all the ordinary least square regressions.

Obviously this is a common concern and stems from the fact that we can expect that the assumptions of the OLS regression model won't hold while using financial data, particularly the assumption that the variance of the error term and of the dependent variable is constant across all observations, i.e., assuming homoscedasticity. If heteroscedasticity is present, despite the fact that the parameters estimated using the least square estimator are correct the reported standard errors are incorrect. As a consequence the *t*-statistics and *p*-values would also be incorrect and therefore there is a risk of reaching the wrong conclusions.

To address this situation the Newey-West (1987) heteroscedasticity-consistent, and adjusted for autocorrelation, standard error estimators are used in the present investigation.

4.2.1 Herd behaviour in the Portuguese stock market

To test for the first hypothesis ("*Herd behaviour is observable in the Portuguese stock market*") we proceed with the estimation of Eq. (9) and the results obtained are presented in Table 4.3:

Table 4.3
Regression results from equation 9. Estimates of herd behaviour in the Portuguese stock market.

	Coefficient	*t*-statistic	Adj *R*-squared
Intercept	0.894	55.89***	0.371
$\|R_{m,t}\|$	0.446	21.12***	
$(R_{m,t})^2$	-0.017	-4.28***	

This table reports the estimated coefficients of the regression model:
$CSAD_t = \alpha + \gamma_1 |R_{m,t}| + \gamma_2 R_{m,t}^2 + \varepsilon_t$
T-statistics are calculated using Newey–West (1987) heteroscedasticity and autocorrelation consistent standard errors.
**** represents statistical significance at the 1% level*
*** represents statistical significance at the 5% level*

This model was estimated for the whole sample period, and it is possible to observe significantly positive coefficients on the linear term (coefficient γ_1) which suggests that the cross-sectional absolute dispersion of returns increases with changes in market return. But, since market return squared, $R_{m,t}^2$, is used to test if the dispersion increases at a decreasing rate and the estimated coefficient for γ_2, regarding that variable, is negative and statistically significant we argue, in relation to the first formulated hypothesis, that there is weak evidence for the existence of herd behaviour in the Portuguese stock market in the period between 2000 and 2016.

Only for robustness purposes we also estimate the regression based on Chiang and Zheng (2010) model. The results are presented in table 4.4:

Table 4.4
Regression results from equation 6. Estimates of herd behaviour in the Portuguese stock market.

	Coefficient	t-statistic	Adj *R*-squared
Intercept	0.889	54.16***	0.379
$R_{m,t}$	0.045	5.17***	
$\|R_{m,t}\|$	0.454	19.62***	
$(R_{m,t})^2$	-0.016	-3.43***	

This table reports the estimated coefficients of the regression model:
$CSAD_t = \gamma_0 + \gamma_1 R_{m,t} + \gamma_2 |R_{m,t}| + \gamma_3 R_{m,t}^2 + \varepsilon_t$
T-statistics are calculated using Newey–West (1987) heteroscedasticity and autocorrelation consistent standard errors.
**** represents statistical significance at the 1% level*
*** represents statistical significance at the 5% level*

It is possible to observe a negative estimated coefficient for $R_{m,t}^2$ which is statistically significant, although weak, leading to the conclusion that returns increase at a rate that is not proportional to the increase of the chosen benchmark and so we conclude that herd behaviour may be present in the Portuguese stock market during the observation period. These results are consistent with the findings of Mobarek *et al.* (2014), Holmes *et al.* (2013) and Economou *et al.* (2011).

As a direct consequence of these results we may face asset mispricing in the Portuguese market and increased volatility during some periods. Since we are in the presence of a small market, a characteristic which makes diversification more difficult to attain, herding will contribute to make diversification even more difficult for PSI 20 investors.

Following Chiang *et al.* (2013), in order to address the issue that herd behaviour may be a time varying process we also estimate the model, represented by equations (10) and (11), in state space form using the Kalman Filter.

