Essays on Collective Investors' Behavior

By Constantinos Gavriilidis

Supervisors: Dr. Vasileios Kallinterakis

Dr. Zhichao Zhang

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Abstract

The 1980s has given rise to a new area of Finance, namely Behavioral Finance, which challenged the so far dominance of the Neoclassical Finance. Particularly, this new area introduced concepts from cognitive psychology in order to explain investors' behavior at the collective level. Two of the most known faucets of collective investors' behavior are herding and feedback trading. The first one is the phenomenon where investors copy the actions of the other investors, often disregarding their own beliefs, whereas the second one involves the chase of trends on behalf of the investors.

Our thesis first examines the relationship between style investing and institutional herding under the context of a concentrated market. Style investing has been found to promote herding in numerous studies; however, given that these studies have been carried out in large markets, there has not been examined what is the impact of market concentration over this relationship, as a concentrated market may produce different trading dynamics than those in large markets. What is next is to examine the impact of the introduction of the Exchanged Traded Funds over noise trading; these relatively new financial products have special characteristics that can make them appealing to the investors and they could positively contribute towards markets' completion. Finally, our research focuses on the issue whether institutional investors herd intentionally at the industry level; this issue has never been explored, to our knowledge, before and we will try examine this by using the interaction of institutional herding with various market and sector conditions.

As a result, our research makes a contribution to the research on herding and feedback trading, examining important issues that have not been addressed before.

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«ΜΑΝΘΑΝΩΝ ΜΗ ΚΑΜΝΕ»

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Chapter 1

1. Introduction

Since the 1970s and the introduction of the concept of the Efficient Market hypothesis by Fama (1970) there has been an overwhelming research trying to either support or challenge its principles. It was during the 1980s where concepts from cognitive psychology were used to explain investors' behavior giving birth to what is known today as Behavioral Finance. The latter tried to shed light on investors' behavior by using concepts from cognitive psychology, as mentioned above, related to biases and heuristics found in human behavior. In addition, Behavioral Finance extended the study of human behavior from the individual perspective to the collective behavior of investors in the market. Perhaps two of the most known forms of collective behavior in capital markets are *herding* and *feedback trading*. *Herding* refers to the phenomenon when investors copy the actions of their peers, often disregarding their own informational sets. *Feedback trading* is the phenomenon when investors try to realize gains by riding on trends of stock prices. Feedback trading may be "positive", where investors buy (sell) stocks when prices rise (fall) as well as "negative" where investors buy (sell) stocks when prices fall (rise). Both the above mentioned trading patterns can be driven by rational as well as behavioral reasons and they may lead to destabilizing effects, driving prices away from their fundamental values. Given the impact these two facets of collective behavior may have on asset prices, there has been a great amount of research, both theoretical and empirical, regarding these two topics.

Starting with *herding*, the seminal works that related this phenomenon to the investors' behavior were those of Banerjee (1992) and Bikhchandani *et al.* (1992); the authors suggested several professional/career and psychological considerations as being the possible sources of this phenomenon. In addition, on the following years, a wealth of researches have empirically tested for the presence of herding in a set of various markets across the world, both at the individual investor perspective, using macro-models, and the institutional investor perspective, using micro-models, as well. In the first case, researchers used aggregate market data [Christie and Huang (1995), Chang *et al.* (2000), Hwang and Salmon (2004)] and in the latter case, researchers used micro-level data [Lakonishok *et al.* (1992), Wermers (1999), Kim and Wei (2002a), Kim and Wei (2002b), Sias (2004), Choi and Sias (2009), Holmes *et al.* (2011)]. The concept of *feedback trading* was initially introduced by De Long *et al.* (1990a) at the theoretical level and then was empirically tested by numerous researches across the world and various classes of assets, such as stocks, options, futures, etc. [Sentana and Wadhwani (1992), Koutmos (1997), Koutmos and Saidi (2001), Antoniou *et al.* (2005), Bohl and Reitz (2006), Chau *et al.* (2008), Salm and Schuppli (2010)]. It is worth noting here that *feedback trading* was associated with various trading strategies such as momentum, contrarian and technical analysis.

Given the extensive research in those two areas, we identified specific gaps in the literature, which we believe are of great importance to both the investment community and the regulatory authorities as well. As such, the first research question of our thesis that we will try to answer is *whether market concentration has an impact over the relationship between style investing and herding*. The relevant literature has identified a relationship between style investing and herding [Grinblatt *et al.* (1995), Wermers (1999)], however all these researches have been carried out in the context of large developed markets; the issue has not been addressed in the context of a small and concentrated market (which is the case for the majority of world financial markets). To that end, we test for this relationship in Portugal, which is characterized by high levels of concentration both in its equity market and its funds' industry. In order to test for the relationship between style investing and herding and how this is affected by the level of market concentration, we apply six different style indicators; those are analysts' recommendations, market value (size), momentum, value/growth, volatility and volume. In addition, we divide our sample period into two sub-periods, pre and post Euronext to account for any effects of the merger of the Portuguese Stock Exchange into Euronext and then we further break the post-Euronext period into pre and post crisis, trying to gauge any effect the credit crisis that broke out in 2008 had over our estimations.

The next issue we address is *the impact of the Exchange Traded Funds' introduction over noise trading*. Exchange Traded Funds (ETFs) constitute a relatively new financial innovation, which combines the advantages of open-end funds with those of close-end funds into one product. Given that ETFs are attractive to both rational and retail investors and taking into consideration that the latter are the prime candidates for noise trading [Barber *et al.* (2009)], the issue arising is what is the impact of the ETFs' introduction over market dynamics. In other words, what we want to examine is whether the introduction of the ETFs promotes market efficiency and depresses noise trading. To test our hypothesis, we use a sample of eight European countries, also controlling for the current financial crisis. In addition, we test for the noise traders' migration hypothesis, i.e. whether noise traders migrate from the spot market to the ETF segment. We believe our research will be of particular interest for market regulators and policy makers as it will provide evidence on whether ETFs could enhance the efficiency of the markets and contribute towards their completeness. In addition, there are important implications for the investment community; since the ETFs are efficiently priced and do not have any destabilizing effect on the spot prices, they can be used as a hedging tool on behalf of investors.

The third research question we try to answer is *whether institutional investors herd intentionally at the industry level*. Institutional investors have been found to significantly herd when investing in industries [Voronkova and Bohl (2005), Choi and Sias (2009), Chen *et al.* (2012)], nevertheless the issue whether their herd behavior is driven by intent or not, at this level, has not been explored before. The only research, to our knowledge, so far to address this issue is that of Holmes *et al.* (2011) in the context of the Portuguese fund industry. However, the authors examined the interaction of herding with a series of market conditions at the aggregate market level. In our research, we expand this approach by testing whether fund managers herd intentionally at the industry level and by using both market and sector conditions, we identify whether it is the market or the sector conditions that affect this intent. To do so, we use quarterly portfolio holdings of Spanish mutual funds for the June 1995-December 2008 period.

Our thesis begins with a detailed literature review in Chapter 2 and the evolution from the Efficient Market Hypothesis to Behavioral Finance. In addition, we present in great detail the relevant theoretical and empirical work carried out for the concepts examined in this thesis, namely *herding* and *feedback trading*.

In Chapter 3 we examine the relationship between style investing and herding in the context of a concentrated market, namely Portugal. We first start by discussing the relative literature that establishes the link between style investing and herding and then elaborate on how market concentration can affect this relationship. The rationale behind this is that since high market concentration can produce different trading dynamics than those produced in large markets, this could have an impact over the relationship between style investing and herding. For example, in a concentrated market institutional investors can monitor their peers easier and as it is more likely that fund managers know each other, it will be more difficult for them to deviate from the market consensus [Do *et al.* (2008)]. Furthermore, since there are less investment options in a concentrated market than in less concentrated markets, then it could be more difficult for fund managers to apply investing styles. As such, given the above characteristics of the highly concentrated markets, style investing could have a limited impact over institutional herding. To test our hypothesis, we apply six different style indicators (analysts' recommendations, market value (size), momentum, value/growth, volatility and volume) and will control for the merger of the Portuguese market into the Euronext platform. In addition, we control for the credit crisis that broke out in 2008 by breaking the post-Euronext period into pre and post crisis. The methodological approach we use for testing our hypothesis is that of Sias (2004) which directly tests the extent to which institutions follow each other over adjacent time periods. Our results support our hypothesis that style investing is of limited importance to herding when it comes to highly concentrated markets. Particularly, we find that the institutional demand over time in the Portuguese market is primarily due to funds following the trades of others (herding) and its significance is not affected when we control for a series of investing styles. What is more, we find that style investing is not a common practice in highly concentrated markets and that it does not have any impact over the significance of herding among fund managers in such market environments.

What is next in chapter 4 is the examination of whether the introduction of ETFs had an impact over noise trading. We first begin with the discussion about the findings on noise trading, its sources and its primary candidates. Moving forward, we provide a detailed description of ETFs and their special characteristics that make them more appealing to rational or retail investors. To test our hypothesis we use the established methodology of Sentana and Wadhwani (1992) which assumes two types of traders, namely rational and feedback traders, into a span of developed markets (i.e. eight European markets). The rationale behind our research question is that if ETFs are more appealing to rational investors, this could have a beneficial role towards the improvement of market efficiency, depressing noise trading. On the other hand, if ETFs are more appealing to retail investors, this could possibly amplify noise trading; hence constituting a destabilizing factor for asset prices. Our results provide supporting evidence to the view that ETFs depress noise trading, since in the entire sample examined, the significance of feedback trading was found to dissipate after the launch of ETFs. What is more, the segment of ETFs appears to primarily be in the hands of rational investors. As such, since Exchange Traded Funds are less prone to noise trader risk, they can be more efficiently priced. To that end, ETFs can promote efficiency in the spot markets they have been introduced to.

In Chapter 5, we test whether institutional investors herd significantly at the industry level and whether this behavior is driven by intent or not, by examining the interaction of herding with a series of market and sector conditions (returns, volatility, volume, concentration of trading). Firstly we provide the theoretical background on the motivations that drive herding, be they intentional or unintentional; then we provide a description of the specific issues related to industry herding. In order to test our hypothesis, we use quarterly portfolio holdings from the Spanish fund industry for the June 1995-September 2008 period and we apply the Sias (2004) methodology. The rationale behind our hypothesis is that if institutional investors herd intentionally at the industry level, then this would be reflected through differences in the significance of their herding across different market/sector conditions. On the other hand, if institutional investors' herding at the industry level is not intentional, then difference in the market/sector conditions would have no impact over the significance of herding. Our results provide supporting evidence to the research of Holmes *et al.* (2011), who found that institutional investors herd intentionally at the market level, as this was reflected through differences in various market conditions examined; this herd behavior being driven by professional and informational reasons. In our case, our study takes a further step finding that fund managers intentionally industry herd in most of the sectors examined and this intent is affected by both market and sector conditions.

Finally, Chapter 6 concludes our thesis by providing a summary of our findings, and it also outlines the implications these may have for the investment community and the regulatory authorities.

Chapter 2

2.1 Introduction

Agora (Αγορά) in Ancient Greece was a place in which traders were exchanging ideas as well as products; in other words agora was the progenitor of today's capital markets. Over the centuries, markets have kept developing and evolving. It was no earlier than in 1602 that the first official stock market was established in Amsterdam and the Dutch East India Company's issuing of shares (the world's first officially documented initial public offering) took place. The underlying exchanged assets in stock markets are securities, be they stocks, bonds, options or other complex financial products. However, the main issue arising among the stock market participants is how these securities should be priced. In other words, how can investors ensure that prices are reflective of their true value?

A first attempt to address the above mentioned question was made by the "Neoclassical" school of thought. One of the buildings blocks of this approach postulated that securities' prices "fully reflected" all available information. Moreover, if a security has a higher return than another it should bear a higher risk; security prices reflect the risk of the asset and their returns exhibit a positive relationship with it. Additionally, no excess returns or predictions regarding future returns of an asset could take place with the available information; prices should randomly change upon the arrival of new information. In other words, the trading decisions of investors are information-based, adjusting to changes of companies' fundamentals. The other building block of the neoclassical approach postulated that investors were "rational". Upon the arrival of new information, they adjust their decisions in a rational way, following Bayes' law. In case of any irrational actors being active, there were assumed to be other rational investors, known as "arbitrageurs", who would restore balance and bring prices back to their fair value. So, either way, prices would always be "rationally" priced under the tenets of this approach.

The problem with this approach, however, is that it relies heavily on the assumption of relative homogeneity in the market, with investors conjectured to be "rational". This issue was picked up by researchers from the so-called behavioral finance camp which contrary to the neoclassical school, and based on tenets emanating from cognitive psychology, suggested that investors cannot be considered as consistently rational, thus throwing the purported homogeneity argument mentioned previously in doubt.

To illustrate its argument, behavioral finance drew heavily upon findings from cognitive psychology related to heuristics and biases in human behavior. The term "heuristics" refers to rules of thumb employed by people when having to take decisions characterized by complexity of uncertainty. Biases are the obstacles that block people from correctly perceiving or interpreting information. Together, biases and heuristics imply a less-than-perfectly rational state for investors' behavior and it is on their premises that behavioral finance research has hinged upon to develop its counter-position(s) to the rational paradigm. Put it simple, whereas the latter implied that investors were ad hoc "rational", behavioral finance claims that rationality constitutes only one of multiple possible states of behavior; as Statman (1999) argued, people are "normal" rather than "rational".

Additionally, behavioral finance extended the study of human behavior from an individual's perspective to the collective behavior of individuals in the market, and tried to identify the outcomes stemming from their interaction. With investors viewed as being subject to psychological impediments (biases) and prone to using heuristics, the make-up of their ranks is expected to be anything but homogeneous, thus contributing further to the complexity of the market environment. The rationale behind this is based on the fact that investors differ among themselves with regards to numerous factors such as their level of education, risk preferences and information. Moreover, the depicted heuristics and biases that affect human behavior bear a differential impact on each investor individually. Thus, contrary to the rational paradigm where investors' homogeneity pointed towards clearer anticipated outcomes, heterogeneity can give rise to multiple possible outcomes, not necessarily motivated through or characterized by rationality exclusively.

Perhaps the two most widely researched modes of collective trading conduct in capital markets are *herding* and *feedback trading*. *Herding* occurs when investors blindly follow other investors' actions, often disregarding their own informational sets. *Feedback trading* is associated with investors trying to succeed gains by riding on trends of stock prices. Feedback trading may be "positive", where investors buy (sell) stocks when prices rise (fall) as well as "negative" where investors buy (sell) stocks when prices fall (rise). Both the above mentioned trading patterns can be motivated through rational as well as behavioral reasons and if their practice proliferates, they are capable of conferring a destabilizing effect, driving prices away from their fundamental values. Whether these patterns' motivations and outcomes can best be explained through rational or behavioral interpretations constitutes the crux of this thesis and will preoccupy us in the next chapters.

Before we expand on these two modes of behavioral conduct, we consider it prudent to begin from the roots underlying them as issues. In the next section of this chapter, we therefore provide a critical comparison of the Neoclassical and Behavioral schools of thought in finance. More specifically, we analyze in depth the crux of the neoclassical approach, namely the efficient market hypothesis, and the challenges arisen against it. Later on, we elaborate on the arguments put forward by Behavioral Finance and the proposed models it suggested, as well as their shortcomings.

2.2 From the Efficient Markets Hypothesis to Behavioral Finance

The main pillar of the Neoclassical camp is considered to be the Efficient Markets Hypothesis (EMH hereafter), as coined by Fama (1970). According to it, asset prices "fully reflect" all information available and they change randomly over time upon the arrival of new information, adjusting to the new fundamentals. Therefore, they follow a random walk, as Samuelson (1965) stated in his "Random Walk Hypothesis", and there are no patterns that investors can exploit in order to realize abnormal returns; in case any excess returns are indeed achieved, these should be attributed to luck or considered as compensation for the excess risk incurred. In other words, investors cannot "beat" the market (at least systematically). Furthermore, Fama (1970; 1991) suggested there existed a "joint hypothesis problem" according to which the efficiency of a market can only be tested in conjunction with a given capital asset pricing model, such as the CAPM of Sharpe (1964), Lintner (1965) and Black (1972), thus drawing a line between the informational efficiency of asset prices and the predicting power of the asset pricing models. So, if asset prices do not represent the fundamental values, it is either due to market inefficiency or due to misspecification of the asset pricing model. The assumptions underlying EMH were the absence of transaction and informational costs in the market, as well as the homogeneity of markets' agents in terms of rationality.

Rationality is the other pillar of the neoclassical approach to finance. It implies that upon the arrival of new information in the market, investors make decisions following the Bayes' law and their choices made are in accordance to Subjective Expected Utility [Barberis and Thaler (2003)]. The later implies that when people make decisions under uncertainty, they choose the one whose outcome has the greatest subjectively expected utility. Yet, although rationality is considered to be granted, this does not necessarily mean that all investors act rationally. There can be cases where investors overreact or under-react to news' arrival; however, these irrational acts take place randomly and cancel each other in the long run (Fama, 1998).

Moreover, in case any investors engage in irrational actions, there are always assumed to be rational investors in the market ready to intervene, arbitrage away the mispricing and force prices back to their intrinsic value. The role of arbitrage in maintaining prices in line with fundamentals can best be shown through the following example. Suppose that the price, representing the fundamental value, of company A is £50. A group of investors, acting irrationally, presumes that this company will not perform well in the future and start selling their shares pushing the price down to £35. Then arbitrageurs, identifying the mispricing of the stock and the opportunity to make profit, will buy stocks of company A and at the same time hedge their bets by going short on a company (call it company B) with characteristics similar to those of company A. So at the end, the buying interest from the arbitrageurs will drive the price of company A back to the fundamental value of £50.

Fama (1970) suggested that there are three forms of market efficiency and various tests have been carried out in order to confirm the EMH. To begin with, there is the *weak form* according to which, all past price movements are reflected in securities' prices and investors cannot gain excess returns (higher than those predicted by an asset pricing model) through technical analysis, i.e. past information. In order to test for the weak form of market efficiency, studies using technical analysis were employed. More specifically, researches such as those of Fama and Blume (1966), Seelenfreund *et al.* (1968) and James (1968) examined whether investors using trading rules based on past stock prices could gain higher profits than randomly chosen stocks. Their results could not provide any evidence that the use of historical prices could offer investors any higher profits. Therefore, these tests proved to be in favor of the weak form of market efficiency.

The *semi-strong form*, according to which, all public information about companies is reflected on their prices and investors cannot obtain excess returns using fundamental analysis, i.e. past and present information. Event studies have been carried out to test the semi-strong from of market efficiency. These studies test how fast new information is incorporated in prices. Ball and Brown (1968) examined the impact of earnings announcements and Fama *et al.* (1969) examined the impact of stock splits on stock prices. They found that the announcement of stock splits had a positive impact on stock prices and more interestingly found evidence that the anticipation of the stock split was two years before the actual split of the stock. Furthermore, Johnson *et al.* (1985) found that the sudden death of a company's CEO had a negative and prompt impact on the stock price of the company.

Finally, the *strong form* of market efficiency states that stock prices reflect all available information, be that public or private, and investors cannot enjoy any abnormal gains even if they possess inside information. In order to test for the strong form of market efficiency, tests on the performance of professional fund managers have been carried out, such as that of Jensen (1968). He argued that, after taking into consideration the transaction costs, fund managers did not enjoy any particularly high excess returns, thus providing evidence in favor of the EMH.

However after the mid-1970s, there appeared a surge in research challenging the EMH and its supporting evidence. More specifically, many researchers found that stock prices tended to exhibit some patterns that could not be explained by the then established asset pricing models, arguing that their presence indicated either that markets were inefficient or the models used were misspecified. These patterns were dubbed as "anomalies". One of the best documented anomalies is the size effect, which purports that smaller capitalization firms tend to outperform larger ones. Among the first researches about this anomaly was that of Banz (1981), who, upon examining the relationship between the return and the market value of common stocks in NYSE for the period 1926-1975, showed that smaller firms recorded higher returns than those predicted by the CAPM. Moreover, his empirical results showed that a portfolio consisting of small firms outperformed a portfolio of larger firms. The initial findings of Banz (1981) were later confirmed by evidence produced by Reinganum (1981), Keim (1983) and Lamoureux and Sanger (1989) to mention only a few. The two most likely explanations given by researchers regarding the size effect are the tax-loss hypothesis[1] [Keim (1983), Reinganum (1983)] and the higher transaction costs[2] for small firms [Stoll and Whaley (1983), Schultz (1983)].

A particular subset of anomalies came to be known as "seasonal" (or "calendar") anomalies, with seasonality here taken to imply the regular presence of abnormal returns during specific periods of time. However, since their identification, more and more investors have been trying to exploit them, thus resulting in these anomalies' gradual decay over the years. The best known calendar anomaly is the January effect, first documented by Wachtel (1942). The underlying theory of this anomaly as its name suggests, is that stocks tend to exhibit higher returns in January compared to the other months of the year. There have been quite a few researches providing evidence in support of this market anomaly, namely these of Rozeff and Kinney (1976), Keim (1983), Reinganum (1983) and Roll (1983). Some of the possible explanations proposed for the existence of the January seasonal are the tax-loss hypothesis [Reinganum (1983), Roll (1983) and Ritter (1988)], the expansionary phase of the business cycles[3] [Kramer (1994)], window-dressing[4] [Haugen and Lakonishok (1987)] and the higher volume in markets during January[5] [Ligon (1997)].

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[1] The size effect was related to a January seasonal and the tax-loss hypothesis states that due to income tax reasons, investors sell their stocks in order to exhibit capital losses. Thus stock prices fall during December and recover at the beginning of January.

[2] Transaction costs beard by investors are usually higher in small stocks because as the latter being low priced stocks their liquidity is higher and investors must trade more often in them in order to achieve a gain. Additionally, it is more costly to gain information or monitor small firms in relation to larger ones.

[3] This hypothesis states that the January effect was found to exist during the expansionary phases of economy's business cycles, whereas during the contraction phases it was undetectable.

[4] Window-dressing hypothesis suggests that the January effect is caused by professionals' portfolio rebalancing in order to influence their performance based remuneration. Thus, professionals want to lock on their profits and sell their risky assets at the end of the year, buying again at the beginning of the year.

[5] Usually, there is high liquidity in the market at the first days of January (people get their bonuses, pension contributions, etc.), thus people intend to trade more during these days.

Similar calendar anomalies were identified through the 1980s, including the weekend effect [French (1980)], according to which stock returns were found to be lower from Fridays through Mondays. This phenomenon was attributed to the fact that people tend to be in better mood in Fridays than in Mondays [Keim and Stambaugh (1984)]. Additionally, the holiday effect [Ariel (1990)] implies that stock returns are higher prior to holidays, due to the better mood people enjoy before leaving for holidays. Finally, another calendar anomaly documented is the intraday effect [Smirlock and Starks (1986), Harris (1986)] according to which stocks tend to have abnormally higher returns in specific time intervals during the trading day.

Further market anomalies that have been identified over the years are the value effect and the IPO effect. The first one indicates that stocks with high price in relation to earnings, dividends, book value or other measures of value give abnormal higher returns. It was firstly identified by Basu (1983) and supporting evidence was found by Fama and French (1992) and Lakonishok *et al.* (1994). The authors suggested that this phenomenon could be attributed to the fact that investors pay too much attention into glamour stocks in relation to value stocks. Finally, the IPO effect, firstly introduced by Ritter (1991) and supported by Loughran and Ritter (1995), suggests that Initial Public Offerings are underperforming in the short run and this could be due to the high expectations investors have about the perspectives of the newly issued companies.

The discovery of market anomalies during the 1980s was the first major challenge to the EMH, since these stock price patterns could not be predicted by an asset pricing model. Yet, although predictability is not the key assumption of the EMH, market anomalies acted as the kick start for a voluminous research that questioned the assumption of investors' homogeneous rationality, the key assumption of EMH. A lot of research that culminated in what came to be known later as Behavioral Finance, started drawing upon issues from cognitive psychology in order to support their argument that human behavior cannot be considered as strictly rational [recall the statement of Statman (1999); people are "normal", rather than "rational" (p.20)]. Psychological impediments ("biases") that greatly influence the behavior of humans and help them deviate from rational judgments have been documented. However, these biases which will be discussed shortly do not affect all people and if they do, they do not affect them at the same level; thus people, in our case investors, differ relative to each other in the way of perceiving, interpreting information and making investment decisions. The latter essentially poses a strong challenge to the first pillar of behavioral finance: neither can the market be considered strictly homogeneous, nor investors strictly rational.

One of the biases that have been found to affect human behavior is *conservatism* [Edwards (1968)]. This phenomenon implies that people tend to react very slowly on newly arrived information. As an example, consider an investor who has invested into the shares of company A, the latter having been quite profitable for the last four years. Suppose that in the last quarter the earnings announcements of company A are negative; then the investor might disregard this news when updating his beliefs since his chosen investment performed quite well during the past years and decides to hold onto the stocks. Now, imagine that in the next quarter the company still has negative results; then the investor starts reassessing his beliefs, thinking whether it might be better for him to sell his stocks or not. It is this late reaction to new information that causes the *conservatism* bias.

Another important bias affecting human behavior is the *overconfidence* bias. Investors tend to be very optimistic about their decisions and think very highly of their investing skills; as a result overconfident investors trade more and more, increasing both market volatility and trading volume [Gervais and Odean (2001)] which often leads them to endure severe losses. Hirshleifer (2001) relates overconfidence to two other biases, *self-attribution* (which posits that investors attribute all the successful decisions on their own skills whereas any negative results that might come up are attributed to bad luck or other factors [Daniel *et al.* (1998)]), and *self-deception* (which argues that people tend to think that they are better than they really are [Trivers (1991)]).

The *disposition effect*, firstly mentioned by Shefrin and Statman (1985) and empirically supported by Odean (1998) and Weber and Camerer (1998), describes the phenomenon where investors are reluctant to sell past losers and more willing to sell recent winners. In fact the opposite should be the case: if investors invested in the wrong stock they should let it go and keep their right choices. A possible explanation of this effect lies in the belief that investors do not want to admit that they made a wrong decision; thus they keep holding their losing stocks, whereas when they sell their winners they can show to others that they are successful and picked the "right" stocks.