Given the fact that estimates based on the Kalman algorithm can produce large parameter values in the initial steps of the estimation process we exclude the first fifty observations to avoid the problem of considering outliers in calculating the mean betas (Gastaldi and Nardecchia, 2003; Mergner and Bulla, 2005).

The estimated time-varying $\beta_{2,t}$ are summarized by mean, variance and range in table 4.3.1.

Table 4.3.1
Summary statistics for the estimated herding parameter via KF methodology

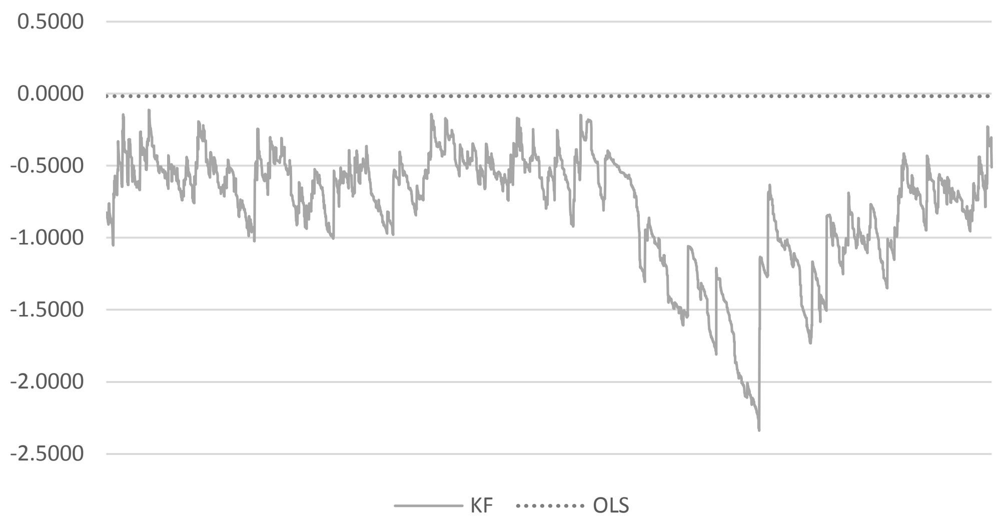
Statistic	$\beta_{2,t}$ KF-RW	β_2 OLS
Mean	-0.7846	-0.017
Standard Deviation	0.3909	
Median	-0.6796	
Range [Min-Max]	-2.2821 / 0.2577	
Observations	3934	

The mean estimated herding coefficient is -0.785, with a minimum of -2.282 and a maximum of 0.258. The results suggest the same conclusions obtained by estimation of Eq. (6) via ordinary least squares (OLS), providing evidence that herding may be present during persistent periods in the Portuguese stock market.

Figure 4.1 describes graphically the evolution of the relevant beta estimates for the period considered. The observation of the graph unmistakably shows that herd behaviour in the Portuguese stock market is time varying. It is also possible to observe that the herding parameter is consistently negative during the period investigated.

Figure 4.2

Comparison of estimates of herd behaviour in the Portuguese stock market using OLS and Kalman Filter methodologies from January 2000 to June 2016



4.2.2 Herding intensity under asymmetric conditions

Concerning the second hypothesis *("Herding intensity is dependent on return asymmetries")* Eq. (12) was estimated and the results are presented in table 4.5.

The table reports the intensity of herding under asymmetric market conditions i.e., when the market shows upward or downward movements, and by observing the coefficients associated with the variable market return squared, $R_{m,t}^2$, we find evidence that is consistent with the results presented above.

Table 4.5
Regression results from equation 12. Herding under asymmetric market conditions

	Coefficient	t-statistic	Adj *R*-squared
Intercept	0.889	54.63***	0.381
$(1\text{-}D)R_{m,t}$	0.512	21.52***	
$DR_{m,t}$	-0.389	-15.20***	
$(1\text{-}D)R_{m,t}^2$	-0.022	-6.71***	
$DR_{m,t}^2$	-0.010	-1.39	

This table reports the estimated coefficients of the regression model:
$CSAD_t = \gamma_0 + \gamma_1(1-D)R_{m,t} + \gamma_2 DR_{m,t} + \gamma_3(1-D)R_{m,t}^2 + \gamma_4 DR_{m,t}^2$
D is a dummy variable that assumes the value 1 on the days where $R_{m,t}<0$*, and 0 otherwise*
T-statistics are calculated using Newey–West (1987) heteroscedasticity and autocorrelation consistent standard errors.
****represents statistical significance at the 1% level*
*** represents statistical significance at the 5% level*

The estimated coefficient γ_3 for $R_{m,t}^2$ is negative and statistically significant indicating that herding exists in the Portuguese stock market during the time span under review during periods of positive returns of the market.

To support the theory that herding is more pronounced in falling markets, expectation that arises from the assumption that panic is a more powerful incentive than euphoria in financial markets for an investor to follow the consensus, we would expect to find $\gamma_4 < \gamma_3$. In other words we would expect γ_4, associated with decreasing markets (since the dummy variable assumes the value 1 when $R_{m,t}$ is negative), to be more negative than γ_3, implying that CSAD is expected to decrease more with a negative market return. However, contrary to our expectations, the evidence shows that the effect of herd behaviour is stronger during periods associated with positive returns. We conclude that herding exists in asymmetric market conditions, in situations of increasing returns, irrespective of the extent of the market movements.

It is worth mentioning that Economou *et al*. (2011) argue that herding in Portugal is more pronounced when the returns are negative.

4.2.3 European sovereign debt crisis

With the intention of analyzing herding during periods of financial distress we build on Econoumou *et al.* (2011), who follow Tan *et al.* (2008). These authors use two different definitions for the crisis period in their papers: one includes the entire period between August 2007 and December 2008 and the other considers the period around the collapse of Lehman Brothers (September 2008–October 2008).

Our understanding of the crisis extension differs from the cited works and in this instance we will consider that the current crisis spans from May 2010 until May 2014. Using the proposed model, also used by Mobarek *et al*. (2014), a dummy variable D^C is used. As explained this variable assumes the value 1 for observations between the beginning of the sovereign debt crisis and the date when the Troika officially left Portugal and allows for the test of the impact of a financial crunch, with the breadth of the ongoing crisis, on herd behaviour.

Table 4.6 shows the results of the estimation of the Eq. (13):

Table 4.6
Regression results from equation 13. Herding during periods of economic distress

	Coefficient	t-statistic	Adj *R*-squared
Intercept	0.892	54.53***	0.373
$\|R_{m,t}\|$	0.451	19.43***	
$R_{m,t}^2$	-0.014	2.96***	
$D_c(R_{m,t})^2$	-0.015	-2.34**	

This table reports the estimated coefficients of the regression model:
$CSAD_t = \alpha + \gamma_1|R_{m,t}| + \gamma_2 R_{m,t}^2 + \gamma_3 D^C R_{m,t}^2 + \varepsilon_t$
T-statistics are calculated using Newey–West (1987) heteroscedasticity and autocorrelation consistent standard errors.
**** represents statistical significance at the 1% level*
*** represents statistical significance at the 5% level*

From the results presented above it is possible to observe that the negative estimated coefficient associated with the dummy variable reveals that dispersion decreases with market return's evolution. This observation leads to the conclusion that our hypothesis holds and therefore that herd behaviour in Portugal increased as a consequence of the European sovereign debt crisis. Given this evidence, and using a different "crisis definition" it is possible to confirm the conclusions of Economou *et al*. (2011) who argue that the global financial crisis caused the intensification of herding patterns in the Portuguese stock market. But, nevertheless, it is interesting to note that according to the same paper that situation only occurs when we consider an equally weighted market return, because when considering a value weighted market return these results are reversed. Also, in the remaining countries observed (Italy, Greece and Spain) there is strong evidence that the cross-sectional dispersion increased with the financial crisis which leads to the conclusion that herding didn't increase during that period.