The presence of these biases and the heterogeneity of investors increase the complexity of the market. To make sense of such a complex environment, investors resort to mental tools, or else rules of thumb, known as *heuristics*. Research on the latter was largely motivated through the findings from earlier psychological experiments conducted by Tversky and Kahneman (1974). By conducting experiments, the two scientists found that the existence of certain biases and heuristics leads human behavior to deviate from rationality. More specifically, they mentioned three heuristics, namely *representativeness*, *availability*, and *adjustment from anchoring*.

The *representativeness* heuristic drives investors' decision-making merely based on the description of an event or the most recent information they posses about it, rather than acting according to the principles of statistical science; as Kahneman and Tversky (1973) posit *"people predict the outcome that appears more representative of the evidence"*. Moreover, it can lead to several biases in human behavior such as the *base rate neglect*, or base rate fallacy. The latter occurs when people underweight the probability of the base rate when calculating the conditional probability of an event, given a *representative* statement. An example of the above could be depicted from the work of Tversky and Kahneman (1983) and goes as follows: *"Bill is 34 years old. He is intelligent, but unimaginative, compulsive, and generally lifeless. In school, he was strong in mathematics but weak in social studies and humanities."* When the persons involved in the experiment were asked to rank the following statements A: *"Bill plays Jazz for a hobby"* and B: *"Bill is an accountant who plays Jazz for a hobby"* they ranked statement B higher than statement A, even though B constitutes a subset of A. The explanation underlying the outcome was that since the description given was more representative of an accountant, the subjects over weighted the description (representativeness) and underweighted the base rate which was statement A; statistically speaking it is more possible for a man to play Jazz than being an accountant and playing Jazz.

Another bias that can be caused from representativeness is the *sample size neglect* which implies that people tend not to take into consideration the size of the samples compared when evaluating different datasets and their outcomes (*"law of small numbers")*. [Tversky and Kahneman (1971)] stated that people often regard a small sample of a population to be equally representative and more reliable compared to a larger sample of the same population. Related to the latter, two other phenomena have been identified known as the *"gambler's fallacy"* and the *"hot hands"* phenomena which will be explained through some examples. The first one can be seen when a gambler is betting in a casino's roulette; if the outcomes were eight reds in a row, then the gambler will most likely think that black will be next, in order to balance the large number of reds. The second example draws from sports, where if a basketball player scores five shots in a row, the fans will believe that this player is in a good shape and will score again. A similar example drawing from financial markets: if a company has been performing well the last three years it is highly likely that investors believe it will continue to do so during the fourth year also; thus this effect can create some trends in stock prices.

The *availability* heuristic suggests that people tend to perceive more recent and salient events as more probable to occur than others; people may perceive the danger of a nuclear accident higher after the recent (2011) catastrophe in Japan. The third heuristic underlined by Tversky and Kahneman (1974) is the *adjustment from anchoring*. According to it, people when making decisions usually have some starting points, ("anchors"), which they adjust over time upon arrival of new information, though most of the times this adjustment is insufficient due to the heavy reliance people exhibit on the starting point.

The main issue arising from financial research at that point is how investors make their decisions under uncertainty. EMH posits that they follow Bayes' law and maximize their expected utility [Von Neumann and Morgenstern (1944)]. However, the behavioral camp, drawing again upon the work of Kahneman and Tversky (1979) and their famous *prospect theory*, argued that investors do not always make decisions under the Expected Utility (EU hereafter) Maximization theory. The *prospect theory* suggested that people, when making risky decisions, depend heavily on gains and losses in terms of some *reference points,* rather than final wealth levels as the EU theory suggested. Moreover, what differentiates *prospect theory* from EU is the shape of the utility function which in the case of prospect theory varies according to whether it lies in the domain of gains or losses. As the authors argued, this *loss aversion* shows that people are more risk averse when they deal with gains and more risk seeking when dealing with losses. The advantage of *prospect theory* is that it appears more realistic in real life than the Expected Utility Theory. Accordingly, many researchers provided supporting evidence in favor of the *prospect theory*. For instance, Barberis *et al.* (2001) incorporating *prospect theory's loss aversion* in their model were able to explain the high volatility and the high mean of stock returns as well as their predictability.

The identification of the role of psychology in investing and the high complexity of the market gave birth to a novel type of investor, known as the "noise" trader. Contrary to the EMH which stated that investors trade on fundamentals, Black (1986) defined noise trading as the behavior of investors trading on non-fundamental information, or information they think is relative but in fact is not; as the author stated *"people sometimes trade on noise as if it were information"*. In addition, Barber *et al.* (2009) went one step further by identifying noise traders with retail investors, stating that it is their trading that increases liquidity and makes markets possible. However, noise traders, by trading not only on fundamentals, cause certain mispricing on stock prices; this mispricing is to be corrected by the 'informed traders" (arbitrageurs) who intervene in the market to exploit the mispricing and profit from it.

This is where the second pillar of Behavioral Finance comes in; in the presence of noise traders, there are certain limits to arbitrage, the latter being neither unlimited nor riskless. If we recall from EMH, arbitrageurs appear to be strictly rational and in case of any mispricing will drive prices back to their fundamental values; however, as we will see below, rational investors may not always be able or willing to do so. The concept of "noise trader risk" was first coined by De Long *et al.* (1990b) who illustrated it through the following example: supposedly some irrational investors are very pessimistic about a stock; then the arbitrageurs come into the market and buy the stock in order to take advantage of the mispricing. However, in case the irrational investors feel even more pessimistic, they drive the price even lower; then the arbitrageurs suffer a loss if they must sell the stock before its price regains its fair value. In other words, it is the risk of further destabilization by noise traders that motivates the noise trader risk. If the arbitrageurs have a short run investment horizon it might be in their best interest not to intervene in certain mispricing acts. Further supporting evidence was provided by Shleifer and Vishny (1997) who introduced another dimension of arbitrage, presenting it as a principal-agent issue. Usually arbitrageurs are a small group of highly skilled, informed professionals who manage other people's money (e.g. fund managers). If their assessment is based on their performance, they might be reluctant to undertake additional risk in order to exploit an extreme mispricing. So, it might not always be the case that arbitrageurs will drive prices back to efficient levels; such an action can often entail a high level of risk that is not in the arbitrageurs' best interest to undertake.

With investors therefore being subject to psychological forces (biases; heuristics) and mispricing not always readily tackled by rational traders, the possibility of disproportionate reaction to news cannot be ruled out. Two ways this can be manifested through are overreaction and under reaction. More specifically, overreaction occurs when the reaction of stock prices upon the arrival of new information is higher than normal, leading them to deviate from their true values but gradually reverting to them at a later stage; overreaction is linked with negative autocorrelation in stock returns. The phenomenon was first identified by DeBondt and Thaler (1985) whose empirical findings showed that a portfolio of prior losers outperformed a portfolio of prior winners by almost 25%. As a primary source of overreaction the authors proposed the *representativeness heuristic*, which leads investors to overweight recent news; for example stocks with a record of good news tend to be overvalued upon news arrival, though they gradually revert to their true value. A way of exploiting this pattern is the use of contrarian trading strategies. The latter suggest that investors could gain abnormal returns by investing in prior losers and selling prior winners. Supporting evidence for the profitability of such strategies are provided, among others, by DeBondt and Thaler (1987) and Antoniou *et al.* (2005). In accordance with overreaction, under reaction implies that stock prices do not react as much as they should upon the arrival of new information; and is linked to positive autocorrelation in stock returns. Again, in line with overreaction's possible explanations, concepts from cognitive psychology were employed by researchers to explain the under reaction hypothesis; particularly, the *conservatism bias* and the *anchoring heuristic.* Given these concepts, investors rely heavily on past news or past performance and they do not adapt their judgments following the new information arriving. A trading strategy aiming at exploiting this pattern is the so called "momentum" strategy; that is buying previous winners and selling prior losers. Evidence in favor of this strategy is provided, among others, by Jegadeesh and Titman (1993) and Galariotis *et al.* (2007). The above mentioned evidence constitutes a challenge to the EMH since investors, by using strategies based on stocks' past performance, can enjoy abnormal returns. Supporters of the behavioral camp came along with proposed models that were able to explain investors' overreaction and under reaction; notably Barberis *et al.* (1998) and Daniel *et al.* (1998).

From the side of the neoclassical theory's supporters, Fama (1998) argued that in an efficient market there will be events where prices sometimes overreact and sometimes under react to; however these events cancel each other out when randomly split in favor of EMH. Moreover, he argued that most of the "market anomalies" found by other researchers are due to misspecification of the model used and when a better methodology is applied these anomalies disappear. Particularly, he supported the view that a model which includes more risk factors than the CAPM, such as that of Fama and French (1993), could explain many of the reported patterns in stock prices. Furthermore, he referred to the importance of the statistical methods used on measuring stock returns, i.e. return metrics, and that these different methods can provide different results (Average Abnormal Returns vs. Buy and Hold Average Returns, Equal Weight Returns vs. Value Weight Returns, etc.). Finally, he attacked the behavioral models of Barberis *et al.* (1998) and Daniel *et al.* (1998) on the grounds that these models explain only the anomalies which they were designed to explain and otherwise perform poorly when trying to explain other anomalies.

2.3 Herding Behavior

2.3.1 Historical Overview

Herding behavior, also known as “crowd behavior”, mainly prompts to the behavior of animals which are very often presented in nature in the form of herds; they relocate, hunt and eat in a collective way. However even in the very early humans’ organized societies, such as in ancient Athens, the power of controlling large amounts of people and manipulating their thoughts has been well documented; as the great ancient Greek philosopher Aristotle said “man is by nature a social animal”, pointing out the need of people to interact and observe each other.

At the end of the 19th century, the French psychologist and sociologist Gustave Le Bon (1895) studied the psychology of crowds and reached up to some very interesting conclusions. According to him, there are three characteristics attributed to people when these become members of a crowd; *absence of responsibility*, *contagion* and *suggestibility*. The first one implies that when an individual becomes part of a crowd, the feeling of responsibility that controls the behavior of an individual disappears; as a result, being a member of a crowd, the individual makes actions he would otherwise not have chosen to. Secondly, *contagion* implies that an individual when being a part of a crowd disregards his personal beliefs and interests and adapts to those of the crowd; the formed belief of the crowd spreads contagiously among its members. Thirdly, *suggestibility* implies that the crowd induces some characteristics into its members; otherwise the latter would not have as individuals and very often these characteristics may be contrary to their interest.

Herding is said to be one of the main causes for the creation of bubbles in the markets; Galbraith (1994) mentioned four cases of economic bubbles where herding behavior played a significant role into their creation. The first one was the “tulip mania”, one of the first “bubbles” in economic history, which took place in the Netherlands in 1637; the mania of people regarding tulip bulbs skyrocketed their contract prices in the first place before seeing them eventually collapsing. The second case, the South Seas’ bubble, took place in England in 1720 and was about a joint stock company that gained the monopoly of trading between England and its South American colonies in return for accumulating the debt of England created during the war; extreme speculation on the stock of the company raised its price to extremely high levels before also seeing it collapsing causing severe losses to its shareholders. Thirdly it was the Mississippi bubble which burst in 1720 as well. Speculation on the stock of the Mississippi Company led the company to spread its profits to its shareholders in forms of paper money. However, the excess supply of banknotes in relation to the gold and silver reserves led to the sharp decrease of the stock price. Last but not least was the famous crash in 1929 where the economic euphoria of the previous years had lead to an enormous rise in stock market prices; the latter sharply dropped, driving many investors to insanity and poverty.

2.3.2 Definition and Sources of Herding

As we discussed in the previous section, individuals, when becoming members of a crowd, change their attitude and often act completely differently than they would if they were to act individually; the driving factors of this phenomenon are the interaction and observation among members of a society. The phenomenon of herding in financial markets has been well documented over the years; financial markets are places where investors interact and observe each other. Moreover, investors are overwhelmed with large amounts of information regarding companies, stock markets and other investors' decisions that can easily mislead or manipulate them and follow wrong trading strategies. According to Hwang and Salmon (2004), "herding arises when investors decide to imitate the observed decisions of others or movements in the market rather than follow their own beliefs and information". There are two different kinds of herding, *spurious* and *intentional* [Bikhchandani and Sharma (2001)]. The first one implies that investors act in the same way not because of imitation of each other but because of the common beliefs they have upon certain events or information, i.e. a decrease in interest rates will make deposits less attractive and investors will prefer investing their money in stock markets. In this case investors are sharing common information about an event which leads to a certain behavior; the latter can be considered as expected. On the contrary, what grabbed the attention of researchers was investors' intentional imitation of other investors' actions; in this case, investors often disregard their own beliefs and information and copy the actions of other investors. The possible explanations of this behavior span across a variety of factors ranging from behavioral to informational and agency ones among others.

As behavioral finance theory posits, investors' behavior is to a large extent influenced by certain psychological biases and heuristics. Prast (2000) suggested, for example, that herd behavior is highly related with *cognitive dissonance*; the latter defined by Festinger (1957) as "Two cognitive elements are in a dissonant relation if, considering these two alone, the obverse of one element follows from the other". In a financial markets' context, *cognitive dissonance* could explain the imitating behavior of investors since the latter feel more comfortable when they know that other investors have made the same choices as they did; thus they herd on their peers' previous behavior and, if the choices made were wrong, they prefer belonging to a group that did the same mistake rather than being alone. Additionally, Prast (2000) suggested *congruity* as a bias inducing herding in investors' behavior. *Congruity* implies that investors react to new information in a biased way; if the new information arrived is not in line with investors' previous beliefs about the information source (this could be a fund manager or an analyst), investors either adjust their decisions towards the information source or the new information itself. Practically, it could be the case that an analyst who made good picks in the past, will keep doing so disregarding new information that would allow him to deviate from his previous choices; a deviating bad choice has a higher cost to the analyst rather than a choice similar to those that performed well in the past, and eventually did not.

One of the most important aspects of herding is the contagion of investors' behavior and decisions; this contagion is often driven by the contagion of media information and the beliefs of other investors. As such, investors feel more comfortable when observing others and performing the same actions as they do; Hirshleifer (2001) described this phenomenon as *conformity*. Moreover, a key characteristic of crowd members is their slow adaptation towards newly arriving information; this phenomenon known as the *conservatism bias*[6] is not met only in herding but in other behaviorally driven patterns of investors such as that of under reaction [Barberis *et al.* (1998)]. Barberis *et al.* (1998) also suggested the *representativeness heuristic*[7] as a driving factor for investors' behavioral patterns; this heuristic can induce herding in investors' behavior when they extrapolate from limited and recent events to imagine patterns that do not exist. What is more, Feng and Seasholes (2004) suggested that investors tend to be more willing to invest into familiar companies in terms of geographical location providing evidence in support of the *home bias*; the latter can

[6] Recall our discussion and the example given in the previous section.
[7] Recall again this heuristic's detailed description in the previous section.

affect investors' behavior and drive them into similar decisions. Conducting their research using data from China, the authors came up with some interesting findings regarding the link of location and correlated trading. Firstly, correlation among investors' trading is more significant when investors are in same location. Secondly, they identify an information asymmetry among investors with those of living closer to a firm's headquarter being able to receive more accurate information regarding the company. Concluding, the authors pointed out the importance of public information upon investors' decisions and suggested that more weight should be given on it when explaining the trading actions of investors.

Herd behavior can also be driven by the *rumor-heuristic* [Buckner (1965)]. Investors, through their interaction with others or through media coverage, are very often affected by rumors, the latter in most of the cases being inaccurate. Individual investors are usually more vulnerable to rumors, especially during crises when panic prevails, whereas professionals being better informed often take advantage (or even spread) the rumors and realize gains from them [Schindler (2007)]; there has been much criticism on hedge funds' speculative actions and their destabilizing role in the markets [Fung and Hsieh (2000)]. Finally, there is the phenomenon of *limited attention* in which investors even though they are exposed to a large amount of information, they pay attention to the more familiar and salient events. Particularly, they tend to overweight certain factors when making investment decisions, such as an analyst's fame, and ignore other more important information [Daniel *et al.* (2002), Hirshleifer and Teoh (2003)].

In the highly competitive context of financial markets, information is most probably the most important ingredient for a successful investment; though many times the gathering of accurate information is both time- and money-consuming for investors.

The latter, particularly those who do not possess sufficient information, may choose to copy the decisions of other investors who are considered to be better informed. Moreover, even investors who do hold their own informational sets often prefer to follow other investors when they feel these have better information than theirs. The choice of investors to free-ride on other investors' decisions eventually leads to a pattern of correlated trading among investors. Researchers have identified this informational asymmetry among investors as a possible source for herd behavior and defined it as *informational cascading*. An *informational cascade* occurs when an investor decides to disregard his own informational set and trade based on other investors' informational sets, the latter reflected through their actions. However, *informational cascades* often play a negative role towards market efficiency. As we already discussed previously, in an efficient market, prices reflect all available information. But since investors ignore their own information, this is not reflected neither on their actions, nor on asset prices. As Hirshleifer and Teoh (2003) posited, this phenomenon causes *information blockages* since not all investors' information is conveyed to the market. To better understand how *informational cascades* work let us provide an example of the real world, as mentioned by Banerjee (1992). Suppose there are two restaurants next to each other, namely A and B, and one hundred persons as possible clients awaiting to dine. Ninety nine of them have an information signal that restaurant B is better than restaurant A and only one's signal indicates the opposite. However, let us suppose that this person gets to arrive first and walks into restaurant A as his signal suggests. The second person arriving will face a dilemma; on the one hand lies the informational signal of the first person suggesting restaurant A being better and on the other hand there is his own signal of preferring restaurant B. These two signals eventually cancel each other out and the rational choice for the second person would be to choose restaurant B. Now up to this point only the information of the first person is conveyed to the population; the second person decided to disregard his own informational set and follow the signal of the first person. The arrival of the third person will end up into the same outcome of the second person. Not knowing that the second person ignored his own signal, he will assume that both previous persons had a signal that restaurant A is better than B. Consequently, he will also end up having his dinner at restaurant A. In the end, everyone will end up at restaurant A event though the aggregate information of the population suggests that restaurant B is better. This example is reflective of how *informational cascades* work and the *informational blockages* that arise in the population. As illustrated, at the end only the signal of the first person is aggregated in the population, whereas the signals of the other persons are kept hidden. Imagine now, that the second person follows his own signal and chooses restaurant B. Upon the arrival of the third person both informational sets of the previous persons are aggregated in the population. In this case it is certain that the third person would end up in restaurant B since his signal would coincide with that of the second person and in the same way the remaining of the persons would choose restaurant B. Summarizing with this example, the key person is the second one; if he decides to follow his own signal and share his information with the rest of population, the latter will also use their own signals. Otherwise if the second person ignores his own signal, an *informational cascade* arises and a herd is created.

It is worth trying to understand why these *informational cascades* occur among investors. Firstly, it might be the case that an investor simply knows his information is not accurate or good enough and free rides on others' information which he perceives as better. Welch (2000) found that the recommendation of an analyst affects the next two analysts' recommendations. Furthermore, he suggests that the lower information aggregation and the higher level of herding that prevail in bullish markets make the later more vulnerable to crashes (increased euphoria in the markets eventually leads to sudden drops in prices). Secondly, it might be too costly to gain accurate information rather than to just follow what others do, which is costless. Calvo and Mendoza (1997), Calvo and Mendoza (2000) studying investors' diversification, found that it is less costly for them to "herd" on other investors' decisions than acquiring their own information. In their argument, the researchers used the example of the Mexican crisis in 1994 where similar countries as Mexico such as Chile, Brazil, etc. were severely impacted by investors' herd behavior. More specifically, investors instead of studying each country's specific characteristics and fundamentals, they simply assumed that countries similar to Mexico, i.e. Latin countries, would follow; as a result after the sharp devaluation of the Mexican peso, the currencies of these countries were also devaluated. Alike then, someone could identify a similar case in the very recent European debt crisis. Following Greece's entrance to the European stability mechanism (ESM hereafter) and the international monetary fund (IMF hereafter) investors assumed that all south European countries would follow this path. The result was the spreads of all South European countries had a huge increase and eventually lead some other members of the E.U., namely Ireland and Portugal, into the ESM. The intuition behind this is that investors' actions were driven by imitating each other rather than by examining each country's specific characteristics.

Apart from the informational reasons underlying herd behavior, an important role to the formation of this behavior is played by the principal-agency problem between the market professionals (fund managers) and their employers (asset management companies). Relative research, supporting the source of *professional reasons* regarding herd behavior, suggests that fund managers may be reluctant to deviate from the market consensus in order to protect their own interests, even though this reluctance is against their clients' best interest. More specifically, it is very often the case that investment managers are evaluated according to their performance; the latter measured in comparison to the performance of their peers. If the fund manager realizes some losses which are shared with the rest of the market, then "bad luck" or other factors can be blamed by him. Thus, it seems more secure for some professionals not to deviate from the market consensus, even though their private information indicates they should. To make it clearer, as Scharfstein and Stein (1990) suggested, it might be the case that less capable managers often copy the decisions of their peers considered as "good" in order to update their status to those of the "good" ones. The "good" professionals, in turn, may also herd in order to protect their high status; as mentioned previously following the market trend is safer than deviating from it since the impact of a possible loss when acting alone is higher than the gain deriving from it.

Similarly, an additional source of herd behavior is also considered to be *reputational reasons*. In their seminal paper, Scharfstein and Stein (1990) stated that professionals often ignore their own information and copy each other due to reputational reasons. To make their argument clearer, the provided an example referring to the bull market during the mid 1980's. Back then, the majority of the fund managers believed that stock prices were already too high and that the market's chances to go down were substantially more than those of going up. Nevertheless, very few of these professionals were willing to sell their stocks because of the small chance of the prices going up and be let alone missing the ride; as the researchers suggested, professionals are willing to realize losses if the rest of their peers do the same than being the ones who might lose a possible ride on prices. Evidence in support to the previous statement was provided by Graham (1999) who showed that analysts are more than willing to sacrifice some future gains in order to protect their reputation. As Welch (2000) posits, analysts are significantly influenced by each other and herd, especially during upwards markets, towards the market consensus. In addition, Trueman (1994) examining analysts' forecasts found that analysts herd in their estimates about future returns and this could be due to reputational incentives implying that it is better for them to make forecasts that meet the market's prior beliefs and expectations. This behavior creates a bias on analysts' forecasts affecting the price changes upon earnings announcements.

Contrary to the assumption of the behavioral finance camp regarding investors' heterogeneity in terms of rationality, another interesting opinion regarding the possible sources of herd behavior is considered to be the *relative homogeneity* of the investors. However, the homogeneity implied by this view regards the professional investors, i.e. fund managers. The latter share some common characteristics that may lead them to a convergent behavior. Let us take for example the investment professionals, the majority of them being graduates of business schools; they have been taught to evaluate investment opportunities in a similar way or to use the same tools and techniques in order to apply their trading strategies. In addition, as mentioned before, fund manager's performance-based compensations may drive them to act in the same way.

Another view that regards professionals again is that the latter often prefer to trade on stocks with certain characteristics; this phenomenon is known as "characteristic herding". More specifically, this view supports that investors are attracted by stocks with certain features such as size, industry or past performance [Falkenstein (1996)].

Holmes *et al.* (2011) suggested that the last two sources of herding described above are related to unintentional herding, in the sense that they give rise to parallel behaviour, yet not due to intent.

2.3.3 Empirical Findings on Herding

Research on herd behavior can be divided into two areas. On the one hand is the research area examining herding using micro-level data (using portfolio accounts e.g. of mutual funds or individual investors) and on the other hand is the area examining herd behavior at the aggregate market level (using aggregate indicators, such as prices). Starting with the first one, the seminal paper was that of Lakonishok *et al.* (1992) examining the behavior of institutional investors, in terms of herding, and its impact upon stock prices. More specifically, the researchers applied their own methodology (LSV) using quarterly data from 1985 till 1989 from 769 US tax-exempt funds (mainly pension funds), the latter managed by 341 fund managers. Their findings indicated some evidence of herding in small capitalization stocks whereas in larger stocks (which accounted for 95% of the stocks traded by pension funds) the level of herding was significantly lower. Similarly, Grinblatt *et al.* (1995) also examined the US fund market and found evidence in support of herd behavior's existence in that market. Particularly, their sample consisted of quarterly data for 155 mutual funds for the period between 1974 and 1984. In addition to the presence of herding, the researchers also found evidence of momentum trading from the fund managers. Moreover, herding was predominantly stronger in growth and income funds; this implies that growth funds hold limited information about their stocks, the latter being relatively small, and as such they have more incentives to herd. Similarly, income funds demonstrate a tendency to hold large stocks (value stocks); as such they tend to herd on that kind of stocks.

Wermers (1999) examining again the U.S fund industry found supporting evidence to the existence of herd behavior. More specifically, for a period of 20 years (1974-1994) it was found that herding was stronger in stocks of small firms and stocks that had high past returns. In line with Grinblatt *et al.* (1995), he also found higher level of herding in growth funds. Further research by Nofsinger and Sias (1999) on the U.S market found herding to be present. Testing for herding on behalf of institutional and individual investors in the New York stock exchange for a twenty-year period (1977-1996), the authors found evidence of herding; however the impact of institutional herding upon stock prices was higher than that of individual herding due to their higher leverage in the volume.

Being concentrated into the U.S. market so far, relevant research on emerging markets has also provided supporting evidence relative to the existence of herd behavior. For instance, Choe *et al.* (1999) examined the impact of foreign investors upon the Korean market during the 1997 Asian Crisis. More specifically, they used data of foreign investors' holdings on 414 stocks for the period 1996-1997. They found that investors significantly herded before the crisis, whereas there was little evidence of herding during the crisis. Furthermore, Kim and Wei (2002a) also examined the behavior of foreign institutional and individual investors in the Korean market. In their paper, the authors examined data from 1996 till 1998, capturing the Asian Crisis of 1997. Their unique database contained important information for each stock listed in the Korean Stock Exchange; particularly, it contained the month-end holding in each stock, the nationality of the investors holding each stock, whether an investor was domestic or foreign and also the type of the investor (individual or institutional).