4.2.4 Herding during extreme market conditions

The coefficient estimates from Eq. (2), used for testing the presence of herd behaviour on the index PSI 20 in conditions of market stress are reported in Table 4.7:

Table 4.7
Regression results from equation 2. Market stress and herd behaviour

	5% Criteria				1% Criteria		
	Coefficient	*t*-statistic	Adj *R*-squared		Coefficient	*t*-statistic	Adj *R*-squared
Intercept	1.658	94.68***	0.514	Intercept	1.707	72.22***	0.312
$D^{L\ 0.05}$	-0.948	-50.47***		$D^{L\ 0.01}$	-1.143	-43.81***	
$D^{U\ 0.05}$	2.651	17.90***		$D^{U\ 0.01}$	4.731	12.82***	

This table reports the estimated coefficients of the regression model:
$CSSD_t = \alpha + \beta^L D_t^L + \beta^U D_t^U + \varepsilon_t$
T-statistics are calculated using Newey–West (1987) heteroscedasticity and autocorrelation consistent standard errors.
**** represents statistical significance at the 1% level*
*** represents statistical significance at the 5% level*

It is observable that dispersion increases during periods of extreme positive market return. Therefore, we suggest that in relation to herding during market stress conditions, its existence can only be observed, given our sample, in a scenario of decreasing markets, with β^L showing negative and statistically significant values in both models (considering stress situations to be, respectively, the 5% and 1% the extreme observations in each tail of the distribution).

We conclude that herd behaviour is observable in the Portuguese stock market during extreme negative market movements. This conclusion implies that dispersion does not increase during extreme falling markets and consequently the predictions of traditional finance may not apply in its full specter to this market in such conditions.

We also observe that during extreme positive market movements the dispersion of returns tends to increase and individual returns do not tend to concentrate around market consensus, confirming the assumptions of rational asset pricing models. So we conclude that in periods of extreme rising returns herd behaviour is not observable in the Portuguese stock market.

It is interesting to point out that the evidence presented in section 4.2.2 indicates that the effect of herd behaviour is stronger during periods associated with positive returns, regardless of the magnitude of the market movement. But, when considering "extreme" market movements, herding is present when the market faces a significant drop.

4.2.5 Cross country effects

Our study follows Economou *et al.* (2011) in the assumption that it is possible to find spillover effects, regarding herding, among similar markets.

As previously discussed Chiang and Zheng (2010) also argue that the US market helps explaining the herd behaviour of less developed, or smaller, markets. Based on these findings we examine the particular influence of the Spanish stock market on the Portuguese market.

Our study expands considerably on the cited work, reflecting a larger sample and, more importantly, examining a more recent period, given the fact that the paper in question only considers stock returns up to December 2008 while the present analysis extends this period to 2016.

Table 4.8, presented below, shows the estimated coefficients for Eq. (14), with the model being estimated including the new explanatory variables related to the performance of the Spanish market.

Table 4.8
Regression results from equation 14. Regression estimates of herd behaviour by incorporating the Spanish factor.

	Coefficient	t-statistic	Adj *R*-squared
Intercept	0.586	20.56***	0.459
$R_{m,t}$	0.046	5.48***	
$\|R_{m,t}\|$	0.375	17.81***	
$R_{m,t}^2$	0.003	0.54	
$CSAD_{sp}$	0.342	12.35***	
$R_{sp,t}^2$	-0.021	-5.58***	

This table reports the estimated coefficients of the regression model:
$CSAD_t = \gamma_0 + \gamma_1 R_{m,t} + \gamma_2 |R_{m,t}| + \gamma_3 R_{m,t}^2 + \gamma_4 CSAD_{sp,t} + \gamma_5 R_{sp,t}^2 + \varepsilon_t$
T-statistics are calculated using Newey–West (1987) heteroscedasticity and autocorrelation consistent standard errors.
**** represents statistical significance at the 1% level*
*** represents statistical significance at the 5% level*