The investors, 2594 in total (735 individuals and 1859 institutions), were classified as domestic institutional investors, foreign institutional investors, domestic individual investors and foreign individual investors. Their findings reveal evidence of significant herding among all categories of investors with the exception of domestic institutional investors. In addition, foreign investors (both individual and institutional) were found to always herd more than their domestic counterparts. Finally, their results indicate that individual investors herded more than institutional investors. Kim and Wei (2002b) reached similar conclusions by comparing the behavior of offshore funds and onshore funds; the researchers found that both types of funds did indeed herd around and during the Asian crisis in the Korean market.

Sias (2004) examined the U.S market once again; however he used a new methodology in contrast to the previous studies that used the LSV measure. This time, by using quarterly data of 894 institutional investors for the period 1983-1997, the author found that institutions do herd indeed and that they exhibit momentum trading tendencies, with the latter though not being the driving force behind herding.

Voronkova and Bohl (2005) examined the behavior of pension fund managers in another emerging market, namely Poland. More specifically, the authors used semi-annual data from 1999 to 2002 for 17 pension funds (the small number of pension funds indicates the high level of concentration in this pension fund market). After classifying the stocks according to size, past performance and industry, the authors found significant herding among pension fund managers, particularly for stocks of small size and specific industries. The study about U.K. fund managers by Wylie (2005) also provided evidence in support of herd behavior. More specifically, the author used semi-annual data for 268 U.K. mutual funds for the period 1986-1993. His results indicate that level of herding in the U.K market is similar to that of the U.S and that it is more prominent for larger and smaller firms. Furthermore, U.K. fund managers were found to exhibit contrarian trading strategies in contrast with their counterparts in the U.S. who were found to be momentum traders in previous studies.

Kim and Nofsinger (2005) examined institutional herding in Japan, in which many firms are members of intra-firm business networks (*keiretsu)*. The authors posited that herding found in their empirical results was lower than that indicated for the U.S. market in similar studies; however the impact of herding upon stock prices was substantially higher in Japan than in the U.S. and especially for *keiretsu* firms. What is more, their empirical evidence suggests that *keiretsu* firms have better information (inside information due to its interrelationships among each other) than individual firms and trade based on their information signals rather than on past performance. To that end, *keiretsu* firms were found to herd less than non *keiretsu* firms.

An interesting study for the Taiwanese market is that of Chen and Hong (2006), which examines the behavior of institutional investors contingent upon analysts' earnings' announcements. What distinguishes their study from others for the specific country is that it uses high frequency (daily) data of institutional holdings for the period 2001-2003. What the authors found was that during the event period institutional investors were more prone to "buy" herd in large firms and "sell" herd out of small stocks. Furthermore, there was more herding in stocks with certain characteristics (high beta, high return-on-equity ratio, high liquidity and volatility). Additionally, they found that the changes of institutional ownership that were taking place during the day were due to herding. Finally, the authors posited that institutional investors appeared to be informative when buying stocks but not when selling them.

Walter and Weber (2006) examined the behavior of German mutual fund managers for the 1998-2002 period with a database consisting of semi-annual portfolio holdings of 60 mutual funds. The researchers found significant levels of herding for the German market, notably higher than those found for the U.S and the U.K. markets from previous researches. Furthermore, Do *et al.* (2008) tested for herding in the Finnish market with their database involving ownership records (from both domestic and international investors – institutional as well as individual ones) of 176 stocks for the 1995-2004 period. The researchers found that institutional investors exhibited herding and that domestic investors (both institutional and individual) herd more than their international counterparts.

Another research by Lin and Swanson (2008) examined the behavior of foreign investors (from 38 emerging and developed countries in total) in the U.S market for the period between 1990 and 2003. Applying both the LSV and the Sias (2004) methodologies, they found weak evidence of herding from foreign investors buying or selling stocks within a month; however, they did find that foreign investors, taken at the country-level, follow each other into the examined market over adjacent periods. Moreover, Choi and Sias (2009) using quarterly data for the 1983-2005 period found that fund managers significantly herded over industries in the U.S. market and that they also style-herd among each other.

Using quarterly data for the 1999-2005 period from the Shanghai and Shenzhen stock exchanges, Zhou and Li (2009) found evidence in favor of herd behavior among Chinese institutional investors. Hung *et al.* (2010) using quarterly data of Taiwanese mutual funds from 1995 till 2006 came to two conclusions. First, fund managers in Taiwan do herd and secondly the authors posit that the fund managers in this specific market tend to pick illiquid stocks of small firms with low B/M ratio and low past returns. Another research for Taiwan by Chang (2010) revealed similar findings. Using weekly order flow data for the 2000-2005 period, he found evidence of herding on behalf of both individual and institutional traders.

Jeon and Moffett (2010) used data for Korean firms for the 1992-2003 period to examine the behavior of foreign investors in the Korean market. Their findings indicate a strong relationship among Korean stock returns and changes in foreign ownership of stocks. Additionally, foreign institutional investors were found to buy/sell stocks which domestic investors were selling/buying.

A more recent study about the U.S. market by Liao *et al.* (2011) used monthly data of 770 funds and 527 stocks for the 2003-2007 period to examine the link between investor sentiment and herding. The results indicated that investor sentiment can explain institutional herding, especially on the sell-side. Finally, a research by Holmes *et al.* (2011) tested for the herd behavior of institutional investors in Portugal (which is a very concentrated market). Their data consisted of monthly portfolio holdings for 45 institutional investors and 80 stocks for the 1998-2005 time period. Their findings indicate significant herding among Portuguese fund managers, which was found to be intentional in nature and driven predominantly by reputational considerations, while interacting with window-dressing.

All the relevant studies using micro-level data provide us with some very interesting findings regarding the herd behavior of institutional investors. First of all, empirical evidence suggests that herding is more prominent among larger and smaller sized firms. In the first case, this could be due to the fact that institutional investors most likely trade on large cap stocks. Many times, institutional investors are required from regional regulatory frameworks to invest in firms with specific characteristics. For example Voronkova and Bohl (2005), as well as Olivares (2008), outline that Polish and Chilean pension funds respectively are obliged from the countries' legislations to exhibit a minimum rate of return; as a result pension fund managers would invest in more secure stocks, these mostly being the large stocks ("blue chips"), in order to meet this requirement. Hence, the imposed regulatory restrictions can grandfather herding among pension fund managers since the latter choose to trade in stocks with similar profiles. Additionally, it is often the case that many funds are linked to specific market indices and assessed using these indices as benchmarks; being this the case it goes without saying that their fund managers will mostly trade on the stocks more related to this index (e.g. if a fund is linked to the DAX index, it is most likely that the fund will load its portfolio heavily towards DAX-stocks). So, the intuition behind this is that since the fund managers are assessed through an index benchmark, they will hold an index mimicking portfolio of stocks, the latter usually being the largest ones (for blue-chip indices).

In the second case, that of small stocks, this could be due to the lack of sufficient amount of information regarding these stocks. It is often very expensive and time consuming for investors, or even the media, to monitor these companies; as a result this lack of information could induce herding among investors on these specific firms. Moreover, the low liquidity of small stocks makes them more vulnerable to mispricing and as Wermers (1999) suggested, institutional investors, when trading in small firms, are more willing to ignore their private information and follow the herd.

Information asymmetries could also be the reason why herding is found to be stronger in emerging markets than developed ones, like the U.S. and their Western European counterparts. Since these markets often lack an efficient regulatory framework, it is often the case that the quality of information in these countries will be very low. It is the lack of credibility in the market environment of emerging countries that discourages institutional investors from basing their trading on the information available and leads them to herd; in the end, if institutional investors cannot trust the market environment of these countries, why should they trust their information?

Apart from the research based on micro-level data, there also has been substantial amount of research based on the aggregate level of markets examining herd behavior. Christie and Huang (1995) were the first researchers to do so by examining the U.S market. Their database consisted of daily data for the period between 1962 and 1988 and monthly data for the period between 1925 and 1988 for US firms. To examine investors' herd behavior, the authors used the cross-sectional standard deviation of returns; their empirical results however did not indicate any herding across all industries examined both at the daily and the monthly frequency. Chang *et al.* (2000) investigated the presence of herding in five markets [U.S.(1963-1997), Hong Kong(1981-1995), Japan(1976-1995), South Korea(1978-1995) and Taiwan(1976-1995)]. The authors using their own methodology, based on that of Christie and Huang (1995) but allowing for market non-linearities, found mixed evidence of herding. More specifically, in the developed markets of their sample (US; Hong Kong; Japan) there was no evidence of herd behavior; however in South Korea and Taiwan there was strong evidence of herding during both extreme positive and extreme negative market conditions. In addition, Hwang and Salmon (2004) in their turn proposed their own methodology that captures factors such as changes in fundamentals and time series volatility among others and tested for herding in the U.S and the South Korean markets for the period between 1993 and 2002. According to their empirical results, there is significant herding in both the U.S and the Korean markets; what is more, herding appeared to be more prominent in periods before and after crises than during them.

In the case of the Italian market, Caparrelli *et al.* (2004) examined the presence of herding during the period between 1988 and 2001. By using both methodologies of Christie and Huang (1995) and Chang *et al.* (2000) the authors found the second model fits better the Italian market and explains the presence of herd behavior during extreme market conditions. Feng and Seasholes (2004) examined investors' behavior in the Chinese market for the 1999-2000 period and found that herding is highly related to the location of investors. Hence, the trades of investors living close to a firm's headquarters bear higher correlation when new information regarding this firm arrives in the market; thus implying that herding is caused, to a high degree, by the home-bias. In another study for the Chinese market by Demirer and Lien (2005), it was found that herding is more prominent during up-markets than down-markets, with the exception of Financials. Additionally, Demirer and Kutan (2006) examined 375 Chinese stocks for the 1999-2002 period and found no evidence of herding.

Henker *et al.* (2006) were the first to examine the presence of herding at the intraday level, besides the daily level. The market tested was Australia and the data used covered the 2000-2001 period for the 200 largest shares of the Australian Stock Exchange. After applying both methodologies of Christie and Huang (1995) and Chang *et al.* (2000), the authors concluded that there was no herding at the market wide level or across industries. Moreover, Tan *et al.* (2008) by further examining the Chinese market and by using daily, weekly and monthly data from the Shenzhen and Shanghai Stock exchanges for the total amount of stocks listed in them and a time period of approximately nine years (1994-2003) found strong evidence of herding. In particular, their findings suggest that herding is a short-run phenomenon since it was stronger at the daily level than at lower frequencies. Blasco and Ferreruela (2008) examined the presence of herding behavior in an international context (the markets examined were France, Germany, Japan, Mexico, Spain, the U.S. and the U.K.). The authors used daily data for the 10 most traded stocks of each market from 1998 to 2004 and applied a modified version of the Christie and Huang (1995) methodology. Their results indicated significant evidence of herding only for Spain, whose significance persists throughout both turbulent and non-turbulent market conditions.

Caporale *et al.* (2008) examined the Greek market for herding in respect with the stock market crash which occurred in 1999. Using daily, weekly and monthly data for the 1998-2007 period and applying the herding measures of Christie and Huang (1995) and Chang *et al.* (2000), the authors found significant herding in the Greek market for the whole sample period. Furthermore, herding was stronger at the daily level than for lower frequencies, indicating that herding is a short-run phenomenon. What is more, herding was found to be more prominent during up-markets and was also present before and during the crisis of 1999, decaying since 2002 due to the changes of the regulatory framework in the Greek stock market.

Dorn *et al.* (2008) examined the presence of herding in the German market by using data from one of the country's three largest brokerage firms. More specifically, their sample consisted of 37.000 client-accounts for the 1998-2000 period; their results provided evidence of herding among Germany's retail investors.

Goodfellow *et al.* (2009) using daily data from 1996 till 2000 examined the presence of herding in the Polish market. One of the features of this market is the existence of two trading platforms in its stock exchange; one of them is dominated by institutional investors and the other by the individual ones. This allowed the authors to distinguish the trades of each group and reach to conclusions for each group separately. What was found was that the platform primarily used by the individuals was more volatile and that there was significant herding in it. According to the authors, this was due to the informational asymmetries of the Polish market, with the individual investors being more heterogeneous and less informed than the institutional investors. Additionally, the herd behavior found was more prominent during down-markets rather than up-markets and the authors attributed this phenomenon to investors' sentiment; implying that investors are more confident on their own beliefs when prices rise. Chiang *et al.* (2010) examined herd behavior across 156 industries in five countries (the U.S, the U.K, Japan, Hong Kong and Germany) from 1987 till 2007 at the daily frequency by applying the Chang *et al.* (2000) herding measure. In all markets examined, the authors found significant evidence of herding. Another research by Demirer *et al.* (2010) examined the Taiwanese market for the existence of herd behavior using daily data of 689 stocks classified in sectors, for the period 1995-2006. By applying three different methodologies, namely these suggested by Christie and Huang (1995), Chang *et al.* (2000) and Hwang and Salmon (2004), they found significant evidence of herding. However, the first methodology used failed to provide evidence of herding across all sectors but that of Electronics. However, the following two methodologies suggested that herding was present across all sectors examined. Their findings provided further support to the view that the assumption of the linear relationship between the dispersion of the returns and the market returns does not hold and that the models that account for non-linearities in the returns are more successful in capturing herd behavior. Fu (2010) using the methodologies of Christie and Huang (1995) and Chang *et al.* (2000) examined monthly data of Chinese companies for the period 2004-2009. Their results indicated weak evidence of herding with the latter being more present for low-turnover stocks. In addition, investors were found to herd more during down-market conditions.

Summarizing the findings of the research regarding herding at the aggregate level, there are three important issues arising from it. One of them is the absence of herding during extreme market conditions; investors seem reluctant to herd when there is turbulence in the market. Studying the methodologies used for the examination of herding, we can see that the method of Christie and Huang (1995) is by construction restricted to measuring herding only during periods of market stress; leaving outside non-extreme market states. In contrast, Hwang and Salmon (2004) argued that herding is more prominent during calm markets. The intuition behind this is that during periods of extreme market conditions, the high volatility that prevails in the market prevents investors from seeing clearly the direction of the market; hence it is very difficult for them to herd towards the market direction and this is the reason why the empirical results do not provide strong evidence of herding during extreme market conditions. On the contrary, during tranquil states of the market investors have better insight of the market direction and as such can more easily herd towards it.

Another important finding for the relevant research on herding is that the models accounting for non-linearities between the dispersion of returns and the market returns perform better in explaining herd behavior than the models following the efficient paradigm in finance and assuming a linear relationship between them instead. The presence of non-linearities in the market could be due to market microstructure reasons (short sale constraints, information disclosure policies, etc.) [Antoniou *et al.* (1997)]. Another possible explanation for the non-linearities could be the overreaction and under reaction of the market to news [DeBondt and Thaler (1985)] and how the market prices are corrected; it s more likely that the complex environment of the market imposes a non linear behavior on asset prices. Market imperfections are also relevant here; for example, the presence of high transaction costs in the market may prevent investors from trading, hence information is not conveyed into the market efficiently and since herding is primarily an informational issue it can be affected by the market's non-linearities. Additionally, non-linearities could take place if the frequency of important information (earning announcements) is lower than the frequency of the prices used [Antoniou *et al.* (1997)]. Finally, empirical evidence suggests that the assumed rationality of investors portrayed by the traditional paradigm of Finance does not hold, and if this is the case the linear relationship between risk and return which linear models use may not be efficient [Antoniou *et al.* (1997)]. In the case of examining herd behavior, empirical evidence reinforces the above mentioned views since the studies using non-linear models such as that of Chang *et al.* (2000) provide more accurate results than the studies using the linear model of Christie and Huang (1995).

Finally, relevant research has indicated that herding is more prone in emerging markets [Chang *et al.* (2000), Goodfellow *et al.* (2009) and Demirer *et al.* (2010) among others) than developed ones. As mentioned previously, this could be due to informational asymmetries and the lack of an efficient regulatory framework in developing markets. However, another reason could be thin trading; by this term we define the phenomenon where stocks with low volume of trading do not see their prices changing for several days and this could lead into spurious results when performing econometric work, as thin trading can induce serial correlation in returns [Antoniou *et al.* (1997)]. Empirical evidence on the relationship between herding and thin trading reveals that the latter does indeed impact upon the former. Evidence in support of this view is provided by the studies of Kallinterakis and Kratunova (2007) and Andronikidi and Kallinterakis (2010) for the Bulgarian and Israeli market respectively. In both cases, the authors found that correcting for thin trading had an impact on both the significance and the structure of the level of herding.

2.4 Feedback Trading

2.4.1 Definition and Sources of Feedback Trading

Feedback trading constitutes a celebration against the weak form of market efficiency; the latter assumes that there can be no abnormal gains by using historical prices of stocks. More specifically, what is all about feedback trading is that investors engaging in such behavior follow past trends of stock prices in order to achieve profit from them. Investors usually involve themselves in such behavior because they believe that past stock prices reveal information not yet reflected in prices. Feedback trading can be positive, where investors buy/sell when stock prices rise/drop, or it can be negative in which case, investors buy/sell when stock prices drop/rise.

The engagement of investors in feedback trading can usually be motivated through technical analysis, a tool for identifying hidden information in past prices and discovering patterns that can be used to achieve profit. In addition, investors who use technical analysis may have an informational disadvantage relative to their peers or it might be difficult for them to monitor other investors' actions; so technical analysis allows them to monitor the actions of other investors, reflected through stock prices, at the aggregate level. Relevant research documented evidence for the profitability of trading strategies based on technical analysis; more specifically the studies by Brock *et al.* (1992), Antoniou *et al.* (1997), Fernández-Rodríguez *et al.* (2000) and Wong *et al.* (2003), among others, indicated that the use of historical prices can, in certain cases, be a profitable technique for trading in stock markets.

Additionally, positive feedback trading is associated with some trading strategies, one of them being "momentum trading". The latter suggests that it can be more profitable for investors to buy stocks that have previously performed well and sell the stocks that have performed the worst. Momentum trading is linked with the under-reaction hypothesis of DeBondt and Thaler (1985) and empirical evidence of its profitability has been provided by Jegadeesh and Titman (1993), Grinblatt *et al.* (1995) and Jegadeesh and Titman (2001).

Another trading strategy, this time associated with negative feedback trading, is the "contrarian strategy". The latter is linked with the "overreaction" hypothesis developed by DeBondt and Thaler (1985) who found in their seminal paper that past (3-5 years) losers were outperforming past (3-5 years) winners in the following 1-3 year period. Relevant research by Mun *et al.* (1999) and Galariotis *et al.* (2007) provided evidence in support of contrarian strategies' profitability.

The possible sources of feedback trading include behavioral biases and heuristics, as in the case of herd behavior previously discussed, and informational reasons. Starting with the behavioral elements that can lead investors to feedback trade, two of them are the *representativeness heuristic* introduced by Kahneman and Tversky (1973) and the *conservatism bias* of Edwards (1968), both of them having been linked to feedback trading by Barberis *et al.* (1998). Since feedback trading involves trend chasing, the *representativeness heuristic* can lead investors to perceive price patterns as trends and ride on them. Inversely, the *conservatism bias* causes investors to be reluctant in updating their beliefs according to recent news, thus leading prices to underreact.

Shefrin and Statman (1985)'s *disposition effect* is another candidate for explaining feedback trading behavior, and particularly negative feedback trading. As discussed previously, the *disposition effect* is the tendency of investors to sell previous winners and hold onto past losers. This phenomenon is highly linked to the prospect theory of Kahneman and Tversky (1979) and how people perceive their gains and losses, with investors being reluctant (suffer more) in realizing any losses (*loss aversion*). Relevant to the *disposition effect* is also *mental accounting*, a term discussed by Shefrin and Statman (1985) suggesting that investors prefer to hold onto past losing stocks since if they keep them they do not get to realize losses as would have been the case of selling them.

Another bias linked to positive feedback trading is *overconfidence* [Odean (1998)] which suggests that investors tend to overvalue their own knowledge and skills even though there might be signals in the market indicating that they are wrong. It is usually the case than an overconfident investor trades more than others - having high confidence in his skills and private signals [Odean (1998)] - and his overconfidence can lead them to overreact to their signals. With prices moving in the direction of his trades, this further boosts his overconfidence - and his overreaction to forthcoming signals arriving at the market – as he attributes any gains to his own skills disproportionately [Daniel *et al.* (2002)].

Apart from the behaviorally driven reasons leading to the use of feedback trading by investors, there also are reasons whose source is based upon an informational point of view. We will try to address this issue by examining it using two cases; the case of *informational superiority* and the case of *informational inferiority*.

In the first case, we consider professional investors, i.e. fund managers, to lie in this category; these investors are perceived to have a superior informational set that allows them to better foresee the market direction than the simple individual investors. Recall now what the Efficient Market Hypothesis postulates regarding these investors; according to it, these investors are the "arbitrageurs" who will drive prices back to their fundamental values in case of any mispricing. However, as relevant research has shown this might not be the case since it is not always to the arbitrageurs' best interest to intervene in the market. De Long *et al.* (1990b) suggested that the increased risk induced by the actions of noise traders bounds rational arbitrageurs from taking actions to correct prices since they are unwilling to undertake the additional risk and the higher underlying cost. In fact exactly the opposite can also be true; De Long *et al.* (1990a) explained how the better informed investors, "rational speculators", can actually strengthen the positive feedback trading behavior of the uninformed investors ("noise investors"). The superior information that rational speculators possess allows them to realize which stocks are possible candidates for positive feedback trading and take early positions on them. This action increases the prices of the chosen stocks and creates a trend and noise investors in their turn ride the trend and further increase the stock prices. At the end, due to their superior information rational speculators sell their stocks at their peak and realize their profits; stock prices begin to fall and noise traders suffer their losses. To better explain the previous argument and how this works in the real market suppose that a rational speculator knows some information about a company will come on time (t) and buys its stock at time (t-1). This action increases the price and noise traders follow the trend buying stocks as well and further pumping the price; when information arrives in the market at (t) prices have already overreacted and the rational speculator knowing the real value of the stock starts selling his stocks and at the same time he takes a "short" position on it in order to achieve additional gains from the upcoming drop of the price. Noise investors in their turn, thinking that the trend is over, start to sell their stocks and when the price reverts to its fair value the speculator enjoys his profit. This kind of behavior by rational speculators and particularly hedge funds has been blamed for the creation of bubbles in the market; for example, there has been a research by Brunnermeier and Nagel (2004) examining the behavior of hedge funds during the technology bubble (NASDAQ stocks) that took place in 1999. More specifically, the authors using data of hedge funds' portfolio holdings for the 1998-2000 period found that the technology stocks amounted to a high percentage of the hedge funds' portfolios prior to the burst of the bubble. During the latter, hedge funds were found to ride on it and just before the bubble burst they unloaded their stocks. What we can learn from this paradigm is that professional investors have the ability to time the market, and this could be due to their superior informational foresight. Andergassen (2005) also suggests that it is optimal for rational speculators to ride on the bubble since in this way they can maximize their profits.

On the other hand, there are investors in the market that lie in the second case mentioned above, that of *informational inferiority*. As the meaning of the term implies, these investors do not have the quality of information or the access to it as their professional counterparts. In order to understand how this informational mismatch can induce feedback trading let us elaborate on the case of domestic and overseas investors. It is clear that the latter cannot possibly have the level of information that their domestic counterparts do; as such they can use the stock prices as a ruler for their investment decisions. In fact, Brennan and Cao (1997) posited that there is a positive relationship between international portfolio flows to a country with that country's stock returns. The authors by examining data from U.S investors' purchases in four developed and sixteen emerging markets found that there was significant positive feedback trading strategies from the investors examined; investors were buying when stock prices in a market increased and they were selling when the prices were falling. The empirical results from this study showed that such kind of trading activity was more prone in emerging markets; nevertheless it was also present in developed countries as well. The intuition behind their results is that the investors investing in a foreign country have an informational gap in relation to their domestic counterparts and they are trying to fill this gap by observing the price patterns in order to translate them into informational signals. The previous mentioned research came to provide supporting evidence to another research, namely that of Shukla and van Inwegen (1995) who compared the performance of U.K. fund managers investing in the U.S. market with that of U.S fund managers investing domestically. Their results indicated that the U.S funds managers outperformed their U.K. counterparts for the 1981-1993 period and the authors attributed this performance dissimilarity to the informational gap between the two parts. Moreover, another study by Shiller *et al.* (1996) examining the causes of the Nikkei crash in the early 1990s revealed a very important and relevant to our discussion finding; by comparing the earnings' forecasts from both the Japanese and the U.S. analysts, they found that there was a significant variation between them, signaling in this way the different level of informational sets the two parts possessed.

A similar case where the *informational inferiority* of investors could lead to the use of feedback trading strategies is when they trade in stocks of small size firms. As discussed previously in this thesis, there is a significant difficulty and a higher cost involved when investors are trying to monitor small size firms as opposed to larger firms. As such, it is often the case that investors cannot have the best quality of information regarding these companies and in their effort to do so, they often rely on the patterns of their stock prices to draw information from them. Here is where the feedback trading strategy enters the picture; investors often perceive the price of these stocks as informative of their fundamentals. If there are some investors buying a particular stock, then they must know something about the company that justifies the increase of the stock price - and in order to take advantage of the perceived information too they ride on the bandwagon even if there is no actual reason/information underlying the rise of a stock price.

Investors may further resort to feedback trading due to reasons related to their observational learning. For the individual investor the market entails high complexity amplifying uncertainty in their mind; as uncertainty in the market grows, so does the need for tools to make sense out of this chaos. Feedback trading can function as such a tool (a "heuristic"), since prices constitute a noisy statistical summary [Hirshleifer and Teoh (2003)] of the underlying trading activity. Therefore, instead of having to observe their peers individually, investors can feedback trade if they believe prices to provide them with valuable information on the aggregate market activity [Vives (1993), Cao and Hirshleifer (1997)].

2.4.2 Empirical findings on feedback trading

In line with the relevant research on herding, feedback trading has been examined at both the micro (funds) and macro (aggregate market) levels. In fact, the two subjects appear to be somewhat interrelated since it is quite often the case that researchers test for herding and feedback trading at the same time.