The introduction of the new variables increases the explanatory power of the model as revealed by the higher adjusted R-squared. We further find that the estimated coefficient associated with the variable $CSAD_{sp}$ is positive and highly statistically significant, sanctioning the intuition that the Spanish stock market is a major influence on the Portuguese stock market, with the dispersion of the former showing a relevant impact on the dispersion of the latter. On the other hand the negative and statistically significant estimated coefficient of $R_{sp,t}^2$ indicates that market return fluctuations in Spain have a direct influence over the behaviour of the domestic market.

The issue related to the influence of the Spanish CSAD is of particular importance, given the implications it has on portfolio management and risk diversification. The co-movements of the two markets imply that Portuguese investors that aim to diversify risk by investing in at least another market should be aware that there is empirical evidence of a strong effect of contagion from the Spanish stock market and consequently herding in one market may result in a spillover effect on the other market.

5. Conclusions

This study empirically tested the existence of herd behaviour in the Portuguese stock market, using several models to estimate its intensity under different market conditions and considering external influences on investor behaviour.

For practitioners in financial markets the research on the subject of herd behaviour offers valuable insights for developing new models able to address the idiosyncrasies of human behaviour. Furthermore, herd behaviour and the destabilization, volatility and the deviation from the fundamental value of assets that often comes with it is a reality that needs to be addressed by supervisors and policymakers as well. If is true that sophisticated investors may benefit from the study of herding patterns by including this knowledge in their models it is also true that this phenomenon is relevant for supervisors who must focus on developing tools to identify speculative trends. In the presence of strong evidence that herding is persistent policymakers have to develop adequate strategies to keep assets at a level consistent with financial fundamentals preventing formation of bubbles. Easier said than done obviously, but that is only one more argument in order to increase the efforts in developing models that include human behaviour or, at least, to study this type of phenomenon in order to understand how and why it starts.

Our findings suggest that the proposed models possess considerable explanatory power and reveals evidence, although weak, which supports the existence of herd behaviour in the Portuguese stock market in the period between 2000 and 2016.

We conclude that the sovereign debt crisis contributed for an increase in herd behaviour and that herding is present during asymmetric market conditions. Nevertheless, contrary to our expectations, the evidence shows that the effect of herd behaviour in the Portuguese stock market is stronger during periods associated with positive returns, irrespective of the extent of the market movement.

The influence of the Spanish market over the Portuguese stock market, which was expected given the strong economic and financial relations between the two countries, implies that investors in PSI20, and that aim to diversify risk, should be aware that there is empirical evidence of a strong effect of contagion between the two markets.

Therefore, we argue that risk diversification cannot be optimally accomplished considering only these two stock exchanges.

The main conclusion of the study is that we may face asset mispricing in the Portuguese stock market and periods of unexplained volatility. Furthermore since the study focuses on an extremely small market, which makes risk diversification more difficult to accomplish, herding will make the diversification an even greater challenge.

We believe that research, in the near future, should increase the efforts in determining not only if herding occurs in a given market, but also in explaining the underlying motivations for its occurrence. In order to accomplish that we would like to deepen our level of understanding of intraday herding, during high volatility periods and, as a consequence, develop models that allow for the detection of the main factors that affect the prevalence of herding in some markets. The proposed approach addresses both sides of the same coin: the study of this phenomenon is relevant to gather knowledge that may benefit those financial players interested in using that same knowledge to improve their strategies but also policymakers and market supervisors with the aim of controlling excesses and prevent economic destabilization.

Although the efficient markets hypothesis continues to be the best framework to interpret price movements in stock markets we consider that a deeper knowledge of the behaviour of investors will benefit the financial industry as well the regulators, because it must be recalled that history is providing evidence, in large doses, that the potential consequences of long periods of financial turmoil are highly destructive for the real economy.

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