Beginning with the empirical evidence of feedback trading at the micro level, the seminal paper was that of Lakonishok *et al.* (1992) examining the U.S. market for the 1985-1989 period; using a sample of 769 pension funds (quarterly data) and their own methodology, they found weak evidence of positive feedback trading which was more prominent for small size stocks. Similarly, Grinblatt *et al.* (1995) using quarterly portfolio holdings from a sample of 274 U.S. mutual funds for a ten-year period (1974-1984) reported that there was evidence of momentum and contrarian trading techniques from the fund managers examined; however the level of feedback trading resulting from these techniques was quite low. Another research by Wermers (1999), using data from U.S. mutual funds for the 1975-1994 period, provided evidence that growth funds tended to exhibit more positive feedback trading compared to other fund-types; it is often the case that growth funds invest in stocks of small size companies, as such since they do not possess enough information on them they draw information on them through their price patterns. Nofsinger and Sias (1999) testing the behavior of U.S. mutual funds for a 20 year period (1977-1996) found evidence in support of institutions' feedback trading through the use of momentum strategies. However, contrary to the previous researches is that of Gompers and Metrick (2001) which used quarterly data of U.S. mutual funds for the 1980-1996 period and found no evidence of feedback trading by institutional investors when controlling for the size of the stocks. Testing for the U.S. market once again, Badrinath and Wahal (2002) used quarterly data of mutual funds' portfolio holdings for the 1987-1995 period to identify any possible feedback trading behavior; their results indicated that fund managers exhibited both momentum and contrarian strategies. More specifically, there was evidence in support of momentum trading when institutional investors entered a stock whereas in the case of exiting a stock or adjusting their current holdings there was evidence of contrarian strategies.

So far we mentioned the relevant research on feedback trading regarding the U.S. market. Nevertheless, there is also quite a lot of research regarding other markets as well, both developed and emerging ones. Brennan and Cao (1997) examined the behavior of U.S. investors when investing in four developed and sixteen emerging countries and found that there was significant positive feedback trading on behalf of them in the sample examined. Choe *et al.* (1999) examining the Korean market during 1996-1997 found that foreign investors were involved in significant positive feedback trading before the Asian crisis in 1997; however during the crisis, the level of positive feedback trading was significantly lower. Grinblatt and Keloharju (2000) examined the Finnish market by using a unique database of daily institutional and individual holdings for the 1994-1996 period; their results produced some interesting findings. More specifically, foreign and domestic institutional investors (the "sophisticated" investors, as the authors suggested) exhibited momentum strategies whereas the domestic individual investors were more prone to contrarian strategies. Another research about the Korean market and the behavior of its investors during the Asian crisis' period, this time by Kim and Wei (2002b), provided evidence regarding the use of feedback trading by offshore funds. First of all, the authors divided the sample period into three sub-periods; pre-crisis, crisis and post-crisis. During the pre-crisis and crisis periods there was no feedback trading, either positive or negative, on behalf of offshore investors; however there was some evidence of contrarian strategies in the post-crisis period. Secondly, the authors found that funds from the U.S and the U.K. exhibited significant feedback trading in all sub-periods; in the pre- and post-crisis periods they were exhibiting contrarian strategies whereas during the crisis there was significant positive feedback trading. What is more, the other Europeans funds exhibited similar behavior with their U.S/U.K. counterparts. Finally, the funds from Hong Kong and Singapore were found to pursue positive feedback trading strategies during the crisis; the latter are not obliged to pay capital gains taxes and as such this could lead to a more aggressive trading from their behalf.

Kaminsky *et al.* (2004) examined the behavior of U.S. investors in a series of emerging markets; the period examined was from 1993 till 1999 and their database consisted of 13 funds investing in the Latin American markets. Their empirical findings revealed a strong tendency for momentum trading from all funds examined and in both crisis and non-crisis periods; however momentum trading was more significant during crisis-periods. Voronkova and Bohl (2005) examining the behavior of 17 pension funds from 1999 to 2002 for the Polish market found significant positive feedback trading with pension funds' managers selling small size stocks that did not perform well previously and buying stocks of larger stocks that performed well in the previous quarter. Walter and Weber (2006) examined the German mutual fund market using a sample of 60 mutual funds for the 1997-2002 period; their results indicated that fund managers in Germany exhibited positive feedback trading in the short run. Another research by Do *et al.* (2008) for the Finnish market during the 1995-2004 period, also provided evidence in support of feedback trading. More specifically, the authors found that overseas institutions investing in Finland were prominent in positive feedback trading. Finally, Jeon and Moffett (2010) also found significant levels of intra-year positive feedback trading on behalf of foreign investors in the Korean market for the 1992-2003 period.

One issue arising from the research regarding feedback trading at the micro level is that feedback trading is more prominent in emerging markets than in developed ones.

This could be due to the lack of information that institutional investors possess about these countries. As in the case of herding discussed previously, the regulatory framework of these countries does not allow foreign investors to have the same quality of information with their domestic counterparts. As such, foreign investors resort in observing the patterns of stock prices in order to identify their informational content. Similarly, as relevant research suggests, feedback trading has been found to be stronger in stocks of small size firms than in larger ones. Again, due to the limited amount of information available for small firms, it is very difficult for large institutional investors to monitor them; as such since prices are indicative of information it is easier for them to follow the price patterns.

So far we have discussed about the relevant research on feedback trading under the micro level perspective; however there is an overwhelming amount of research for the macro level as well. One of the pioneering research papers on feedback trading is considered to be that of Sentana and Wadhwani (1992); the authors by using daily returns of the Dow Jones index from 1885 till 1988 found significant evidence of positive feedback trading, which was higher during down market states. Koutmos (1997) examined the presence of feedback trading in an international context using daily data from six countries (Australia, Belgium, Germany, Italy, Japan and the U.K.); his empirical results showed that in all six countries examined there was significant evidence of positive feedback trading and in four out of the six countries of the sample, positive feedback trading was stronger during down market conditions. Another study examining feedback trading in international foreign exchange markets is that by Aguirre and Saidi (1999) who used data from eighteen developed and emerging countries[8]. However the authors did not find significant evidence of feedback trading in these countries; and in case where evidence of feedback trading was present, it was negative feedback trading that was prevailing.

Säfvenblad (2000) examined the Swedish stock market by using daily data of 62 stocks for the 1980-1995 period; he suggested that feedback trading strategies are the prime candidate for explaining the index return autocorrelation in the market of Sweden. Koutmos and Saidi (2001) using daily data for the 1990-1996 period from six emerging market in Asia, namely Hong Kong, Malaysia, Philippines, Singapore, Taiwan and Thailand, found significant evidence of positive feedback trading during market declines but very weak evidence of it during upward markets. In addition, Watanabe (2002) examining the Japanese market for a 20 year period (1979-1996) also found significant evidence of positive feedback trading and as in the previous researches' findings this was stronger during market declines. What is more, the author found that positive feedback trading was highly related with the margin requirements and he concluded that much of positive trading found in Japan was due to margin trading. A research by Antoniou *et al.* (2005) using data from six developed countries (Canada, France, Germany, Japan, the U.K. and the U.S.) examined whether the introduction of futures has an impact on feedback trading; it is usually expected that the introduction of futures would attract more rational investors in the market who in their turn would make prices more efficient, informational wise, by applying the use of futures as an additional tool for risk management. Their results indicate that indeed upon the introduction of futures there was a decline on the impact of positive feedback trading upon prices. Bohl and Reitz (2006) examining the German stock

[8] The countries examined were: Belgium, Denmark, Greece, Hong Kong, Indonesia, Ireland, Korea, Malaysia, Mexico, Netherlands, Norway, Philippines, Portugal, Singapore, Sweden, Switzerland, Taiwan, Thailand.

market for the 1998-2002 period provided evidence of significant positive feedback trading. Also, Chau *et al.* (2008) examined whether the introduction of universal stock futures (USF) had an impact on the level of feedback trading across a series of markets; although the level of feedback trading was rather low both before and after the introduction of the USFs, there was a slight decrease on feedback trading level after their introduction. Finally, Salm and Schuppli (2010) examined the presence of feedback trading on the premises of stock index futures in 32 markets, both developed and emerging. Their results provided supporting evidence in favor of the existence of feedback trading strategies with positive feedback trading found to be stronger during market declines, as found in previous researches.

The main issue that arises from the relevant research about feedback trading at the macro level is that it appears to be significantly stronger during declining markets. The primary explanation for this phenomenon seems to be the tendency of investors to evacuate the market during large declines in order to avoid any further losses. This could be done through stop loss orders with which investors set a limit to their losses and when this limit is reached they start liquidating their stock holdings. In turn these actions reinforce the trend of the stock prices and as such the level of feedback trading. Finally, as relevant research suggests, margin trading as well as portfolio insurance through the use of various hedging tools (derivatives) play an important role in explaining the feedback behavior of investors.

2.5 Conclusion

The present chapter has outlined in detail the key differences between the Neoclassical and the Behavioral schools of thought in modern finance theory. Contrary to the traditional view reflected through the efficient markets hypothesis, investors are considered by the “behavioral” camp as being subject to a series of psychological impediments (biases) leading them to resort to non-rational tools (heuristics) to counter the complexity observed in capital markets. With the influence of psychological factors varying laterally (in terms of their numbers) as well as horizontally (across investors), it is evident that their presence only helps amplify the aforementioned complexity. The latter is expressed through a series of behavioral trading patterns, of which mention was made earlier in this chapter. Our research in the forthcoming empirical chapters shall focus on the behavioral strategies of herding and feedback trading which constitute facets of collective trading conduct; the choice of these patterns to study emanates from the gaps we managed to identify in the aftermath of our literature review.

Our first empirical chapter raises an issue never explored before, namely that of the impact of market concentration over the relationship between style investing and herd behavior. Style has been found in a series of studies [Lakonishok *et al.* (1992), Sias (2004)] to produce a positive effect over herding. This is because the presence of a style implies that those following it adhere to a strategy with a common denominator, thus implying commonality in their trades. The identity of these “denominators”, i.e. the indicators upon which styles are based, is not important; what is important here is that they exist and drive people’s investment towards stocks with specific features (e.g. past winners for momentum strategies). Much work [Sias (2004)] has produced evidence in favor of style’s positive impact over herding in developed capital markets; in other words, style has been found to promote herding. However, the issue here is that there exists a multitude of markets across the world that are either of small size or still at their early stages of development and thus have a small universe of stocks listed on their board; put it simple, many markets internationally are typified by very high concentration. The issue with concentration is that it bears an effect over the decision to invest in terms of both motivations (investors may find it easier to monitor each other, something particularly important when it comes to investment professionals due to performance assessment considerations) and choices (there are less stocks to choose from). As a result, we would expect the style-herding relationship to be affected in such market environments and it would be interesting to examine empirically whether this is indeed the case. To explore the impact of market concentration over the style-herding relationship we first begin by identifying the issue theoretically, constructing a framework of arguments originating from the extant literature, both analytical and empirical. Moving on to the empirical investigation of the issue, we examine it on the premises of the Portuguese capital market[9] drawing upon a unique database provided by the Portuguese Securities Markets Commission (CMVM). The database includes month-end portfolio holdings of all Portuguese funds investing in Portuguese equities and stretches across the period from July 1996 to June 2011. We then proceed by employing the approach proposed by Sias (2004) to measure herding among fund managers in Portugal. To account for style, we utilize six strategies as proxies, namely momentum [Jegadeesh and Titman (1993)], value [Lakonishok *et al.* (1994)], analyst recommendations [Chen and Cheng (2005)], size [Banz (1981), volatility [Busse (1999)] and volume [Chen *et al.* (2001)]. We further break up our sample into the pre-EURONEXT and post-EURONEXT access period in order to gauge the effect of changes in the regulatory environment over the style-herding relationship in such a concentrated environment. We believe this chapter to contribute significantly to research in behavioral finance as it theoretically presents

[9] Portugal maintains a very small equity market, with about 50-odd stocks listed on its main board and a smaller number on its alternative segment. Over the past 20 years the number of stocks listed at any point in that market has not managed to exceed 100 by far.

and empirically examines the impact of market concentration over the style-herding relationship for the first time in the literature. Furthermore, it bears important implications for the investment community and, in particular, its institutional segment, more so in view of the prolific employment of styles in funds' investments and the fact that many funds are active in emerging markets whose size is often small. Finally, this chapter's findings are bound to be of interest to regulatory authorities and policymakers alike, as institutional herding can (due to funds' dominant position in today's volumes) produce destabilizing outcomes in the market; since style constitutes a possible source of herding, assessing the impact of market concentration over the style-herding relationship can allow useful insight into the determinants of institutional herding in highly concentrated markets.

Our second empirical chapter deals with the identification of the issue of the impact of the introduction of exchange traded funds (ETFs) over noise trading in capital markets. ETFs constitute a relatively recent (10-15 years old) innovation in international markets and whereas their launch was primarily aimed at rational investors aiming at improving their risk management, they do bear several features rendering them quite attractive to uninformed investors. We first present a theoretical framework on this by introducing a series of arguments in support of ETFs being capable of both promoting as well as reducing the intensity of noise trading in the market drawing upon a series of analytical and empirical studies from the extant literature. We then explore the issue empirically by drawing upon a sample of emerging and developed markets' ETFs and employing the empirical framework proposed by Sentana and Wadhwani (1992). The latter assumes the interaction of two distinctive investor-types, namely rational speculators who maximize their expected utility and feedback traders who invest based on the market's performance one period back. We run this model for the spot index series of each market before and after the introduction-date of the first ETF in each, while we then assume different specifications of this model to control for robustness. An advantage of the Sentana and Wadhwani (1992) model is that it allows us to further explore the link between feedback trading and volatility, thus providing insight into whether noise traders bear a destabilizing effect over capital markets. The findings from this chapter are bound to yield valuable insight into the implications of the introduction of ETFs over noise trading in stock exchanges and will be of particular interest to regulators/policymakers as they will inform them of the impact of the introduction of ETFs as financial innovations over market dynamics.

Our final chapter looks into the issue whether institutional investors herd intentionally at the industry level. This is something that has not been examined in the literature before as the only evidence so far whether institutional investors herd intentionally or not has been the study by Holmes *et al.* (2011); the latter used the interactions of institutional herding and several market conditions to address this issue. However, in that case the authors examined the intent of fund managers to herd at the overall market level, whereas our scope is to examine whether fund managers herd intentionally at the industry level. In order to address this issue we use data consisted of quarterly portfolio holdings of Spanish mutual funds for the 1995-2008 period. What is more, on contrast with Holmes *et al.* (2011) that used only market conditions, we use both market and industry conditions in order to spot whether it is the first or the latter that are more reflective of the intent of fund managers to herd. Our results can bear important implications both for the investment community (especially those engaged in sector investing) and the regulatory authorities (in their effort to try to minimize the incentives of fund managers to herd).

Chapter 3

3.1 Introduction

Style investing constitutes a form of characteristic trading through which, investors trade on stocks with similar characteristics; as such, these may trade on stocks with similar past performance, market capitalization or trading volume. Research has identified a relationship between investment styles and herding [Grinblatt *et al.* (1995), Wermers (1999), Sias (2004)], particularly on behalf of institutional investors. The intuition behind this is that if investors follow the same investing style, then their trades will be correlated, hence this would amplify herding in the market. However, the majority of these studies have been carried out in large markets, mostly in the U.S and in a lesser extent to some European and Asian markets.

What has not been addressed before is the effect of market concentration upon the relationship between herding and style investing. As high market concentration can produce different trading dynamics than those produced in large markets, this could have an impact over the relationship between style investing and herding. First of all, a highly concentrated market environment allows institutional investors to monitor their peers easier; in addition, since in such kind of environments it is more likely that fund managers know each other, it will be more difficult for them to deviate from the market consensus [Do *et al.* (2008)]. Secondly, in a highly concentrated market environment, it would be more difficult for fund managers to apply investing styles since there are less investment options compared to less concentrated markets. These two characteristics of highly concentrated markets could bound the significance of style investing on institutional herding and we are going to test this hypothesis under the context of a highly concentrated market. More specifically, we are going to conduct our research under the premises of the Portuguese mutual fund industry, which is characterized by a high level of market concentration. In order to test for the relationship between style investing and herding and how this is affected by the level of market concentration, we will apply six different style indicators, namely analysts' recommendations, market value (size), momentum, value/growth, volatility and volume. Furthermore, we will break our sample period into two sub-periods, pre and post Euronext to account for any effects of the merger of the Portuguese Stock Exchange into Euronext. In addition, we will further break the post-Euronext period into pre and post crisis, trying to gauge the effect the credit crisis that broke out in 2008 had over our estimations.

The chapter is arranged as follows: section (3.2) provides the theoretical grounding and the findings of the relevant literature about the relationship between herding and style investing (3.2.1) and how this relationship is affected by market concentration (3.2.2). Section (3.3) describes the applied styles used in our research in order to test for the relationship between herding and style investing whereas section (3.4) provides a description of the Portuguese market. Section (3.5) describes the data and methodology used in this research and section (3.6) presents our empirical findings; in particular, section (3.6.1) presents the results for our full sample data, Section (3.6.2) presents the results for the pre and post Euronext periods, and section (3.6.3) presents the results for the pre and post crisis periods. Section (3.7) discusses the findings of our empirical results and finally Section (3.8) concludes.

3.2.1 Style investing and herding

Style investing is a term used to describe the strategies investors use in order to maximize the returns of their investments; it usually involves the categorization of assets according to specific characteristics. There have been documented quite enough investment styles; in fact it is often the case that many mutual funds are often characterized according to the investment style they employ. As such there can be, for example, "growth" as well as "value" funds (whereby the former invest in growth stocks[10] and the latter in value stocks[11]) or "small cap" and "large cap" funds (contingent upon whether they invest in small or large stocks). Furthermore, an investor could choose to follow a passive or an active trading style depending on their preference. In addition, momentum or contrarian strategies have also been applied by investors to achieve higher returns. Another common style among mutual funds is investing in stocks of specific industries; for example, a technology fund would be one investing in stocks of the technology industry. Similarly, there can be index-tracking funds or index-linked ETFs which follow the performance of a specific index. Finally, a more recent fashion in investment styles involves investing in stocks of companies with certain social or ethical codes of practice; this may entail companies that exhibit high social responsibility, are environmentally friendly or follow a specific religious code[12].

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[10] Growth stocks, or "glamour stocks", are the stocks of companies which have a high rate of growth in their earnings. [Lakonishok *et al.* (1994)]

[11] Value stocks are the stocks of companies which have a relatively low growth rate in their earnings and often exhibit low P/E ratios and a high dividend yield among other characteristics [Lakonishok *et al.* (1994)]

[12] For example, funds that follow the Islamic code do not invest in stocks of the tobacco or brewery industries. [Wilson (1997)]

However, apart from just being considered an investment strategy, style investing bears a behavioral connotation as well. As we mentioned in the previous chapter, stock markets have a high level of complexity and investors derive heuristics (rules of thumb) in order to make sense out of this complexity. As such, if at the beginning of stock markets it was easy for investors to monitor and analyze the fundamentals of the companies, the present markets' complexity with the thousands of assets being traded lead to the adoption of investment strategies from investors in order to simplify their stock-selection process.

Style investing is associated with several psychological biases such as the *representativeness heuristic* which states that investors often tend to misjudge information about stocks by overweighting more recent news about them. DeBondt and Thaler (1985) were the first researchers to identify that a strategy of going long on losers and short on winners exhibited significantly high returns and attributed this phenomenon to investors' overreaction to news. The authors suggested that investors' overreaction is caused by the *representativeness heuristic.* Similarly, Lee (2010) also posits that overreaction is caused by *representativeness*. More specifically, the author found that the reaction of growth investors to recent news is higher than that of value investors suggesting that the *representativeness* heuristic is related to style investing. Sirri and Tufano (1998) found that over a twenty-year period there were significant cash flows in mutual funds with high past performance in the previous periods. So, investors, paying too much attention on the recent past performance, flock into these mutual funds.

The *limited attention* bias is also a relevant factor for style investing; Peng and Xiong (2006) suggested that the *limited attention* bias makes it easier for investors to analyze information under a category basis (category learning) rather than examine individually each firm's characteristics. What is more, the model the authors suggest combines *limited attention* and investors' *overconfidence* and provides a better explanation of the comovement of returns than other models following the traditional paradigm. *Limited attention* implies that it is almost impossible for people to pay equal attention on all possible features of an issue. So, investors are more prone to style-invest since this automatically reduces the amount of investment options they have; instead of thousands of stocks they now focus on a subset (or subsets) of them with specific features. As such, the lesser options they have to choose from, the more likely it is for them to converge to some of them; the more the investors focus on the same investment style, the more likely it is for them to move similarly on its basis and herd.

Conformity suggests that people feel more comfortable when doing what others do. In our case if an investment style has been quite successful in the past and is used by the majority of investors, then it is more likely that investors will keep following the same style and as such choose stocks according to the characteristics suggested by the specific style. Similarly, *Conservatism* can also have an effect on style investing and herding. Investment managers may be reluctant to deviate from the established styles that have been proven profitable and used by their peers, thus inducing herding since using the same investment styles leads to the trading of the same stocks.

Apart from the behavioral issues of style investing and herding there are also the agency-related issues. More specifically, there can be reputational and professional reasons for fund managers to follow some investment styles. More specifically, it can be the case that "bad managers" will follow the actions of their successful peers (good managers) because of performance assessment reasons; this behavior will inevitably lead to the trading of the same stocks. Finally, the adoption of investing styles from professionals makes it easier for investors to assess their performance as it can easily be linked to a certain benchmark according to the strategy they follow. In their turn, fund managers in order to meet the required rate of return, as this is indicated by the benchmark of the style, they will choose stocks which best represent the benchmark they have.

In addition to the former reasoning, style investing can be driven by informational reasons as well. It is easier for investors to analyze the information signals that apply to the same category of stocks than if those had to be analyzed for each stock separately. So, through the classification of stocks into categories investors minimize their research cost and thus achieve a more efficient allocation of their funds, both cost- and time-wise. Instead of choosing among thousands of assets, investors can choose the right style according to their risk and return preferences.

3.2.2 Style investing, herding and market concentration

In the previous section we talked about the relationship between style investing and herding. In this section, we will focus on the impact of market concentration on this relationship; more specifically we will examine how market concentration affects each of the style investing determinants of herding discussed in the previous section. As Do *et al.* (2008) suggested, a concentrated market will differ from a large market in terms of transparency levels (information-wise), the amount of traded assets in the market and the high level of ownership-concentration by large institutional investors. Generally speaking, in the context of a concentrated market we would expect a high level of peer monitoring; the latter could increase the possibility of imitation among the investors and thus herding. However, we have shown that style investing is also positively related to herding, in the sense that it can promote herding tendencies among investors using similar styles. One thing, though that is not clear cut is the relationship between high concentration and style investing. Put it simple, the issue here is whether the presence of high concentration affects the ability of style investing to generate significant herding.

We have shown how style investing can give rise to herding through various avenues by making explicit reference to behavioral as well as non-behavioral determinants of the style-herding relationship. Starting with the *representativeness heuristic*, market concentration can actually affect the style-herding relationship both negatively and positively. If we recall from our literature review, this heuristic is associated with the *sample size neglect*, which implies that investors tend to perceive a small sample to be equally representative and reliable with a larger sample of the same population. In a concentrated market the sample of stocks out of which investors must make their decisions is already limited; thus, there exists less complexity in the decision making process and less need for investment styles. Consequently, style-investing would be expected to be of smaller importance as a determinant of herding in highly concentrated environments. On the other hand, Barberis *et al.* (1998) suggested that due to the *representativeness heuristic* investors often extrapolate from recent and limited events to imagine patterns that do not exist and create trends. In the context of a highly concentrated market, where low trading volumes are very often the case, the amount of volumes, i.e. investors, that are needed to start a trend is significantly smaller in relation to that of a large market; as such, trends are easier to kick-start in concentrated environments and since certain investment styles are trend-based (e.g.

contrarian/momentum trading) it could be the case that market concentration can amplify the use of such styles[13] and the herding emanating from them.

The *limited attention bias* is positively related to investment styles since the latter narrow the available options of investors and ease the process of decision making. However, in a concentrated environment, where the available investment options are not so many compared to larger markets, the use of investment styles is of less significance as a heuristic because there is already a small amount of stocks to choose from, thus reducing the need for category learning (investment styles) since it is easier for investors to monitor individual stocks. If so, the importance of style as a determinant of herding would be expected to dissipate in such markets. On the other hand, investment styles are not applied only for simplifying purposes but for maximizing profits as well. When styles are applied in a concentrated market, the categorization of stocks will limit the available options of investors even more and as mentioned earlier in this chapter the less options investors have the more possible it is for them to converge to one of them [Bikhchandani *et al.* (1992)] and herd[14].

Similarly, in the context of a highly concentrated market, *conformity* can positively affect herding through the use of investment styles since in such an environment there is a greater sense of belonging to that market as well as more monitoring, so deviant actions are easier to detect. As such, professionals following the same investment

[13] DeBondt and Thaler (1985) depicted the *representativeness heuristic* as the main cause for the overreaction of investors to news, thus raising the issue of whether *ad hoc* developed investment styles aimed at profiting from this overreaction, such as contrarian trading, could in fact deliver systematic gains

[14] An example would perhaps help clarify this point. Imagine an investor following a style that involves buying the top 10 percent of each month's winners and selling the bottom 10 percent (the top losers). The amount of stocks traded a momentum strategy like that would involve would obviously be different between a market with 1,000 stocks and a market with 100 stocks. In the former case (the market's with 1,000 stocks) this would involve trading a couple of hundred stocks each month; in the latter case (the market's with 100 stocks) this would involve trading probably no more than a couple of dozen.

style feel more comfortable when doing what their peers are doing since a wrong investment decision would have a bigger impact on their reputation/assessment than that of a successful one when deviating from their peers. So due to the high competitiveness of the market investors prefer to play safe and it is more likely for them to herd towards their peers' actions.

Moving on to the rational determinants of the style-herding relationship, there are career-driven reasons that can affect herding through style investing. As discussed in the previous chapter, professionals often disregard their clients' interests and act according to their own; as such, since professionals are compared to their peers, it is safer for them to act in a similar way with them to avoid the risk of deviating from them and making a wrong choice that can affect their performance. In the same way, young and inexperienced professionals that follow the same style with their more experienced peers will most likely copy the actions of the latter. Since in a concentrated market there are relatively few professionals, one can find it easier to observe the actions of their peers and follow them. What is more, professionals often herd due to reputational reasons. As Scharfstein and Stein (1990) suggested, it is often the case that professionals disregard their own private informational set and copy their peers' actions due to reputational reasons; a highly concentrated market could strengthen this behavior because firstly the market for professionals is too small and these would be more willing to protect their reputation (the smaller the market, the easier it is to know the reputation of each) and secondly it will be easier for professionals to monitor their peers and herd on their actions.

Information-wise, the level of informational transparency will differ between concentrated and large markets [Do *et al.* (2008)]. The issue here is twofold. On the one hand, information in highly concentrated environments tends to be in the hands of a few large market players, thus implying that price moves are mostly conditioned upon these players' trades. As a result, styles are less applicable in such markets; perhaps, those styles aiming at mimicking the behavior of informed players[15] - thus minimizing the importance of style as a determinant of herding. The possibility of herding rising due to style in these jurisdictions is when those big players are actually the ones practicing style-investing themselves. In this case, style can boost herding decisively, since the rest of the investors will resort to it as a means of extracting informational payoffs from their informed peers' trades.

Apart from the above mentioned reasons, relevant research has documented that institutional investors tend to exhibit characteristic trading [Sias (2004)], that is select stocks with certain characteristics; however in a small concentrated market where the pool of available stocks to choose from is relatively small, the chances of convergence among managers who follow the same style is quite high [Do *et al.* (2008)]. Finally, Sias (2004) posited that institutional herding could be due to institutions following their own lagged trades of the same assets; Do *et al.* (2008) suggested that there are higher chances of institutions following their own lagged investments in a concentrated market than in a larger one.

Summarizing the given reasoning as described above, we can see that there is a gap in the literature on how the environment of a highly concentrated market can impact the style-herding relationship. Both the behavioral and non-behavioral determinants of this relationship can be either amplified or reduced in a highly concentrated market, with concomitant effects over the significance of herding; this is where our research intends to contribute to the literature, namely by examining whether style investing is capable of generating significant herding in a concentrated market environment.

[15] This is the case, for example, of trade-based manipulation, as described by Allen and Gale (1992)

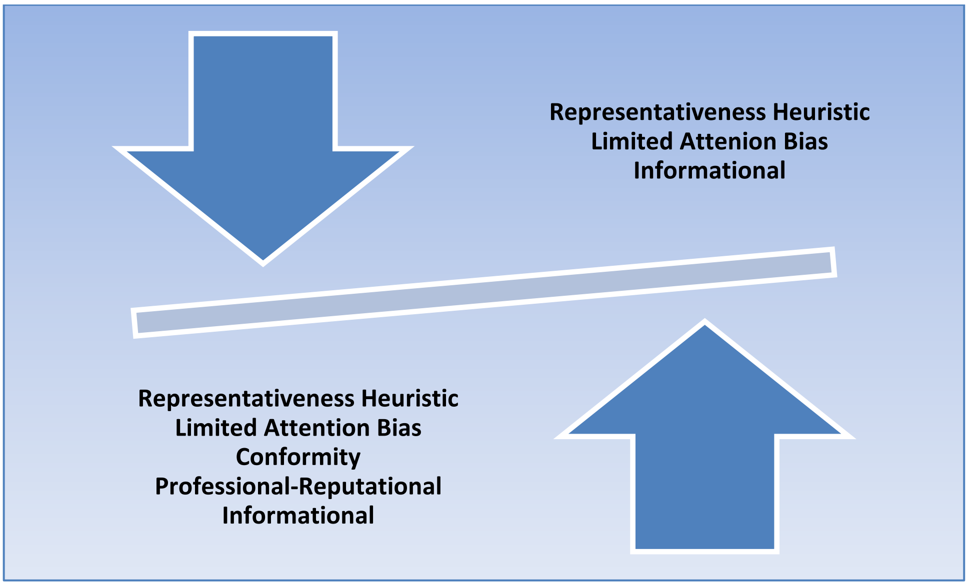

Figure 3.1 – Biases affecting Herding

3.3 Style Indicators

Over the last decades, the importance of investment styles has been widely recognized by institutional investors as a means to diversify their portfolios more efficiently and what is more as a tool to evaluate their performance and compare it versus each other. Today there are numerous investment styles, applied from investors; in our research we will study the best documented ones and those that will better aid us in examining the impact of market concentration upon the link of style investing and herding on the premises of institutional investors.

3.3.1 Momentum

Momentum strategies have been widely applied by investors in order to maximize their profits. Such kinds of strategies involve buying stocks that performed well in the past and sell stocks that performed poorly; in other words this strategy has to do with chasing stock trends and is associated with positive feedback trading. There have been many possible explanations given by researchers on the sources of such strategies. One of them suggests that investors who have an informational disadvantage compared to their peers often use past prices, through technical analysis, in order to infer information from them as they believe that past prices contain information about companies. Furthermore, stop-loss orders and portfolio insurance may account for the fact that investors often sell stocks that underperformed in the past. What is more, Conrad and Kaul (1998) suggested that the documented profitability of momentum strategies could be explained by the cross-sectional variation in mean returns.

However, there is the “behavioral” view regarding the underlying causes of momentum strategy which draws upon cognitive psychology. More specifically, the supporters of the behavioral explanation [De Long *et al.* (1990a), Barberis *et al.* (1998), Daniel *et al.* (1998) among others] argue that momentum profitability is driven by investors’ under-reaction to news. Among the first researches on momentum strategies is that of Jegadeesh and Titman (1993); more specifically, using data from 1965 till 1989 for the U.S market, they found significantly higher returns for the portfolios comprised of winner stocks in contrast to the ones comprised of loser stocks. Grinblatt *et al.* (1995) found evidence of momentum strategies in the U.S market on behalf of institutional investors. The research by Rouwenhorst (1998) examined the profitability of momentum strategies in 12 European countries for the 1980-1995 period; his findings suggest that indeed a portfolio of past winners outperformed the one consisted of prior losers and that the returns were higher in small firms than in large ones. Forner and Marhuenda (2003) examining the Spanish market for the 1963-1997 period found significant positive returns for momentum strategies in a 12-month horizon. Galariotis *et al.* (2007) examining the U.K. market with a sample of 6531 firms for the 1964-2005 period found evidence of momentum strategies' profitability, though these were more prominent in the short-run.

3.3.2 Value vs. Growth

A common categorization of investment funds is according to the type of stocks they invest in, whether the latter are value or growth stocks. By the term "value" we define stocks that exhibit low P/E ratios and have high dividend yields [Lakonishok *et al.* (1994)]; in other words these are the stocks that trade below their true value. On the other hand, "growth" stocks are those with high P/E ratios and low dividend yields and represent companies with high earnings growth rate [Lakonishok *et al.* (1994)]. Since this investment style is based on companies' fundamentals (earnings, dividends, cash flows, book value of company, etc.) it can be considered as a rational style on behalf of investors.

There is overwhelming research suggesting that a strategy investing in value stocks surpasses the returns of a strategy investing in growth stocks. Among the first researches that documented the relationship of the P/E ratio and the expected returns of the firms is that of Basu (1977). More specifically, the author using monthly data from over 1400 NYSE firms for the period 1956-1971 examined whether stocks with low P/E ratios had significantly higher returns than those with high P/E ratios. After constructing portfolios of high and low P/E stocks, his empirical results reported significantly higher returns for the low P/E portfolios. Another research for the Japanese market by Chan *et al.* (1991), using the size, book to market ratio (B/M), cash flow yield (C/P) and earnings yield (E/P) as the fundamental variables, provided supporting evidence of the profitability of the value strategies. More specifically, using monthly data from the Tokyo Stock Exchange from 1971 till 1988, the authors concluded that stocks with high ratios of the examined variables had higher returns than those with low ones. Now at this point, Fama and French (1992) argued that the documented superior performance of value stocks is due to the higher underlying risk of these stocks. Lakonishok *et al.* (1994) suggested that the higher returns achieved by value strategies are due to the fact that these are "*contrarian*" to the strategies of noise traders. The latter tend to pay too much attention on recent earnings growth and tend to overreact to good or bad news. As a result they tend to overprice the growth ("glamour") stocks and since they overreact to companies that performed poorly in the recent past, these companies become underpriced. As such, investors who follow value strategies and invest in undervalued companies will eventually achieve higher returns than those investing in growth stocks. Using data from 1963 till 1990 from NYSE and AMEX, Lakonishok *et al.* (1994) concluded that indeed value strategies outperformed the growth ones; what is more, they argued that value stocks did not exhibit any higher fundamental risk than the glamour stocks contrary to the given explanation by Fama and French (1992). Supporting evidence to the findings of Lakonishok *et al.* (1994) was provided in the research by Porta *et al.* (1997). The authors using data from NYSE, AMEX and NASDAQ for the period 1971-1993 also documented that value stocks outperformed glamour stocks. After rejecting the risk-based explanation for the high performance of value stocks, the authors gave a behavioral reasoning for this phenomenon. More specifically, they suggested that investors often make errors in their expectations about the future earnings of glamour stocks; thus when the earnings are actually announced, value stocks, whose expectations were lower, outperform glamour stocks. Several researches have been carried out to support the superiority of value strategies. Chin *et al.* (2002) examining the market of New Zealand for the 1988-1995 period also found that the value strategies based on accounting ratios outperformed similar growth strategies. Finally, Petkova and Zhang (2005) concluded that time-varying risk is close to explaining the premium of value stocks, however it fails to do so and that other driving factors of the value premium should be explored such as overreaction mispricing or APT- and ICAPM-related risks.

3.3.3 Analysts' Recommendations

Although analysts' recommendations do not formally present themselves as candidates for style indicators, there has been an increased interest regarding the link between analysts' recommendations and mutual fund managers and how the former affect the decision making process of the latter. Relevant research suggests that institutional investors are affected by the recommendations of market analysts [Chen and Cheng (2005), Busse *et al.* (2008)]; what is yet to be examined in depth however, is if and to what extend the relationship between analysts' recommendations and fund managers affect institutional herding. The theoretical background of this hypothesis is that professionals that have an informational disadvantage relative to their peers will often be more prone towards following financial analysts in their attempt to infer information from them; this sounds logical, as the majority of investment houses do not have in-house analysts as their large counterparts. Nevertheless, even the large fund management houses which have their own research departments and analysts tend to pay attention to other analysts' forecasts as well. As Brown *et al.* (2009) and O'Brien and Bhushan (1990) suggest, this is due to the fact that fund managers are obliged to apply the "prudent man rule", namely act to their clients' best interest; thus paying attention to other analysts' recommendations, and not only those of their in-house analysts, is often viewed by fund managers as evidence of good and ethical practice. Inevitably, the tendency of fund managers to go in line with the market analysts will lead to an increase of herding levels; more specifically, if the majority of fund managers in a market is leaning towards analysts' recommendations then it is more likely that they will invest in the same stocks (those suggested or revisited by the market analysts). The primary candidate for explaining the tendency of fund managers towards following analysts' recommendations is their career; as Kacperczyk and Seru (2007) suggest, there is an inverse relationship between managerial skills and responses to public information, i.e. bad managers are influenced more from analysts' recommendations than good managers.

3.3.4. Market Value ("Size")

Perhaps the most common investing style that one meets in the market is that of the categorization of stocks according to their size. In fact, there is a plethora of mutual funds characterized as "Small-cap" or "Large-cap" reflecting their focus on investing towards small sized and large sized firms respectively. The importance of firms' size and its impact upon stock prices has been initially brought up by Banz (1981); the latter examining the NYSE market, for the 1926-1975 period, found that smaller firms tended to exhibit higher returns than those predicted by the CAPM, outperforming the larger firms. This phenomenon, widely known as the "size effect" and identified as a market anomaly, has been empirically supported by numerous studies in the Finance literature [Reinganum (1981), Keim (1983)].

These researches were the kick-start for the investment community, both individuals and institutional, to use firms' size as an investing style. Indeed, there has been a vast amount of research about size as a style determinant used by mutual funds. Brown and Goetzmann (1997) examining the US fund industry for the 1976-1994 period found evidence for the adoption of size as an investment style by mutual funds. Similarly, Chan *et al.* (2002) examined U.S funds for the 1976-1997 period and found that size was a consistent determinant for style investing on behalf of mutual funds. What is more, a factor that drives institutional investors to adopt size as an investment style is the regulatory authorities. For example, in certain countries where pension fund managers are obliged by regulations to exhibit a certain rate of return, they often invest in stocks of a certain size, most likely large ones that are representative of the market index, in order not to fall behind the market return [Voronkova and Bohl (2005)]. As such, we can see that in contrast to certain styles that decay over time (such as investing in mortgage-backed bonds, Barberis and Shleifer (2003)), the use of size as a style by investors still continues to persist to a large extent.

3.3.5 Volatility

Volatility is chosen as a style indicator in our research due to the special relationship it has with institutional trading; the latter is typified with a high quality of information, something that can be positively or negatively related with volatility, i.e. the more informational trading in the market the more volatility prevails since prices have to respond in more information [Ross (1989)]. As such, there should be a positive relationship between volatility and institutional trading. However, still this issue remains controversial, whether informational trading is positively or negatively related to volatility. For example a relevant research by Li and Wang (2010) has found that institutional trading in China is negatively related to the volatility of prices. Though, apart from institutional trading, there is a vast amount of research verifying the relationship between volatility and stock returns. Pindyck (1984) found that there is a strong relationship between expected stock returns and market volatility and more specifically a negative one. However, another research by Poterba and Summers (1986) argues that changes in volatility, due to their short run nature, do not have that significant effect on stock price changes. Another research by French *et al.* (1987) also documented a negative relationship between volatility and stock price changes. What is more, Campbell and Hentschel (1992) also found a negative relationship between expected returns and volatility, though not so important. Finally, Busse (1999) showed that fund managers' trading behavior and compensation is affected by market volatility.

3.3.6 Volume

The trading volume of stocks often plays an important role as to whether the latter will be picked by investors or not; the more one stock is traded the more information about it is conveyed into the market and the more likely it is for investors to pick it. What is more, as Chordia and Swaminathan (2000) suggest, stocks with high volume tend to react faster upon the arrival of new information in the market than low volume stocks. As such volume seems to be a key determinant of investment styles followed by investors.

Among the first researches about the relationship between stock returns and trading volume is that of Crouch (1970);the author examining the NYSE found a positive relationship between trading volume and price changes on both the aggregate market level and the individual stock level. Similarly, Epps (1975) also linked trading volume with stock returns proclaiming that bull markets are associated with high trading volumes and vice versa. What is more, the trading volume is found to be linked with another investment style, namely momentum; as Lee and Swaminathan (2000) postulate, the profitability of the momentum strategies, as these were exhibited by Jegadeesh and Titman (1993), was higher for high volume stocks.

Chen *et al.* (2001), examining nine markets for the 1973-2000 period, found that there is a positive relationship between trading volume and stock price changes. Additionally, Gervais *et al.* (2001) examined the existence of the "*high volume premium*" on the premises of the NYSE for the 1963-1996 period; their findings reveal a premium in high volume stocks in the short-run, i.e. they exhibit higher returns when compared to those of low volume stocks.

3.4 The Portuguese market

Up until the 1990s, the Portuguese market was very small in terms of volume and market capitalization. However, in 1993 the Maastricht treaty, which relaxed the trade barriers and capital transfer across the countries that voted for it, allowed Portugal to attract significant capital flows from other countries through FDIs and securities' investments. This single fact alone led to an increase of 53.2% in the general index of the Portuguese market and a 53.3% increase in terms of market capitalization [Balbina and Martins (2002)]. In 1996, there was the initial trade of derivative instruments at the Oporto Derivatives Market which allowed investors to trade in more complex financial products. What is more, further interest rate cuts and the decrease of the inflation fed up the market with additional capital boosting not only the stock market but the economy as a whole (GDP growth, exports, etc.); at the same time, the privatization of an enormous number of public companies took place during this period. Additionally, the inclusion of the Portuguese market into the MSCI index of developed markets in 1997 attracted additional foreign investors seeking to invest in such countries. Last but not least, the announcement that Portugal would be among the first EU countries that would enter the European Monetary Union (EMU) played an important role to the evolution of the market there. It is worth noting that from 1993 since mid 1998 the main index of Portugal rose by approximately 470% (Figure.1 shows how the main index evolved throughout the years).

However, the crises of 1999 (Asian and dot com bubble) did not leave the Portuguese market unaffected; to the contrary, there was a sharp decline in the securities' prices which led to an overwhelming delisting of firms from the Portuguese Stock Exchange. Another milestone for the Portuguese Stock Exchange was its merger into the Euronext platform in 2002. From that point onwards started the slow recovery of the stock market which was boosted after 2005 and peaked in 2008 where the debt crisis came along. During 2009, there has been a recovery from the lowest point of the previous year, however during the last couple of years there has been a high turbulence in the market due to the uncertainty as to whether Portugal will be able to pay its high debt back.

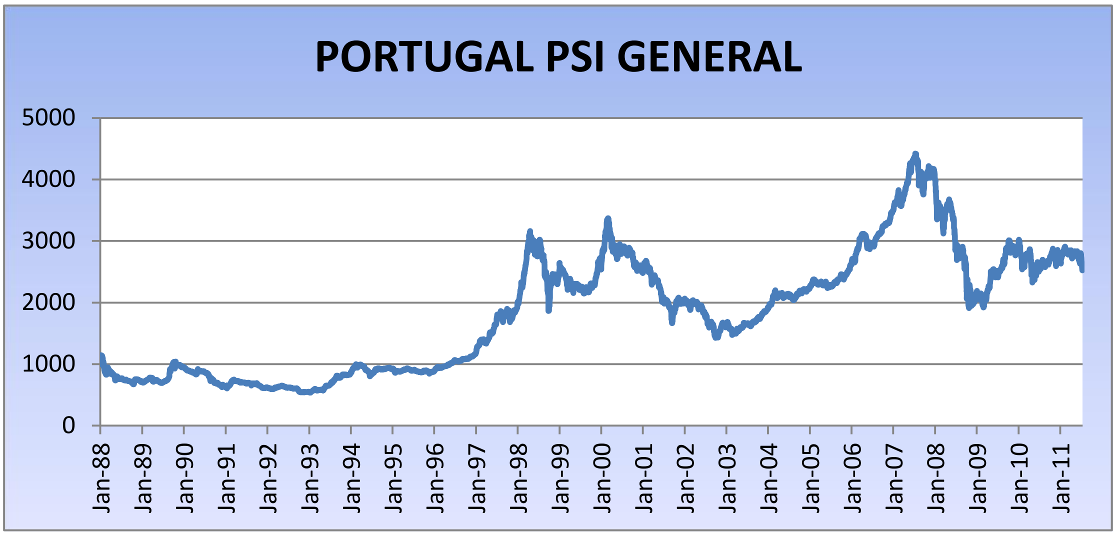

Figure 3.2 - The Evolution of the Portugal Index

Now, regarding the market of mutual funds in Portugal; with the first mutual fund being introduced in 1985, the market is characterized by an analogous course with the country's economy. More specifically, the rapid growth and expansion of the mutual funds' market during the 1990s was followed by the sharp fall that took place during the end of the 1990s. After the crisis the funds' market shrunk as many funds were either terminated or merged with others. Again the fund market started recovering after 2003 and especially from 2005 onwards. As Holmes *et al.* (2011) suggest the mutual funds' market of Portugal is heavily concentrated. For instance by June 2011 there were 305 funds managed by 19 investment companies with an asset-pool under their management worth of approximately 12.89 billion Euros; out of these 305 funds the 10 largest held approximately 32.9% of the market and the 5 largest investment companies held over 80% of the market, in terms of market capitalization[16].

[16] Source: www.cmvm.pt

3.5 Data and Methodology

Our data comprises of monthly mutual fund holdings for the Portuguese market[17] from July 1996 till June 2011. After we limited our data to funds that invest only into Portuguese stocks, our sample in its final form consists of 65 mutual funds and 99 stocks. What our sample consists of, is the code and the name of the fund, its description, the code and the name of the assets and the number of stocks each fund holds for every month of our sample.

There have been several models used for testing the herd behavior of investors. Among the first ones is that of Lakonishok *et al.* (1992) (LSV hereafter). However, the LSV measure had some drawbacks. The two most important are the following: Firstly, the specific measure takes into account the amount of buyers and sellers of a specific stock, but not the amount of stock each party trades. So, in a case where buyers and sellers of an asset are similar in absolute numbers but the amount of the asset traded by buyers is larger than that of sellers, the LSV measure would not indicate any herding even if that existed. Secondly, the LSV measure shows the persistence of herding in a stock but it can't show whether it is the same institutions that herd or others. To mitigate these issues, Sias (2004) proposed an approach which we employ here and which we shall now describe.

The first thing to do is calculate the fraction of institutions of each security that are buyers for it every month[18]. Sias named that ratio the "raw fraction of institutions buying" for security k at quarter t:

[17] The data was provided by CMVM.

[18] Sias (2004) used quarterly data due to unavailability of higher frequency data in his case.

$$RawΔ_{k,t} = \frac{No.of\ institutions\ Buying_{k,t}}{No.of\ institutions\ Buying_{k,t} + No.of\ institutions\ Selling_{k,t}}$$

He then assumed this ratio and standardized it as follows:

$$\Delta_{k,t} = \frac{\mathrm{Raw}\mathit{Δ}_{k,t} - \overline{RawΔ_t}}{\sigma(RawΔ_{k,t})}$$

Where, $\overline{RawΔ_t}$ is the cross-sectional average raw fraction of institutions buying in quarter *t* and $\sigma(RawΔ_{k,t})$ is the cross-sectional standard deviation of the raw fraction of institutions buying in quarter *t*. Then in order to identify the existence of herding, Sias examined the cross-sectional regression of the standardized fraction of institutions buying security k ($Δ_{k,t}$) during the current quarter on the standardized fraction of institutions buying security *k* the previous quarter.

$$Δ_{k,t} = \beta_t Δ_{k,t-1} + \varepsilon_{k,t} \qquad (1)$$

In addition, Sias decomposed the correlation between institutional demand this quarter and institutional demand the previous quarter into two components in order to identify whether the correlation observed is due to institutional investors following "their own trades" or institutional investors following "the trades of others". So, the slope coefficient of the above equation is written as follows: $\beta_t = \rho(\Delta_{k,t}, Δ_{k,t-1})$

$$= \left[\frac{1}{(K-1)\sigma(RawΔ_{k,t})\sigma(\mathrm{Raw}\Delta_{k,t-1})}\right] \times \sum_{k=1}^{k=K} \left[\sum_{n=1}^{N_{k,t}} \frac{(D_{n,k,t} - \overline{RawΔ_\tau})(D_{n,k,t-1} - \overline{RawΔ_{t-1}})}{N_{k,t}N_{k,t-1}}\right]$$

$$+\left[\frac{1}{(K-1)\sigma(Raw\Delta_{k,t})\sigma(\mathrm{Raw}\Delta_{k,t-1})}\right] \times \sum_{k=1}^{k=K}\left[\sum_{n=1}^{N_{k,t}}\sum_{m=1,m\neq n}^{N_{k,t-1}}\frac{\left(D_{n,k,t}-\overline{Raw\Delta_{\tau}}\right)\left(D_{m,k,t-1}-\overline{Raw\Delta_{t-1}}\right)}{N_{k,t}N_{k,t-1}}\right] \quad (2)$$

Where $N_{k,t}$ is the number of investors trading security k in month t and $D_{n,k,t}$ is a dummy variable equal to one (zero) when trader n is a buyer (seller) of security k in month t. Likewise, $N_{k,t-1}$ is the number of investors trading security k in month t-1 and $D_{n,k,t-1}$ is a dummy variable equal to one (zero) when trader n is a buyer (seller) of security k in month t-1. $D_{m,k,t-1}$ is a dummy variable that equals one (zero) when investor m (m≠n) is a buyer (seller) of security k in month t-1.

The first term on the right hand side of the above equation is the portion of the correlation resulting from investors following their own trades. It will be positive if investors tend to follow their trades over adjacent months. Otherwise, if investors' transactions in month t are independent of their own transactions in the previous month, the first term will be zero. In case where investors reverse the transactions of the last month the term will be negative.

The second term on the right hand side of the above equation is the portion of the correlation resulting from investors following other investors. It will be positive if investors tend to follow each other over adjacent months. If investors buy (sell) the securities that other investors sell (buy) over the previous month, the term will be negative. And in case the transactions of investors are independent of the other investors' transactions, the term will be zero.

The same procedure will be tested for five different thresholds; stocks traded by one fund or more, by two or more and so on up until stocks traded by five funds or more. Now, in order to test for the herding-style relationship, namely analysts' recommendations, momentum, size, value/growth, volatility and volume we will input an additional variable in order to control for investment styles.

$$\Delta_{k,t} = \beta_t \Delta_{k,t-1} + \beta_2 X_{k,t-1} + \varepsilon_{k,t} \qquad (3)$$

For example, consensus analysts' recommendations ranked according to the Thomson DataStream classification (1-1.49 = "strong buy"; 1.5–2.49 = "buy"; 2.5–3.49 = "hold"; 3.5–4.49 = "underperform"; 4.5–5 = "sell"). So, when the coefficient β_2 is negative this implies an improvement in the recommendation on behalf of the analysts and vice versa.

Table 3.1 provides the descriptive statistics of our data. As one can see at first glance, our sample market is typified by high concentration. More specifically, the total number of funds is 65 and the number of traded stocks is 99. Furthermore, the average number of traded stocks by more than one fund is 37.8 for the whole period, peaking in 1998 to 54.8 and declining to 32.5 at the end of our sample period. Likewise, the number of average funds per share for the whole period is 7.7, reaching a peak in 1999 with a number of 10.4 and falling to 7.5 at the end of our sample period. As such, one can infer from the above figures that there is a high level of concentration in the market examined which could possibly amplify herding; for example, with almost 8 active funds for each stock in each month, that means that each fund manager has seven other fund managers to monitor.

Table 3.1 - *Descriptive Statistics*

No. of Stocks	99																
No. of Funds	65																
No. of Stock-holdings positions	129276																
No. of Stock-months	6767																
Average No. of active stocks per month traded by	Aug 1996-Jun 2011	1996 (Aug-Dec)	1997	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011 (Jan-Jun)
≥1 fund	37,8	49,2	52	54,8	51,8	43,8	35,3	30,7	26,9	28,5	32,4	33,8	32,9	34,8	35,2	34,3	32,5
≥2 funds	34,3	44,2	47,5	49	47,1	38,3	29,5	25,7	23,1	25,5	29,6	32,4	32,1	33,3	33,2	31,8	30,8
≥3 funds	31,2	39,6	43,6	44,8	42,2	35,1	26,5	23,5	20,5	22,3	26,3	30,4	29,7	31,2	30,8	29	25,8
≥4 funds	28,7	34,6	40	41,8	39,1	32,3	24,3	21,7	18,5	20,5	23,7	27,8	26,8	29,8	29,1	26,7	24,7
≥5 funds	26,4	31,6	37,2	39,6	37,1	30,1	21,3	19,4	15,7	18,2	21,2	25,4	25,4	27,7	26,3	24,5	22
Average No. of active funds per stock per month	Aug 1996-Jun 2011	1996 (Aug-Dec)	1997	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011 (Jan-Jun)
≥1 fund	7,7	7,7	9,3	10,3	10,4	9,7	7,6	7,0	4,4	8,3	5,9	6,6	7,0	7,3	6,9	7,9	7,5
≥2 funds	8,2	8,0	9,5	11,0	10,7	10,2	8,6	7,8	5,2	9,1	5,8	7,1	7,2	7,6	7,0	8,0	7,5
≥3 funds	8,7	8,2	9,7	11,8	12,0	10,4	9,1	9,0	6,2	9,3	6,3	7,0	7,4	7,9	7,6	8,3	8,4
≥4 funds	8,9	8,9	10,2	12,9	12,0	10,8	9,4	9,1	6,4	9,0	6,6	7,4	7,6	8,0	7,7	8,3	8,6
≥5 funds	9,2	9,5	11,0	13,4	12,3	10,9	10,5	9,1	6,8	9,2	6,7	7,2	7,5	7,8	7,6	8,6	8,8

3.6 Research Hypothesis

Based on the evidence of the relevant literature discussed previously, we would expect that in a concentrated environment, such as that of the Portuguese market, style investing will have no, or a minimal, impact on the significance of herding. Particularly, the sources that are responsible for herding (both rational and irrational) are amplified under the context of a concentrated environment. As such, our hypotheses are formalized as following:

H_0: Market concentration does not have an impact over the relationship between institutional herding and style investing.

H_1: Market concentration has an impact over the relationship between institutional herding and style investing.

3.7 Empirical Results

3.7.1 Full Sample

This section presents the empirical findings of our research. We begin our presentation with the results for the whole sample period where table 3.2 shows the results from equation 1 and equation 2 with the β_t coefficient and its decomposition. Particularly, we can see that the β_t coefficient is positive and highly statistically significant at the 1 percent level with a value of 0.3307. This means that institutional demand in a month is highly dependent on the institutional demand of the previous month. The partitioning of this coefficient reveals that the month-on-month dependence of institutional demand is mostly due to institutions following each other (herding). More specifically, the part of the coefficient indicating institutions following themselves is 0.1037 (highly significant at the 1 percent level) and the part of the coefficient indicating institutions following each other is 0.2270 (also highly significant at the 1 percent level); in other words, herding accounts for 69% of the dependence in institutional demand month-on-month.

The next step of our research is to test whether our results remain robust when we take into consideration the most popularly traded stocks. As such, we repeat our tests using various sequential thresholds of stocks, namely considering only stocks traded by ≥2, ≥3, ≥4 and ≥5 funds. Contrary to the research paper of Sias (2004) which tests for stocks traded even by twenty or more funds, we limit out threshold to that of stocks traded by five or more funds, as Holmes *et al.* (2011) did, due to the small size of the market examined and the number of funds trading in it. Starting with the first threshold, we exclude stocks that are traded by only one fund; in this case we observe that all coefficients are positive and highly significant (1 percent level) as well as a slight increase of the β_t coefficient and its part indicating the presence of herding. Particularly, in this threshold, herding accounts for 73% of the month-on-month correlation in institutional demand. The next threshold (≥3) includes stocks that are traded by 3 or more funds. Again, all coefficients are highly significant (1 percent level), though there is a slight decrease on the percentage of the herding component which now accounts for 66% of the correlation in institutional demand month-on-month. Moving on to the next threshold that includes stocks traded by 4 or more funds, we report similar results; very highly significant (1 percent level) coefficients and a 62% part of β_t due to herding. Finally, the last threshold is the one that accounts for stocks traded by five or more funds. Here, as in the previous thresholds, all coefficients are positive and highly significant (1 percent level); what is more, we come across the largest value of the β_t coefficient indicating a month-on-month correlation of institutional demand equal to 0.3440, out of which 63% (0.2173) is due to herding.

Continuing with our findings, we will analyze the results from equation (3) which relate to the applied investing styles in our study. Since the month-on-month-correlation of institutional demand is mostly due to herding, as our results have indicated, we are going to examine what is the direct impact of various investment styles upon the institutional demand month-on-month (and indirectly upon herding since the latter largely accounts for it). Firstly, we will examine the effect of analyst recommendations upon institutional demand which is outlined in table 3.3. In order, to gauge analyst recommendations we use the monthly consensus analysts' recommendations by Thomson DataStream (which uses a 1-5 scale and offers the following classifications: 1-1.49 = "strong buy"; 1.5–2.49 = "buy"; 2.5–3.49 = "hold"; 3.5–4.49 = "underperform"; 4.5–5 = "sell") for all the stocks held by our funds at any point during our sample period. Consensus analysts' recommendations enters the equation (3) in standardized form and a positive value of β_2 implies that institutional demand increases (decreases) as consensus analysts' recommendations deteriorate (improve)[19]. Conversely, a negative value of γ_t implies that institutional demand increases (decreases) as consensus analysts' recommendations improve (deteriorate).

As we can see from our results, the correlation coefficient of institutional demand month-to-month is once again positive (0.3134) and highly significant at the 1 percent significance level. Regarding the analysts' recommendations coefficient β_2, this is

[19] As consensus analysts' recommendations increase in value (i.e. move from 1 to 5), this means that the analysts' outlook on a particular stock worsens. Therefore, a positive value of β_2 would suggest that institutional demand increases as consensus analysts' recommendations increase in value (i.e. as analysts' outlook deteriorates).

almost equal to zero, as well as statistically insignificant, indicating that institutional demand is not affected by analysts' recommendations.

Table 3.2 -Test for herding.

The table presents the results from equation (1) : $\Delta_{k,t} = \beta_t \Delta_{k,t-1} + \varepsilon_{k,t}$

*indicates significance at the 10% level, **indicates significance at the 5% level and ***indicates significance at the 1% level.

	Partitioned Slope Coefficient		
Average Coefficient (β)	Funds Following their own trades	Funds following others' trades	Average R^2
Stocks traded by ≥1 fund			
0,3307 (20,44)***	0,1037 (9,76)***	0,2270 (16,87)***	0,1537
Stocks traded by ≥2 funds			
0,3396 (19,50)***	0,0907 (9,04)***	0,2489 (16,10)***	0,1631
Stocks traded by ≥3 funds			
0,3417 (20,32)***	0,1149 (8,59)***	0,2268 (13,10)***	0,1642
Stocks traded by ≥4 funds			
0,3339 (18,70)***	0,1255 (8,74)***	0,2085 (10,88)***	0,1620
Stocks traded by ≥5 funds			
0,3440 (18,21)***	0,1267 (8,31)***	0,2173 (10,66)***	0,1810

As previously, we follow the same procedure with the thresholds in order to test whether using stocks traded by numbers of funds over and above certain thresholds produces different results. The results indicate that in all thresholds examined, the coefficient of institutional demand month-to-month is always positive, ranging from 0.3276 to 0.3188 for the most widely traded stocks, and highly significant at the 1 percent significance level. The coefficient of analyst recommendations has turned negative, implying that institutional demand increases as analyst recommendations improve, nevertheless it still appears insignificant at all the thresholds of our sample.

Table 3.3 – Analysts' Recommendations

The table presents the results from equation (3) : $\Delta_{k,t} = \beta_t \Delta_{k,t-1} + \beta_2 X_{k,t-1} + \varepsilon_{k,t}$
where $X_{k,t-1}$ the variable controlling for the recommendations of analysts.
*indicates significance at the 10% level, **indicates significance at the 5% level and ***indicates significance at the 1% level.

Average Coefficient (β_1)	Analysts' Recommendations Coefficient (β_2)	Average R^2
Stocks traded by ≥1 fund		
0,3134	0,0011	
(17,27)***	(0,07)	0,1924
Stocks traded by ≥2 funds		
0,3276	-0,0078	
(17,90)***	(-0,48)	0,2015
Stocks traded by ≥3 funds		
0,3240	-0,0142	
(17,91)***	(-0,76)	0,2076
Stocks traded by ≥4 funds		
0,3120	-0,0139	
(15,42)***	(-0,68)	0,2173
Stocks traded by ≥5 funds		
0,3188	-0,0150	
(14,87)***	(-0,68)	0,2374

The next investing style, that we account for, is market value (size). In order to gauge size we use the end-of-month market capitalization values[20] for all the stocks held by our funds at any point during our sample period. These market capitalization values enter lagged in the equation (3) in standardized form and a positive (negative) value of β_2 implies that institutional demand is a straight (inverse) function of stock size. As table 3.4 indicates and in line with the previous findings, the correlation coefficient of institutional demands remains positive and highly significant at the 1 percent significance level. In contrast with the previously discussed style, all the size coefficients are negative and the majority of them are also significant; hence, according to our results institutional demand month-to-month is significantly negatively related to size. So, starting with the results of our full sample period, there

[20] Source: Thomson DataStream.

is a high dependence of institutional demand month-to-month as the β_t coefficient (0.3452) suggests. The β_2 coefficient indicating the market value of firms is negative (-0.1748) and significant at the 5 percent level. The picture is similar in the next two thresholds examined, stocks traded by two or more funds and by three or more funds. Where we observe a different picture is in the next two thresholds which include the most traded stocks. Particularly, whereas the correlation coefficient of institutional demand remains positive and highly significant (1 percent level), the coefficient of market value becomes less significant and at the final threshold it is insignificant.

Table 3.4 – Market Value

The table presents the results from equation (3) : $\Delta_{k,t} = \beta_t \Delta_{k,t-1} + \beta_2 X_{k,t-1} + \varepsilon_{k,t}$
where $X_{k,t-1}$ the variable controlling for the market value.
*indicates significance at the 10% level, **indicates significance at the 5% level and ***indicates significance at the 1% level.

Average Coefficient (β_1)	Market Value Coefficient (β_2)	Average R^2
Stocks traded by ≥1 fund		
0,3452 (20,39)***	-0,1748 (-2,68)**	0,1857
Stocks traded by ≥2 funds		
0,3507 (20,00)***	-0,1852 (-2,61)**	0,1950
Stocks traded by ≥3 funds		
0,3498 (20,29)***	-0,2212 (-2,68)**	0,2020
Stocks traded by ≥4 funds		
0,3410 (18,56)***	-0,1759 (-1,89)*	0,2096
Stocks traded by ≥5 funds		
0,3543 (18,48)***	-0,1602 (-1,61)	0,2297

We next account for the relationship between momentum trading and institutional demand month-on-month. In order to gauge momentum we use the end-of-month closing prices[21] for all the stocks held by our funds at any point during our sample period and calculate their monthly log-differenced returns[22]. These calculated stock returns enter lagged in the equation (3) in standardized form and a positive value of β_2 implies the presence of momentum trading since institutional demand increases (decreases) as stock performance improves (decreases). Conversely, a negative value of β_2 implies contrarian trading (the opposite of momentum trading) since in that case institutional demand increases (decreases) as stock performance worsens (improves). Table 3.5 summarizes our findings which, in the full sample of stocks, indicate once more a high correlation of institutional demand over periods (0.3483) and a high level of significance at the 1 percent significance level. The "momentum" coefficient reflecting the relationship between institutional demand and stock's monthly returns is negative (-0.0210), thus presenting evidence of contrarian strategies on behalf of institutional investors in Portugal. However, whereas the β_t coefficient is significant (1 percent level), the "momentum" coefficient is insignificant. Similar results we get from the next threshold examined, i.e. stocks traded by two or more funds.

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[21] Source: Thomson DataStream.

[22] The monthly log-differenced return for each stock is given by the difference of the natural logarithms of prices at the end of months t and t-1, respectively.

Table 3.5 – Momentum

The table presents the results from equation (3) : $\Delta_{k,t} = \beta_t \Delta_{k,t-1} + \beta_2 X_{k,t-1} + \varepsilon_{k,t}$ where $X_{k,t-1}$ the variable controlling for the past returns.
*indicates significance at the 10% level, **indicates significance at the 5% level and ***indicates significance at the 1% level.

Average Coefficient (β_1)	Momentum Coefficient (β_2)	Average R^2
Stocks traded by ≥1 fund		
0,3483	-0,0210	
(20,28)***	(-1,37)	0,1968
Stocks traded by ≥2 funds		
0,3478	-0,0248	
(19,78)***	(-1,54)	0,2026
Stocks traded by ≥3 funds		
0,3460	-0,0366	
(19,79)***	(-2,14)**	0,2030
Stocks traded by ≥4 funds		
0,3341	-0,0443	
(18,18)***	(-2,55)**	0,2090
Stocks traded by ≥5 funds		
0,3492	-0,0364	
(17,65)***	(-2,11)**	0,2278

The picture changes when accounting for the next three thresholds of the most traded stocks. More specifically, whereas the correlation coefficient of the institutional demand month-to-month remains positive, ranging from 0.3460 to 0.3492 in the last threshold, and highly significant at the 1 percent significance level, the β_2 coefficient remains negative (-0.0443) indicating a relationship between contrarian strategies and institutional demand month-to-month, though in these thresholds the coefficient is significant at the 5 percent significance level contrary to the first two thresholds.

The next style that is being examined is that of value/growth strategies (Table 3.6). The proxy that we choose to use in our research is the P/E ratio where value strategies usually pick stocks with low P/E and growth strategies pick stocks with higher P/E ratios. Particularly, in order to proxy for value/growth trading we use the end-of-month price-earnings (P/E) values[23] for all the stocks held by our funds at any point during our sample period. The calculated month-end price-earnings values enter lagged in the equation (3) in standardized form and a positive (negative) value of β_2 implies that institutional demand is a straight (inverse) function of P/E[24]. Our findings do not provide any evidence of a relationship between these strategies and the institutional demand month-to-month since the β_2 coefficient of the P/E ratio is insignificant at all thresholds of our sample. More specifically, the correlation coefficient of institutional demand month-to-month is positive, ranging from 0.3479 to 0.3409 in the last threshold, and highly significant at the 1 percent significance level.

Table 3.6 – Value Strategies

The table presents the results from equation (3) : $\Delta_{k,t} = \beta_t \Delta_{k,t-1} + \beta_2 X_{k,t-1} + \varepsilon_{k,t}$ where $X_{k,t-1}$ the variable controlling for the P/E ratio.
*indicates significance at the 10% level, **indicates significance at the 5% level and ***indicates significance at the 1% level.

Average Coefficient (β_1)	P/E Coefficient (β_2)	Average R^2
Stocks traded by ≥1 fund		
0,3479	-0,0001	
(20,18)***	(0,00)	0,2018
Stocks traded by ≥2 funds		
0,3524	-0,0068	
(19,88)***	(-0,33)	0,2077
Stocks traded by ≥3 funds		
0,3487	-0,0064	
(19,18)***	(-0,26)	0,2168
Stocks traded by ≥4 funds		
0,3328	0,0067	
(16,90)***	(0,28)	0,2191
Stocks traded by ≥5 funds		
0,3409	0,0175	
(16,29)***	(0,73)	0,2342

[23] Source: Thomson DataStream.
[24] A positive value of β_2 indicates that funds increase (decrease) their demand as the stocks' P/E increases (decreases); in other words, funds in that case prefer "expensive" (high P/E) stocks, on average. A negative value of β_2 indicates that funds increase (decrease) their demand as the stocks' P/E decreases (increases); in other words, funds in that case prefer "cheap" (low P/E) stocks, on average.

Regarding the coefficient of the P/E ratio, this appears negative at the first three thresholds and switches to positive in the last two with the most widely traded stocks; in all cases however, as mentioned before, the coefficient of the style indicator is insignificant.

The next examined style is that of volatility (Table 3.7). In order to proxy for volatility we use the approach by Schwert (1989) which calculates volatility as the monthly standard deviation of daily log-differenced returns for each of the stocks held by our funds at any point during our sample period. This volatility measure's values enter lagged in the equation (3) in standardized form and a positive (negative) value of β_2 implies that institutional demand is a straight (inverse) function of volatility[25]. Yet again, the β_t coefficient of intertemporal institutional demand month-on-month is positive (ranging from 0.3323 to 0.3502) and highly significant at the 1 percent significance level at all the thresholds examined. The β_2 coefficient of volatility in its turn is positive, except in the threshold including stocks traded by two or more funds, and statistically insignificant at all the thresholds examined. As such, our results do not indicate any relationship between volatility and institutional demand month-to-month.

[25] A positive value of β_2 indicates that funds increase (decrease) their demand as the stocks' volatility increases (decreases); in other words, funds in that case prefer riskier stocks, on average. A negative value of β_2 indicates that funds increase (decrease) their demand as the stocks' volatility decreases (increases); in other words, funds in that case prefer less risky stocks, on average.

Table 3.7 - Volatility

The table presents the results from equation (3) : $\Delta_{k,t} = \beta_t \Delta_{k,t-1} + \beta_2 X_{k,t-1} + \varepsilon_{k,t}$ where $X_{k,t-1}$ the variable controlling for the volatility.
*indicates significance at the 10% level, **indicates significance at the 5% level and ***indicates significance at the 1% level.

Average Coefficient (β_1)	Volatility Coefficient (β_2)	Average R^2
Stocks traded by ≥1 fund		
0,3470	0,0057	
(19,98)***	(0,26)	0,1935
Stocks traded by ≥2 funds		
0,3426	-0,0017	
(20,06)***	(0,08)	0,1983
Stocks traded by ≥3 funds		
0,3502	0,0019	
(21,36)***	(0,08)	0,2013
Stocks traded by ≥4 funds		
0,3323	0,0367	
(18,05)***	(1,44)	0,2102
Stocks traded by ≥5 funds		
0,3490	0,0316	
(17,90)***	(1,12)	0,2322

The last style that we examine is that of volume, presented in table 3.8. In order to proxy for volume we use the monthly volume (calculated by aggregating all daily volume observations[26] within a month) for each of the stocks held by our funds at any point during our sample period. These calculated monthly volume values enter lagged in the equation (3) in standardized form[27] and a positive (negative) value of β_2 implies that institutional demand is a straight (inverse) function of volume. As our results indicate, the β_t coefficient of inter-temporal dependence of institutional trades is positive (ranging from 0.3374 to 0.3581) and highly significant at the 1 percent significance level, whereas the β_2 coefficient appears negative at all the thresholds

[26] Source: Thomson DataStream.
[27] Standardized monthly volume values are calculated here by replacing $Raw\Delta_{k,t}$ with the monthly volume values in equation (2).

examined. Particularly, the latter is significant at the 5 percent significance level at the first two thresholds (stocks traded by one or more funds and stocks traded by two or more funds) and appears to gradually lose its significance till the last thresholds (stocks traded by five or more funds) where it appears to be insignificant. As such, our results suggest a negative relationship between institutional demand month-to-month and the volume of traded stocks.

Table 3.8 – Volume

The table presents the results from equation (3) : $\Delta_{k,t} = \beta_t \Delta_{k,t-1} + \beta_2 X_{k,t-1} + \varepsilon_{k,t}$ where $X_{k,t-1}$ the variable controlling for the volume.
*indicates significance at the 10% level, **indicates significance at the 5% level and ***indicates significance at the 1% level.

Average Coefficient (β_1)	**Volume Coefficient (β_2)**	**Average R^2**
Stocks traded by ≥1 fund		
0,3374	-0,0222	
(19,50)***	(-2,30)**	0,1913
Stocks traded by ≥2 funds		
0,3492	-0,0200	
(19,18)***	(-1,99)**	0,2026
Stocks traded by ≥3 funds		
0,3533	-0,0185	
(19,99)***	(-1,80)*	0,2093
Stocks traded by ≥4 funds		
0,3430	-0,0181	
(17,95)***	(-1,71)*	0,2176
Stocks traded by ≥5 funds		
0,3581	-0,0118	
(17,90)***	(-1,15)	0,2342

So far, our results indicate a highly significant (1 percent level) institutional demand over the months; what is more, this institutional demand appears to be due to funds following the trades of other funds and it is robust when accounting for a number of investing styles. Consistent to our hypothesis, there is limited evidence of style investing in such a concentrated environment as half of the style-indicators employed in this study (analysts' recommendations, price-earnings, and volatility) appear insignificant. However, in the Portuguese fund industry, there is evidence of contrarian trading as well as a preference towards trading on stocks of small capitalization and lower volume stocks.

3.7.2 Pre and Post Euronext

Another test of robustness that we are going to apply is to break the sample into two periods, pre-Euronext and post-Euronext. In September 2002, the Portuguese Stock Exchange was merged into Euronext and it will be interesting to see whether this had any effect on both institutional demand month-on-month and the examined investment styles. So, our first sub sample covers the period July 1996 till August 2002 and the second one covers the period September 2002 till June 2011.

Starting our analysis with the full sample results, there are some interesting findings revealed in table 3.9. Starting with the β_t coefficient of the inter-temporal dependence of institutional demand month-on-month, we see that it is still significant pre and post Euronext at the 1 percent significance level. However, the value of the β_t coefficient was lower before Euronext (0.2806) than in the post-Euronext period (0.3647); as the t-test of the relative change between these two periods indicates, this increase was significant (at the 5 percent level).

Table 3.9 – Herding pre and post Euronext

The table presents the results from equation (1) : $\Delta_{k,t} = \beta_t \Delta_{k,t-1} + \varepsilon_{k,t}$
*indicates significance at the 10% level, **indicates significance at the 5% level and ***indicates significance at the 1% level.

			Partitioned Slope Coefficient							
Average Coefficient (β)			**Funds Following their own trades**			**Funds following others' trades**			**Average R^2**	
Pre-Euronext	Post-Euronext	**t test**	Pre-Euronext	Post-Euronext	**t test**	Pre-Euronext	Post-Euronext	**t test**	Pre-Euronext	Post Euronext
Stocks traded by ≥1 fund										
0,2806 (12,98)***	0,3647 (16,33)***	(-2,71)**	0,0694 (5,74)***	0,1269 (8,20)***	(-2,93)**	0,2112 (10,41)***	0,2378 (13,27)***	(-0,98)	0,1089	0,1842
Stocks traded by ≥2 funds										
0,3129 (13,61)***	0,3588 (14,68)***	(-1,33)	0,0541 (5,47)***	0,1156 (7,77)***	(-3,42)***	0,2588 (10,75)***	0,2422 (11,97)***	(-0,53)	0,1293	0,1861
Stocks traded by ≥3 funds										
0,3072 (13,65)***	0,3652 (15,50)***	(-1,78)*	0,0731 (4,66)***	0,1433 (7,41)***	(-2,82)**	0,2341 (8,31)***	0,2219 (10,09)***	(-0,34)	0,1282	0,1886
Stocks traded by ≥4 funds										
0,3231 (14,19)***	0,3413 (13,25)***	(-0,53)	0,0813 (4,99)***	0,1555 (7,41)***	(-2,79)**	0,2418 (8,49)***	0,1858 (7,26)***	(1,46)	0,1290	0,1844
Stocks traded by ≥5 funds										
0,3382 (12,79)***	0,3480 (13,26)***	(-0,26)	0,0788 (4,44)***	0,1592 (7,21)***	(-2,84)**	0,2593 (8,11)***	0,1888 (7,20)***	(1,71)*	0,1545	0,199

Likewise, there was a significant increase (5 percent level) in the first component of the β_t coefficient, indicating funds following their own trades; as such in the period before Euronext the coefficient had a value of 0.0694 and increased to 0.1269, both values being significant at the 1 percent level. Contrary to the previous coefficients, the herding coefficient did increase but the relative change over these two periods was insignificant as the t-statistic suggests. So, before Euronext the herding component had a value of 0.2112 and after Euronext increased to 0.2378, both values being significant at the 1 percent level. What is more, the herding component accounted for 75% of the institutional demand month-on-month before Euronext and fell to 65% in the period following the merger into Euronext.

As previously, we will use some thresholds to test whether our findings remain robust when accounting for more widely traded stocks. The first threshold is that of stocks traded by two or more funds. At first glance we can see that the β_t coefficient and its two components are all positive and highly significant at the 1 percent level. The β_t coefficient appears increased in the second period, from 0.3129 to 0.3588, though this change is not significant. What is significant (at the 1 percent level) is the change of the first component which increased from 0.0541 in the first period to 0.1156 in the second one. The second component of the β_t coefficient, measuring herding, appears to be slightly decreased in the second period after Euronext from 0.2588 to 0.2422; however this change is not significant. Overall, the percentage of herding on the dependence of institutional demand month-on-month fell from 83% to 68%.

The next threshold examined is that of stocks traded by three or more funds. Accordingly, the coefficient of temporal dependence of institutional demand and its two components are significant at the 1 percent significance level. What is more, there is a significant increase (10 percent level) on the β_t coefficient from 0.3072 to 0.3652 over the two periods and a significant increase (5 percent level) of the first component from 0.0731 to 0.1433 over the two periods. In contrast, there is a decrease, though not significant, of the herding component from 0.2341 to 0.2219 over the two periods. As such the percentage of herding over the institutional demand month-on-month fell from 76% in the first period to 61% in the second one. Moving forward to the next threshold, that of stocks traded by four or more funds, we document a similar picture; with the β_t coefficient and its two components being significant (1 percent level) the former one increases over the two sub-periods, though not significantly, from 0.3231 to 0.3413 and so does its first component from 0.0813 to 0.1555, though this change is significant at the 5 percent significance level. As in previous cases, the herding component decreases from 0.2418 to 0.1858, though not significantly, and its percentage over the total institutional demand month-on-month correlation falls from 75% to 54%.

In the last threshold, with stocks trade by five or more funds, yet once more the β_t coefficient and its two components are significant (1 percent level) at both periods. The β_t coefficient and its first component have increased, the first one insignificantly so and the second one significantly at the 5 percent level, whereas there is a significant decrease (10 percent level) on the herding component from 0.2593 to 0.1888 over the two periods. Finally, the contribution of herding on month-on-month institutional demand correlation fell from 77% to 54% from the first period of our sample to the second one.

What is next is to analyze the findings regarding our applied investing styles and their relationship with institutional demand. Table 3.10 shows the results regarding analyst recommendations. Starting with the sample of all stocks, we can see that the correlation coefficient of institutional demand month-to-month is positive and highly significant at the 1 percent significance level. Furthermore, we document an insignificant increase from 0.2870 in the first period to 0.3314 in the second period. Regarding, the analysts' recommendations coefficient, this is positive (0.0043) in the pre-Euronext period and negative (-0.0010) in the post Euronext period, though insignificant in both cases and without any significant change over these two periods.

The next threshold includes stocks traded by two or more funds. As we can see, the case is the same for the β_t coefficient, i.e. it is positive and highly significant (1 percent level). Particularly, there is an insignificant increase in the β_t coefficient (from 0.3211 to 0.3321), whereas the coefficient of analysts' recommendations is negative in both pre and post Euronext periods, (-0.0046) and (-0.0099) respectively, contrary to the previous threshold where it was positive in the first period, and this increase is insignificant. In the third threshold, i.e. stocks traded by three or more funds, we document that the β_t coefficient is positive and highly significant (1 percent level), increasing from 0.3146 to 0.3303. Furthermore, once again the coefficient of analyst recommendations remains negative at both periods (-0.0183 and -0.0115 respectively) and its relative increase over the two periods is insignificant as well.

Things begin to change from the next threshold onwards. More specifically, in the threshold that includes stocks traded by four or more funds, the β_t coefficient appears for the first time to decrease over the two periods (from 0.3328 to 0.2978), though not significantly. As regards the coefficient of the analysts' recommendations this remains insignificant over the two periods, however there is a switch of its sign from negative in the first period to positive in the second one, (-0.0428) and (0.0057) respectively.

Table 3.10 – Analysts' recommendations pre and post Euronext

The table presents the results from equation (3) : $\Delta_{k,t} = \beta_t \Delta_{k,t-1} + \beta_2 X_{k,t-1} + \varepsilon_{k,t}$
where $X_{k,t-1}$ the variable controlling for the analysts' recommendations.
*indicates significance at the 10% level, **indicates significance at the 5% level and ***indicates significance at the 1% level.

Average Coefficient (β)			**Analysts' recommendations Coefficient (β_2)**			**Average R^2**	
Pre-Euronext	Post-Euronext	**t test**	Pre-Euronext	Post-Euronext	**t test**	Pre-Euronext	Post Euronext
Stocks traded by ≥1 fund							
0,2870 (12,00)***	0,3314 (12,88)***	(-1,26)	0,0043 (0,20)	-0,0010 (-0,05)	(0,18)	0,1504	0,2210
Stocks traded by ≥2 funds							
0,3211 (13,57)***	0,3321 (12,64)***	(-0,31)	-0,0046 (-0,21)	-0,0099 (-0,44)	(0,17)	0,1644	0,2267
Stocks traded by ≥3 funds							
0,3146 (13,31)***	0,3303 (12,77)***	(1,97)***	-0,0183 (-0,69)	-0,0115 (-0,44)	(-0,18)	0,1697	0,2333
Stocks traded by ≥4 funds							
0,3328 (13,96)***	0,2978 (9,96)***	(0,92)	-0,0428 (-1,53)	0,0057 (0,20)	(-1,21)	0,1796	0,2429
Stocks traded by ≥5 funds							
0,3467 (12,34)***	0,2998 (9,83)***	(1,13)	-0,0479 (-1,70)*	0,0073 (0,23)	(-1,30)	0,2018	0,2615

Lastly, when accounting for stocks traded by five or more funds, we see yet again that the correlation coefficient of institutional demand month-to-month is still positive and significant (1 percent level) and more specifically that it is insignificantly decreasing over the two periods (from 0.3328 to 0.2978). There is also another change in this threshold compared to the previous ones and this has to do with the coefficient of analysts' recommendations which appears to be statistically significant (10 percent level) in the pre-Euronext period. Again, the sign of the coefficient appears increasing over the two periods from (-0.0479) to (0.0073).

The next style that we are going to examine is that of market value. Again, as table 3.11 indicates, the β_t coefficient is positive and highly significant (1 percent level) at both periods, pre and post Euronext; what is more, we document a significant (5 percent level) increase on the β_t coefficient (from 0.2872 to 0.3846). Regarding the coefficient of market value, this appears negative on both periods, however it is only significant (1 percent level) at the post Euronext period and its decrease over these two periods is also statistically significant at the 5 percent level. The next threshold, i.e. stocks traded by two or more funds, reveals similar results. Particularly, the β_t coefficient (significant at the 1 percent level) has statistically (10 percent level) increased over the two periods (from 0.3160 to 0.3742). Again, the market value coefficient appears negative on both periods (-0.0277 and -0.2921 respectively), though significant (1 percent level) at the post Euronext period with its relative decrease over the two periods being statistically significant (10 percent level). A similar picture is witnessed on the threshold examining stocks traded by three or more funds. More specifically, the β_t coefficient which is significant (1 percent level) at both periods appears to significantly (5 percent level) increase over the two periods from (0.3086 to 0.3778).

Table 3.11 – Market Value

The table presents the results from equation (3) : $\Delta_{k,t} = \beta_t \Delta_{k,t-1} + \beta_2 X_{k,t-1} + \varepsilon_{k,t}$
where $X_{k,t-1}$ the variable controlling for the market value.
*indicates significance at the 10% level, **indicates significance at the 5% level and ***indicates significance at the 1% level.

Average Coefficient (β)			Market Value Coefficient (β_2)			Average R^2	
Pre-Euronext	Post-Euronext	**t test**	Pre-Euronext	Post-Euronext	**t test**	Pre-Euronext	Post Euronext
Stocks traded by ≥1 fund							
0,2872 (11,99)***	0,3846 (17,02)***	(-2,96)**	-0,0105 (-0,12)	-0,2864 (-3,14)***	(2,20)**	0,1369	0,2189
Stocks traded by ≥2 funds							
0,3160 (13,26)***	0,3742 (15,32)***	(-1,71)*	-0,0277 (-0,29)	-0,2921 (-2,94)***	(1,92)*	0,1561	0,2213
Stocks traded by ≥3 funds							
0,3086 (13,18)***	0,3778 (15,80)***	(-2,07)**	-0,0292 (-0,29)	-0,3516 (-2,95)***	(2,07)**	0,1562	0,2332
Stocks traded by ≥4 funds							
0,3208 (13,63)***	0,3546 (13,44)***	(-0,96)	-0,0079 (-0,07)	-0,2901 (-2,17)**	(1,58)	0,1663	0,2391
Stocks traded by ≥5 funds							
0,3414 (12,64)***	0,3631 (13,69)***	(-0,57)	0,0274 (0,20)	-0,2877 (-2,07)**	(1,62)	0,1954	0,2529

Moreover, the coefficient of market value is again highly significant (1 percent level) on the second sub-period and its decrease from (-0.0292) to (-0.3516) over these two periods is also significant (5 percent level).

When looking into stocks traded by four or more funds, we again observe that the correlation coefficient of institutional demands month-to-month is positive and highly significant (1 percent level) and that there is an insignificant increase. Yet again the coefficients of market value appear significant only at the post Euronext era, though this time they are significant at the 5 percent significance level instead of the 1 percent level in the previous thresholds. What is more, their decrease over the two periods is not statistically significant, differentiating from the previous thresholds.

The next style that we are going to analyze is momentum, i.e. whether trading strategies affect institutional demand over periods. As table 3.12 indicates, the correlation coefficient of institutional demand is positive and highly significant (1 percent level) at both periods in all the thresholds examined. Furthermore, we can see that it appears to increase over the two periods, with this relative increase being significant (5 percent level) only at the thresholds of the full sample stocks and those traded by three or more funds. The momentum coefficient in its turn is insignificant in the pre Euronext periods, whereas in the post Euronext periods it appears negative and significant at all thresholds except the last one, i.e. stocks traded by five or more funds.

Table 3.12 – Momentum

The table presents the results from equation (3) : $\Delta_{k,t} = \beta_t \Delta_{k,t-1} + \beta_2 X_{k,t-1} + \varepsilon_{k,t}$
where $X_{k,t-1}$ the variable controlling for the past returns.
*indicates significance at the 10% level, **indicates significance at the 5% level and ***indicates significance at the 1% level.

Average Coefficient (β)			**Momentum Coefficient (β_2)**			**Average R^2**	
Pre-Euronext	Post-Euronext	**t test**	Pre-Euronext	Post-Euronext	**t test**	Pre-Euronext	Post Euronext
Stocks traded by ≥1 fund							
0,2925 (12,08)***	0,3862 (16,75)***	(-2,80)**	0,0129 (0,63)	-0,0440 (-2,06)**	(1,92)*	0,1403	0,2352
Stocks traded by ≥2 funds							
0,3160 (13,01)***	0,3695 (15,16)***	(-1,55)	-0,0016 (-0,07)	-0,0406 (-1,83)*	(1,23)	0,1588	0,2323
Stocks traded by ≥3 funds							
0,3051 (12,41)***	0,3737 (15,66)***	(-2,00)**	-0,0204 (-0,79)	-0,0476 (-2,09)**	(0,79)	0,1629	0,2303
Stocks traded by ≥4 funds							
0,3192 (13,16)***	0,3441 (13,16)***	(-0,70)	-0,0317 (-1,16)	-0,0529 (-2,34)**	(0,60)	0,1756	0,2317
Stocks traded by ≥5 funds							
0,3326 (11,54)***	0,3605 (13,40)***	(-0,71)	-0,0426 (-1,54)	-0,0322 (-1,46)	(-0,29)	0,2009	0,2461

The next style examined is that of value/growth strategies (table 3.13). Once more, the coefficient of institutional demand month-to-month is positive and highly significant (1 percent level) at both periods in all the thresholds examined; what is more, there is a significant increase on the β_t coefficient (1 percent level) in all thresholds as well. Regarding the coefficient of the P/E ratio, which is used as a proxy for the value/growth strategy, this appears insignificant both in the pre and post Euronext period. In a few words, we can say that there are mixed results regarding the use of value/growth strategies as these are reflected through our P/E proxy. More specifically, in some cases the sign of the coefficient is positive and in others negative. If we concentrate on the majority of the cases we could say that there are indications of value strategies; however since in all cases the coefficients were insignificant we can say that there is no impact of these strategies upon the institutional demand month-to-month in both the pre and post Euronext periods.

The next indicator examined is that of volatility (Table 3.14). Again here, the coefficient β_t remains positive and highly significant at both pre and post Euronext periods with the relative increase being significant (5 percent level) only in the first and third thresholds examined. The volatility coefficient in its turn appears positive and insignificant in the pre Euronext period, with the exception of the second and third thresholds where it appears significant at the 5 percent and 10 percent significance levels respectively.

Table 3.13 – Value/Growth strategies

The table presents the results from equation (3) : $\Delta_{k,t} = \beta_t \Delta_{k,t-1} + \beta_2 X_{k,t-1} + \varepsilon_{k,t}$
where $X_{k,t-1}$ the variable controlling for the P/E ratio.
*indicates significance at the 10% level, **indicates significance at the 5% level and ***indicates significance at the 1% level.

Average Coefficient (β)			**P/E Coefficient (β_2)**			**Average R^2**	
Pre-Euronext	Post-Euronext	**t test**	Pre-Euronext	Post-Euronext	**t test**	Pre-Euronext	Post Euronext
Stocks traded by ≥1 fund							
0,2758	0,3969		0,0208	-0,0142			
(11,82)***	(17,17)***	(-3,69)***	(0,87)	(-0,55)	(0,99)	0,1424	0,2422
Stocks traded by ≥2 funds							
0,2872	0,3966		-0,0076	-0,0063			
(12,18)***	(16,36)***	(-3,24)**	(-0,25)	(-0,22)	(-0,03)	0,1594	0,2405
Stocks traded by ≥3 funds							
0,2763	0,3979		-0,0118	-0,0028			
(11,75)***	(15,92)***	(-3,54)***	(-0,34)	(-0,08)	(-0,18)	0,1669	0,2507
Stocks traded by ≥4 funds							
0,2854	0,3650		0,068	0,0066			
(11,51)***	(12,98)***	(-2,12)**	(0,18)	(0,21)	(0,00)	0,1745	0,2494
Stocks traded by ≥5 funds							
0,2927	0,3737		0,0361	0,0049			
(10,11)***	(12,97)***	(-1,98)**	(1,01)	(0,15)	(0,65)	0,1984	0,2586

In the post Euronext period, the volatility coefficient appears insignificant at all thresholds; furthermore, it is negative in the first three thresholds examined whereas in the last two thresholds of the most traded stocks it appears positive. The only cases where there is a significance decrease (5 percent level) of the coefficient is on the second and the third threshold. Overall, we could say that there is weak evidence of a negative relationship between volatility and month-on-month institutional demand and this is present only in two thresholds, namely in those with stocks traded by two or more funds and those traded by three or more funds, hence in less widely traded stocks.

The final style that is examined is that accounting for the trading volume (table 3.15). Once more, the β_t coefficient remains positive and significant (1 percent level) in both sub-periods at all the thresholds examined. As our results indicate, there is a significant (5 percent level) increase in the β_t coefficient in the first and the third threshold whereas in the other cases the relative change between the two sub-periods is insignificant. The volume coefficient is positive and insignificant in the first sub-period at all the thresholds examined whereas in the post Euronext period shifts to negative and significant at the 1 percent significance level in the first three thresholds and at the 5 percent significance level in the last two thresholds. Moreover, its relative change over the two periods is also significant (5 percent level) at all thresholds.

Table 3.14 – Volatility

The table presents the results from equation (3) : $\Delta_{k,t} = \beta_t \Delta_{k,t-1} + \beta_2 X_{k,t-1} + \varepsilon_{k,t}$
where $X_{k,t-1}$ the variable controlling for the volatility.
*indicates significance at the 10% level, **indicates significance at the 5% level and ***indicates significance at the 1% level.

Average Coefficient (β)			**Volatility Coefficient (β_2)**			**Average R^2**	
Pre-Euronext	Post-Euronext	**t test**	Pre-Euronext	Post-Euronext	**t test**	Pre-Euronext	Post Euronext
Stocks traded by ≥1 fund							
0,2962	0,3742		0,0320	-0,024			
(12,22)***	(16,21)***	(-2,33)**	(1,12)	(-0,87)	(1,41)	0,1583	0,2175
Stocks traded by ≥2 funds							
0,3216	0,3642		0,0608	-0,0318			
(14,35)***	(14,68)***	(-1,28)	(2,19)**	(-1,05)	(2,26)**	0,1463	0,2214
Stocks traded by ≥3 funds							
0,3040	0,3816		0,0586	-0,0366			
(13,56)***	(16,94)***	(-2,44)**	(1,76)*	(-1,22)	(2,12)**	0,1668	0,2248
Stocks traded by ≥4 funds							
0,3141	0,3446		0,0329	0,0393			
(13,85)***	(12,85)***	(-0,87)	(0,94)	(1,10)	(-0,13)	0,1719	0,2361
Stocks traded by ≥5 funds							
0,3362	0,3577		0,0157	0,0424			
(12,90)***	(12,96)***	(-0,57)	(0,40)	(1,08)	(-0,48)	0,2003	0,2539

Table 3.15 – Volume

The table presents the results from equation (3) : $\Delta_{k,t} = \beta_t \Delta_{k,t-1} + \beta_2 X_{k,t-1} + \varepsilon_{k,t}$
where $X_{k,t-1}$ the variable controlling for the volume.
*indicates significance at the 10% level, **indicates significance at the 5% level and ***indicates significance at the 1% level.

Average Coefficient (β)			**Volume Coefficient (β_2)**			**Average R^2**	
Pre-Euronext	Post-Euronext	**t test**	Pre-Euronext	Post-Euronext	**t test**	Pre-Euronext	Post Euronext
Stocks traded by ≥1 fund							
0,2903 (12,29)***	0,3693 (15,51)***	(-2,36)**	0,0106 (0,84)	-0,0444 (-3,31)***	(3,00)**	0,1409	0,2255
Stocks traded by ≥2 funds							
0,3183 (13,39)***	0,3701 (14,32)***	(-1,48)	0,0138 (1,13)	-0,0429 (-2,99)***	(3,01)**	0,1564	0,2340
Stocks traded by ≥3 funds							
0,3113 (13,01)***	0,3818 (15,56)***	(-2,06)**	0,0128 (1,04)	-0,0397 (-2,69)***	(2,73)**	0,1581	0,2441
Stocks traded by ≥4 funds							
0,3241 (13,81)***	0,3558 (12,77)***	(-0,87)	0,0114 (0,89)	-0,0381 (-2,50)**	(2,49)**	0,1634	0,2543
Stocks traded by ≥5 funds							
0,3430 (12,86)***	0,3684 (12,99)***	(-0,65)	0,0149 (1,24)	-0,0300 (-1,99)**	(2,33)**	0,1855	0,2674

What can one infer upon the results from tables 3.10-3.15, is that the styles that appear significant in the full period sample draw their significance in the post-Euronext period; in addition, in the post-Euronext period, there is a decrease in the "funds following the trades of others" and an increase in the part "funds following their own trades". A possible explanation of this phenomenon could be that the induction of the Portuguese stock market into the Euronext improved the transparency and the quality of the information in the market. As such, fund managers had fewer incentives to herd on their peers and started to apply their own investing strategies. The latter view, is strengthened though the fact that the style-indicators are significant in the post-Euronext period, as tables 3.10-3.15 indicate. However, the post-Euronext period includes the current financial crisis, the effect of which we are going to examine in the next section.

3.7.3 Pre and Post Crisis

In order to identify any possible effects of the financial crisis into our results we will break our second sub-period (post-Euronext) into two sub-samples, namely pre and post crisis. The crisis began in the U.S market due to the real estate bubble and the sub-prime mortgages. Later on, the crisis spread to the European markets as many of the European banks were exposed on such kind of investments, often referred to as toxic bonds; there have been several cases where private banks were bail out from the governments in order not to declare bankruptcy. What is more, the debt crisis outbreak in a numerous European countries, such as Ireland, Greece and Portugal which is still undergo when this thesis is written. As such, we will try to gauge whether the results that came up on the post Euronext period are robust or were subject to other factors and more specifically whether the crisis outbreak in 2008 affected the behavior of institutional investors in terms of herding (through month-to-month institutional demand) and the impact of style investing on it. Accordingly, the first period will be from 1/9/2002 till 31/12/2007 and the second sub-period will be from 1/1/2008 till 31/6/2011.

As we can see from table 3.16, the β_t coefficient and both its components are positive and highly significant at the 1 percent significance level for both the pre and post crisis periods. Particularly, the β_t coefficient appears insignificantly decreasing from 0.3672 to 0.3609, whereas its first component, i.e. institutions following themselves, increases from 0.1221 to 0.1343, though the relative change over the two periods is insignificant. Regarding the herding component, this appears insignificantly decreasing from 0.2451 to 0.2265 and its overall percentage over the β_t coefficient decreases from 67% to 63% over the two periods.

What is next is to examine whether there are differences in the results when we account for more widely traded stocks. As such, in the threshold with stocks traded by two or more funds we again observe that the correlation coefficient and its two components are positive and highly significant at the 1 percent significance level at both periods. Starting with the β_t coefficient we can see that there is a small increase from 0.3569 to 0.3590 in the second period, though this relative increase is insignificant. Once more, the first component increases over the two sub-periods, namely from 0.1015 to 0.1370, though again this change is insignificant. Lastly, the herding component appears to decrease over the two periods from 0.2554 to 0.2220 and its contribution over the month-to-month institutional demand falls from 72% to 62%.

Table 3.16 – Herding pre and post Crisis

The table presents the results from equation (1) : $\Delta_{k,t} = \beta_t \Delta_{k,t-1} + \varepsilon_{k,t}$
*indicates significance at the 10% level, **indicates significance at the 5% level and ***indicates significance at the 1% level.

			Partitioned Slope Coefficient							
Average Coefficient (β)			**Funds Following their own trades**			**Funds following others' trades**			**Average R^2**	
Pre-Crisis	Post-Crisis	**t test**	Pre-Crisis	Post-Crisis	**t test**	Pre-Crisis	Post-Crisis	**t test**	Pre-Crisis	Post-Crisis
Stocks traded by ≥1 fund										
0,3672	0,3609		0,1221	0,1343		0,2451	0,2265			
(12,01)***	(11,21)***	(1,98)	(8,28)***	(4,17)***	(2,00)	(9,72)***	(9,42)***	(1,98)	0,1900	0,1753
Stocks traded by ≥2 funds										
0,3569	0,359		0,1015	0,137		0,2554	0,2220			
(10,35)***	(10,62)***	(1,98)	(7,46)***	(4,32)***	(2,00)	(9,15)***	(7,82)***	(1,98)	0,1946	0,1732
Stocks traded by ≥3 funds										
0,3629	0,3685		0,126	0,1695		0,2369	0,1990			
(10,90)***	(11,70)***	(1,98)	(6,95)***	(4,21)***	(2,00)	(7,70)***	(6,68)***	(1,98)	0,1973	0,1754
Stocks traded by ≥4 funds										
0,3415	0,341		0,1315	0,1919		0,2100	0,1490			
(9,80)***	(8,98)***	(1,99)	(6,30)***	(4,56)***	(2,00)	(5,95)***	(4,20)***	(1,98)	0,1936	0,1703
Stocks traded by ≥5 funds										
0,3531	0,3401		0,1409	0,1870		0,2122	0,1531			
(9,98)***	(8,73)***	(1,99)	(6,26)***	(4,25)***	(2,00)	(5,77)***	(4,36)***	(1,98)	0,2107	0,1811

The next threshold examines stocks that are traded by three funds or more; again our results indicate that the coefficient of institutional demand month-to-month and its two components are positive and high significant at the 1 percent significance level at the periods pre and post crisis. The β_t coefficient appears to insignificantly increase from 0.3629 to 0.3685 over the two periods, as its first component does; the latter increases (insignificantly) from 0.1260 to 0.1695 over the two periods. The herding component appears decreasing once more, though insignificantly, from 0.2369 to 0.1990 over the two periods; accordingly its contribution over the institutional demand month-to-month decreases from 65% to 54% over the two periods.

Moving on to the next threshold that includes stocks traded by four or more funds we document that the β_t coefficient and both its components are positive and highly significant at the 1 percent significance level at both periods. The first one insignificantly decreases from 0.3415 to 0.3410 in the second sub period whereas its first component increases, though insignificantly, from 0.1315 to 0.1919. The herding component appears to insignificantly decreasing from 0.2100 to 0.1490 and its percentage over the β_t coefficient falls from 61% to 44%.

The results from our final threshold, i.e. stocks traded by five or more funds, are similar to the previous thresholds'. Particularly, the β_t coefficient and both its components are positive and highly significant (1 percent level) at the pre and post crisis periods. More specifically, the β_t coefficient insignificantly decreases from 0.3531 to 0.3401 over the two periods whereas its first component increases (insignificantly) from 0.1409 to 0.1870. The herding component appears decreasing (insignificantly) over the two periods from 0.2122 to 0.1531 with its percentage over the correlation coefficient of institutional demand month-to-month falling from 60% to 45%.

The next step in our analysis is to examine the impact of the crisis on both the correlation of month-on-month institutional demand and investment styles. Starting with the analysts' recommendations (table 3.17) we observe that the correlation coefficient of institutional demand month-to-month is positive and significant at the 1 percent significance level at both periods, pre and post crisis, in all the thresholds examined; particularly, the correlation coefficient of institutional demand month-to-month decreases over the two periods insignificantly in the first three thresholds and significantly so at the 10 percent and 5 percent significance levels in the last two thresholds respectively. Regarding the coefficient of analysts' recommendations, this appears insignificant in the pre crisis period at all the thresholds examined. In the post crisis period, the coefficient of analysts' recommendations in insignificant in all the thresholds but the last two ones with the most widely traded stocks of our sample where it is significant (10 percent level) and positive; in addition the relative change over the two periods in these last thresholds is also significant at the 5 percent significance level.

Table 3.17 – Analysts' recommendations

The table presents the results from equation (3) : $\Delta_{k,t} = \beta_t \Delta_{k,t-1} + \beta_2 X_{k,t-1} + \varepsilon_{k,t}$
where $X_{k,t-1}$ the variable controlling for the analysts' recommendations.
*indicates significance at the 10% level, **indicates significance at the 5% level and ***indicates significance at the 1% level.

Average Coefficient (β)			**Analysts' recommendations Coefficient (β_2)**			**Average R^2**	
Pre-Crisis	Post-Crisis	**t test**	Pre-Crisis	Post-Crisis	**t test**	Pre-Crisis	Post-Crisis
Stocks traded by ≥1 fund							
0,3376	0,3218		0,0100	-0,0178			
(9,42)***	(9,04)***	(1,98)	(0,34)	(-0,62)	(1,98)	0,2396	0,1925
Stocks traded by ≥2 funds							
0,3546	0,2978		-0,0139	-0,0039			
(10,05)***	(7,68)***	(1,99)	(-0,44)	(-0,13)	(1,98)	0,2552	0,1831
Stocks traded by ≥3 funds							
0,3616	0,2827		-0,0304	0,0175			
(10,66)***	(7,21)***	(1,99)	(-0,82)	(0,54)	(1,98)	0,2669	0,1820
Stocks traded by ≥4 funds							
0,3400	0,2335		-0,0301	0,0602			
(9,01)***	(4,89)***	(1,99)*	(-0,72)	(1,81)*	(1,98)**	0,2780	0,1893
Stocks traded by ≥5 funds							
0,3523	0,2198		-0,0411	0,081			
(9,40)***	(4,43)***	(1,99)**	(-0,93)	(1,95)*	(1,98)**	0,2997	0,2033

Table 3.18 – Market Value

The table presents the results from equation (3) : $\Delta_{k,t} = \beta_t \Delta_{k,t-1} + \beta_2 X_{k,t-1} + \varepsilon_{k,t}$
where $X_{k,t-1}$ the variable controlling for the market value.
*indicates significance at the 10% level, **indicates significance at the 5% level and ***indicates significance at the 1% level.

Average Coefficient (β)			Market Value Coefficient (β_2)			Average R^2	
Pre-Crisis	Post-Crisis	**t test**	Pre-Crisis	Post-Crisis	**t test**	Pre-Crisis	Post-Crisis
Stocks traded by ≥1 fund							
0,3870 (12,25)***	0,3810 (12,26)***	(1,98)	-0,3776 (-3,11)***	-0,1475 (-1,08)	(1,99)	0,2284	0,2043
Stocks traded by ≥2 funds							
0,3793 (11,14)***	0,3664 (10,86)***	(1,98)	-0,3928 (-2,88)***	-0,1386 (-1,00)	(1,98)	0,2363	0,1985
Stocks traded by ≥3 funds							
0,3757 (11,18)***	0,3809 (11,77)***	(1,98)	-0,3822 (-2,38)**	-0,3051 (-1,72)*	(1,99)	0,2426	0,2189
Stocks traded by ≥4 funds							
0,3527 (9,76)***	0,3577 (9,41)***	(1,98)	-0,3513 (-1,87)*	-0,1968 (-1,10)	(1,98)	0,2515	0,2203
Stocks traded by ≥5 funds							
0,3667 (10,29)***	0,3577 (9,02)***	(1,99)	-0,3558 (-1,83)*	-0,1838 (-0,97)	(1,98)	0,2679	0,2302

The next style that we are going to examine is market value. As table 3.18 indicates, the correlation coefficient of month-to-month institutional demand is positive and highly significant at the 1 percent significance level in pre and post crisis, at all the thresholds examined. Regarding the coefficient of market value this appears negative in the pre crisis period at all the thresholds examined but its significance appears to weaken over the thresholds; as such in the first two thresholds it is significant at the 1 percent significance level, in the third threshold its significance lowers into the 5 percent significance level whereas in the last two thresholds falls to the 10 percent significance level. In the post crisis period, the coefficient of market value still appears negative at all the thresholds examined, though it is insignificant with the only exception being the third threshold where it is significant at the 10 percent significance level.

Then next style indicator examined is that of momentum whose results are exhibited in table 3.19. As we can see, the correlation coefficient of institutional demand month-on-month is positive and highly significant at the 1 percent significance level at both periods in all the thresholds of our sample; furthermore, it appears decreasing over the two sub-periods, though not significantly. Regarding the momentum coefficient this appears negative at both periods in all the thresholds examined. Most importantly, it appears significant at the 5 percent significance level in the last three thresholds of our sample.

Table 3.19 - Momentum

The table presents the results from equation (3) : $\Delta_{k,t} = \beta_t \Delta_{k,t-1} + \beta_2 X_{k,t-1} + \varepsilon_{k,t}$
where $X_{k,t-1}$ the variable controlling for the past returns.
*indicates significance at the 10% level, **indicates significance at the 5% level and ***indicates significance at the 1% level.

Average Coefficient (β)			**Momentum Coefficient (β_2)**			**Average R^2**	
Pre-Crisis	Post-Crisis	**t test**	Pre-Crisis	Post-Crisis	**t test**	Pre-Crisis	Post-Crisis
Stocks traded by ≥1 fund							
0,3993 (12,33)***	0,3663 (11,78)***	(1,98)	-0,0567 (-1,77)*	-0,0247 (-1,07)	(1,98)	0,2536	0,2072
Stocks traded by ≥2 funds							
0,3834 (11,15)***	0,3482 (10,74)***	(1,98)	-0,0434 (-1,28)	-0,0365 (-1,60)	(1,98)	0,2531	0,2007
Stocks traded by ≥3 funds							
0,3832 (11,33)***	0,3594 (11,40***	(1,98)	-0,0457 (-1,29)	-0,0504 (-2,43)**	(1,98)	0,2447	0,2083
Stocks traded by ≥4 funds							
0,3523 (9,83)***	0,3318 (8,85)***	(1,98)	-0,0423 (-1,29)	-0,0690 (-2,46)**	(1,98)	0,2424	0,2154
Stocks traded by ≥5 funds							
0,3763 (10,37)***	0,3363 (8,49)***	(1,99)	-0,0081 (-0,25)	-0,0690 (-2,54)**	(1,98)	0,2592	0,2261

Table 3.20 – Value/Growth strategies

The table presents the results from equation (3) : $\Delta_{k,t} = \beta_t \Delta_{k,t-1} + \beta_2 X_{k,t-1} + \varepsilon_{k,t}$
where $X_{k,t-1}$ the variable controlling for the P/E ratio.
*indicates significance at the 10% level, **indicates significance at the 5% level and ***indicates significance at the 1% level.

Average Coefficient (β)			**P/E Coefficient (β_2)**			**Average R^2**	
Pre-Crisis	Post-Crisis	**t test**	Pre-Crisis	Post-Crisis	**t test**	Pre-Crisis	Post-Crisis
Stocks traded by ≥1 fund							
0,3987	0,3941		0,0069	-0,0464			
(12,44)***	(12,16)***	(1,98)	(0,19)	(-1,33)	(1,98)	0,2523	0,2268
Stocks traded by ≥2 funds							
0,3995	0,3922		0,0125	-0,0350			
(12,08)***	(11,14)***	(1,98)	(0,31)	(-0,95)	(1,98)	0,2546	0,2191
Stocks traded by ≥3 funds							
0,4008	0,3936		-0,0100	0,0081			
(11,69)***	(10,99)***	(1,98)	(-0,20)	(0,20)	(1,98)	0,2679	0,2246
Stocks traded by ≥4 funds							
0,3710	0,3557		0,0025	0,0129			
(9,74)***	(8,61)***	(1,99)	(0,05)	(0,34)	(1,98)	0,2687	0,2198
Stocks traded by ≥5 funds							
0,3870	0,3533		-0,0105	0,0284			
(10,27)***	(7,86)***	(1,99)	(-0,22)	(0,71)	(1,98)	0,2774	0,2299

Table 3.21 – Volatility

The table presents the results from equation (3) : $\Delta_{k,t} = \beta_t \Delta_{k,t-1} + \beta_2 X_{k,t-1} + \varepsilon_{k,t}$
where $X_{k,t-1}$ the variable controlling for the volatility.
*indicates significance at the 10% level, **indicates significance at the 5% level and ***indicates significance at the 1% level.

Average Coefficient (β)			**Volatility Coefficient (β_2)**			**Average R^2**	
Pre-Crisis	Post-Crisis	**t test**	Pre-Crisis	Post-Crisis	**t test**	Pre-Crisis	Post-Crisis
Stocks traded by ≥1 fund							
0,3732	0,3756		-0,0308	-0,0149			
(11,50)***	(12,00)***	(1,98)	(-0,89)	(-0,31)	(1,99)	0,2233	0,2086
Stocks traded by ≥2 funds							
0,3706	0,3545		-0,0649	0,0187			
(10,95)***	(9,86)***	(1,98)	(-1,79)*	(0,36)	(1,99)	0,2308	0,2071
Stocks traded by ≥3 funds							
0,3855	0,3756		-0,0508	-0,0149			
(12,30)***	(12,00)***	(1,98)	(-1,32)	(-0,31)	(1,99)	0,2354	0,2086
Stocks traded by ≥4 funds							
0,3405	0,3508		0,0227	0,0647			
(9,45)***	(8,76)***	(1,99)	(0,50)	(1,09)	(1,99)	0,2451	0,2225
Stocks traded by ≥5 funds							
0,3602	0,3540		0,0117	0,0891			
(10,00)***	(8,15)***	(1,99)	(0,23)	(1,43)	(1,99)	0,2702	0,2291

The next style indicator analyzed is that of the P/E ratio which is used as a proxy for value/growth investment styles; table 20 exhibits the results of our research. As we can see the correlation coefficient of institutional demands month-to-month is positive and highly significant at the 1 percent significance level in both periods examined, at all the thresholds of our sample. In addition, this coefficient appears to decrease over the two periods, though insignificantly. Regarding the P/E coefficient, this appears insignificant at both periods, pre and post crisis, at all the thresholds examined.

The next investment style that we are taking into consideration is volatility (table 3.21). As our results indicate, the correlation coefficient is positive and significant at the 1 percent significance level at both periods and throughout the thresholds examined. Regarding the volatility coefficient is insignificant in both periods in all thresholds examined, except in that with stocks traded by two or more funds.

The final style indicator examined in our research is that of volume. As table 3.22 indicates, the coefficient of institutional demand month-to-month is positive and highly significant (1 percent level) at both periods, at all the examined thresholds. As regards the volume coefficient, this appears negative in the pre crisis period at all the thresholds examined and significant at the 1 percent level except for the last threshold where it is significant at the 5 percent significance level. In the post crisis period, the volume coefficient is insignificant at all the thresholds and in the vast majority of the cases it is positive (except for the third threshold). Moreover the relative change over the two periods is significant at the 5 percent significance level except for the last threshold where it is significant at the 10 percent significance level.

Table 3.22 - Volume

The table presents the results from equation (3) : $\Delta_{k,t} = \beta_t \Delta_{k,t-1} + \beta_2 X_{k,t-1} + \varepsilon_{k,t}$
where $X_{k,t-1}$ the variable controlling for the volume.
*indicates significance at the 10% level, **indicates significance at the 5% level and ***indicates significance at the 1% level.

Average Coefficient (β)			**Volume Coefficient (β_2)**			**Average R^2**	
Pre-Crisis	Post-Crisis	**t test**	Pre-Crisis	Post-Crisis	**t test**	Pre-Crisis	Post-Crisis
Stocks traded by ≥1 fund							
0,3611	0,3819		-0,0748	0,0019			
(10,79)***	(11,87)***	(1,98)	(-4,14)***	(0,11)	(1,98)**	0,2432	0,1985
Stocks traded by ≥2 funds							
0,3706	0,3695		-0,0719	0,0013			
(10,33)***	(10,23)***	(1,98)	(-3,64)***	(0,07)	(1,98)**	0,2588	0,1961
Stocks traded by ≥3 funds							
0,3743	0,3931		-0,0635	-0,0033			
(10,95)***	(11,59)***	(1,98)	(-3,14)***	(-0,17)	(1,98)**	0,2680	0,2077
Stocks traded by ≥4 funds							
0,3467	0,3697		-0,0631	0,0000			
(9,20)***	(9,01)***	(1,99)	(-3,03)***	(0,00)	(1,98)**	0,2785	0,2175
Stocks traded by ≥5 funds							
0,3657	0,3725		-0,0528	0,0048			
(9,64)***	(8,73)***	(1,99)	(-2,60)**	(0,23)	(1,98)*	0,2943	0,2263

The results from tables 3.17-3.22 show that the style-indicators found insignificant in the previous tests (analysts' recommendations, value/growth and volatility), remain insignificant when we account for the financial crisis; the only exception is that of analysts' recommendations which appears significant (10 percent level) for the stocks most widely traded. The other three style-indicators were indeed affected by the financial crisis. More specifically, the size and the volume, which were found significant in the post-Euronext period, appear to be significant in the pre- but insignificant in the post-crisis period. Inversely, the contrarian trading seems to be a product of the crisis, as it appears insignificant in the pre-crisis period but turns to be significant in the post-crisis period.

3.8 Discussion

Table 3.23 - Significance of Herding and Investment Styles

	Sample Period				
	Full Period	**Pre-Euronext**	**Post-Euronext**	**Pre-Crisis**	**Post-Crisis**
HERDING	√	√	√	√	√
INVESTMENT STYLE					
Analyst's Recommendations	-	-	-	-	√
Size	√	-	√	√	-
Momentum	√	-	√	-	√
Value/Growth	-	-	-	-	-
Volatility	-	-	-	-	-
Volume	√	-	√	√	-

In this section we will discuss our empirical results and their contribution to the research upon institutional investors' herd behavior in the context of a concentrated market. One of the most important findings of our research is that the inter-temporal dependence of institutional demand month-to-month in the Portuguese market is very high and significant. The latter, after applying the Sias (2004) methodology and decomposing it into funds following their own trades and funds following others, has been found that to a large extend is due to herding. What is more, our results remain robust even when we test for various thresholds of funds; more specifically, the accountability of herding for the inter-temporal institutional demand month-to-month varies from 62% to 73% into the different thresholds we used, which is a quite high percentage. These results confirm previous arguments by Do *et al.* (2008) that herding is more likely to occur in a concentrated environment. As discussed in the theoretical part of this research, this can be due to several reasons. First of all, since the concentrated environment allows investors to monitor each other and it is easier to follow the actions of their peers, in contrast with a larger market where investors are many more in absolute numbers and it can be more difficult to observe the actions of other investors. Furthermore, since the stocks traded in a concentrated market are relatively few compared to a large market, it is more likely that investors will trade roughly in the same stocks. Finally, due to the fact that institutional investors are relatively few in a concentrated market and they know each other, it is more likely that they will herd on others' action for career/reputational reasons.

Our findings are in line with previous research regarding institutional investors' herd behavior in the Portuguese market. More specifically, Holmes *et al.* (2011) using the same methodology with ours found evidence of herding on behalf of institutional investors; however our results indicate a stronger evidence of herding since our levels of herding are far higher and more significant that those found in the previous mentioned research. Since the methodology applied is the same in both researches, the differences in the findings can be attributed to two different approaches. Firstly, in order to measure the position of institutions holding a security each month we used each stock's volume (the number of shares each fund owns for every month) instead of the stock's market value (the value of stocks each funds has every month). We believe that this measure is more accurate than the one used in the research by Holmes *et al.* (2011), since the number of shares one fund has might be the same over the months, however through the difference in the price of the stock, this would appear that a mutual fund has increased or decreased its position in the stock, whereas it might have not. Secondly, the difference in our results could be due to the larger database we used; particularly, our sample examined is double the size of the one used in the other research (fifteen years instead of seven years). Nevertheless, our findings do not contradict with those found in the research of Holmes *et al.* (2011), on the contrary they provide supporting evidence to their findings.

Another important finding of our research is that the inter-temporal dependence of institutional demand month-to-month, which indirectly is a proxy for herding, is weakly related to style investing. Particularly, having tested for six different investment styles in our research, we have found that when the latter are input in our model the lagged coefficient of institutional demand month-to-month remains highly significant at the 1 percent significance level, hence implying that investment styles have no impact at herding in a concentrated market. Nevertheless, we have found some evidence of a weak relationship between institutional demand and some investing styles, namely size, volume and contrarian strategies.

In the first two cases, our findings are in line with previous researches arguing that herding is more pronounced in small stocks; this phenomenon can be attributed to informational reasons. Particularly, since there is less information in such kinds of stocks, investors could infer information from the actions of others (investigative herding). Likewise, low volume stocks are candidates for herding since in order for investors to trade on them, they have to trade when others do (create volume); thus this is the point when interactive observation among investors take place and it is more likely for them to follow the trades of the others. In the case of trading strategies, several studies have found evidence for their relationship with herding; however the majority of them associated herding with momentum trading whereas in our research there was evidence of contrarian strategies associated to herding. Nevertheless, as our results indicate, the effect of these styles on the coefficient of institutional demand month-to-month is very small. Since all our data is standardized, the coefficients of the lagged institutional demand month-to-month and those of the styles can be directly compared. As such, after we input the variables for style, there was a minor change on the correlation coefficient of institutional demand month-to-month, thus implying that styles do not affect the level of herding. For example, in the case of size, when we input a (standardized) lag of the size variable, the correlation coefficient of the institutional demand month-to-month increased from 0.3307 to 0.3452, which is not an important difference. What is more, the lagged institutional demand is 50% greater than the lagged size variable (in the full sample of stocks); hence, since our variables are standardized as we already discussed, one standard deviation change in the correlation coefficient of institutional demand of the previous month predicts 50% greater change in the following month's institutional demand than a one standard deviation change of the lagged size variable. The case is the same with the other two styles found significant.

In order to further examine the herd behavior of institutional investors in our market we break the sample into two periods, pre and post Euronext. Our results indicate that the correlation coefficient of institutional demand month-on-month increased over the two periods, and so did the coefficient indicating institutions following their own trades. On the contrary, the component of herding has decreased, especially in the most widely traded stocks of our sample where the level of herding fell from 77% to 54%, though it remained significantly high. The only exception where the herding component has increased was in the sample of stocks that included stocks traded by one institutional investor. The fact that the coefficient showing institutions following their own trades significantly increased over the two periods and at the same time the one indicating the level of herding decreased could be an indication of the effect of the improvements in the regulatory framework of Portugal. More specifically, it could be the case that the merger of the Portuguese Stock exchange into Euronext improved the quality of the first one in terms of transparency, trading costs and liquidity [Malkamäki (1999), Pagano (1989)]. The latter imply that institutional investors in Portugal could take advantage of these improvements, hence feel more confident on their own informational sets (since the market will be more transparent and more information will be widely available) and as such they might have less need herding on their peers' actions.

What is striking is the almost absolute absence of any significance of investing styles on behalf of the institutional investors in the pre Euronext period; both the size effect (market value and volume) and the contrarian strategy found in our full sample is only evident and significant in the post Euronext period. This could indicate that as one concentrated market develops and its regulatory framework improves, its investors become more sophisticated. Put it differently, styles are often applied to alleviate complexity, so the entry of the Portuguese Stock Exchange into the Euronext brought forth new realities in the investment business that pushed the local funds towards style investing.

What is more, it could be the case that after the merger with the Euronext, the Portuguese institutional investors started engaging in style investing due to professional reasons. More specifically, it could be the case that after the merger with Euronext, Portuguese funds are most probably assessed versus their peers from Euronext. As such, since an investment style can be a benchmark, Portuguese funds may have resorted style as a means of comparability to their peers from Euronext. The only style indicator that had some presence in the pre Euronext period is that of volatility, with the latter being present in the less widely traded stocks (only in one threshold was it highly significant) and disappearing in the post Euronext period.

Going further deep into institutional investors' herd behavior, we once more partitioned the second sub-sample (post Euronext) into two more sub-samples, before the global credit crisis, taken place in 2008, and after the crisis; in this way we tried to capture any effect the crisis had over herding. The results indicate that the institutional demand month-to-month remained more or less at the same levels at both periods. What has changed, especially in the most widely traded stocks, is that the level of institutions following their own trades has increased, whereas the level of herding has decreased, particularly in the most widely traded stocks where the level of herding fell from 60% to 45%; still however, as the numbers indicate the presence of herding is more than evident in the market even during the crisis. This finding is in line with the findings of previous research that herding is less evident during extreme market conditions, i.e. crises. This is because during crises, the market is so unstable that there is no certain direction which investors can herd towards. Moreover, our findings are in line with the previous research of Choe *et al.* (1999) who found, on the premises of the emerging market of Korea, that institutional investors herded less during the Asian crisis.

Equally interesting findings we get to see regarding the use of style investing on behalf of institutional investors, when we analyze the pre and post crisis periods. Particularly, we can see that analysts' recommendations enter the picture by turning to positive and significant (though not highly significant) in the post crisis period. The intuition behind these results is that institutional investors' behavior is affected by the selling recommendations of the analysts[28] during a crisis. More specifically, during a crisis and as a fund manager wants to be safe, in terms of career and reputation, he may decide on following the market consensus and thus be in line with the suggestions of the analysts. This could be a reasoning why in the most widely traded stocks of our sample, analysts' recommendation become significant. Regarding the size effect found earlier, this becomes insignificant in the post crisis period, as both the market value indicator and the

[28] Consensus analysts' recommendations ranked according to the Thomson DataStream classification (1-1.49 = "strong buy"; 1.5–2.49 = "buy"; 2.5–3.49 = "hold"; 3.5–4.49 = "underperform"; 4.5–5 = "sell"). So, when the coefficient β_2 is negative this implies an improvement in the recommendation on behalf of the analysts and vice versa.

volume indicator suggest. This could be due to the fact that during a crisis, investors avoid to invest on small and risky stocks, which are also characterized by less informational transparency, and prefer investing in safer stocks, these usually being the larger ones. Finally, as regards the contrarian strategy found earlier, the case here appears the other way around; more specifically, in the pre crisis period there is no sufficient evidence for the use of contrarian strategies on behalf of institutional investors, however this appears present in the post crisis period and for the more widely traded stocks (stocks traded by three or more funds). A possible explanation of this phenomenon could be that during crises, where stock prices often overreact to bad information, there will be mispricing in the market with the prices of stocks often trading below their fundamental values. If this is the case, then institutional investors who are better informed than the individual investors will step in the market and take advantage of this mispricing, building positions on stocks whose prices trade lower than their fundamentals imply, in order to achieve profit for them when the prices recover to their fair values. As such, as our results indicate that institutional investors engage in contrarian strategies, investing in stocks which performed poorly in the past months.

Summarizing our findings, we come up with some interesting and useful conclusions. First of all, we can see that in a concentrated environment herding is dominating the market; in all samples and thresholds examined the levels of herding were very high. Secondly, in a concentrated market with a low quality regulatory framework and a lack of information transparency there is no evidence of the use of investing styles on behalf of institutional investors. As such, there is no case that investment styles can promote herding in such countries. Furthermore, the improvement of the regulatory framework and the development of a concentrated market seem to alter the sophistication of its institutional investors since after the merger into the Euronext, they appeared to engage in the use of investment styles. Thus, as the market develops, herding decreases (as our results indicated) and investors are more confident about their own information. However, it is the development of the market that causes herding to decrease and not the use of investing styles, as the latter had little impact upon the institutional demand month-to-month according to our results. So, even in the case of market development, investing styles are not found to promote herding; this finding is in line with similar researches in large countries which found that institutional herding was not due to the use of various styles, such as momentum trading [Sias (2004)]. What is more, even during crises where some investing styles make their appearance and others disappear, there is no supporting evidence that the use of investing styles can be held responsible for the herd behavior of institutional investors.

Finally, we would say that our research sheds light on the relationship between style investing and institutional herding on the premises of a concentrated market. Our findings provide clear evidence that the impact of style investing upon herding is negligible and that the latter dominates the market in all states of it. Our findings bear important implications for the professional fund managers as well as their clients and they are applicable to concentrated markets, especially to the emerging ones. A useful thought for further research would be to test for the profitability of the investing styles found in this research and whether these are useful for institutional investors when they invest in concentrated markets, though this is not the scope of this thesis; what we wanted and managed to show is that style investing does not affect herding in concentrated markets.

Furthermore, since when we wrote this chapter, the debt crisis was still going, it would be interesting to re-examine the relationship between style investing and institutional herding after the end of the crisis (when this happens) in order to examine whether there should be any significant difference on the findings of our research.

3.9 Conclusion

Institutional herding has been found to be promoted by style investing in quite a few studies. However, the majority of the research has been undertaken in very large markets such as the U.S. The gap that we identified in the relevant literature and examined in this chapter was the impact of market concentration over the relationship between institutional herding and style investing; an issue that has not been explored before. In order to do so, we used data from the Portuguese mutual fund industry, which is typified by a high level of market concentration. More specifically, we used monthly portfolio holdings for a period of fifteen years, namely from 1996 till 2010.

Our results indicate that institutional demand over time appears highly significant in the Portuguese fund industry and it is due to funds following the trades of other funds (herding). In addition, our results indicate that in the context of a concentrated market, style investing has no significant impact upon the persistence of institutional demand which remains significant throughout all tests carried out. Particularly, we found that herding levels in a concentrated market are quite high and that these remain robust when we account for various investment styles (consensus analysts' recommendations, momentum, size, value/growth, volatility, and volume). More specifically, we found that some (consensus analysts' recommendations, value/growth, and volatility) of them exhibit no significance at all, whereas others (momentum, size, and volume) exhibit evidence of trading patterns on behalf of the Portuguese mutual funds. The latter appear to be contrarian traders and exhibiting greater persistence in their demand when trading on stocks of smaller size and lower volume.

When we accounted for the entrance of the Portuguese market into the Euronext, we saw that the styles which were significant in the full sample period (momentum, size, and volume) appear significant only in the post-Euronext period. A possible explanation could be that as the market develops, information quality and transparency in the market is enhanced; hence, fund managers have fewer incentives to herd on their peers' actions. Furthermore, after the breaking up of our sample into pre and post crisis periods, the results indicate a decrease in herding and the disappearing of investing styles, with the exception of contrarian strategies. However, when we split the post-Euronext period into pre-and post-crisis, the results do not appear robust. More specifically, the style-indicators of size and volume, previously found significant in the post-Euronext period, now appear significant only in the pre-crisis period indicating that crisis did have an impact upon these styles. Inversely, the contrarian trading found for the Portuguese mutual funds in the post-Euronext period, appears significant only in the post-crisis period indicating that this investing style is a product of the crisis itself. Again, it is worth noting that the institutional demand over time remains significant in all tests carried out.

Concluding, what one can infer from our findings is that the institutional demand over time in the Portuguese market is mostly due to funds following the trades of others (i.e. herding) and its significance is not amended when accounted for a series of investing styles. What is more, the significance of the Portuguese funds' style investing is sensitive to the period tested for. Finally, our results indicate that style investing is not a common practice in highly concentrated markets and that it does not bear any effect upon the significance of herding among fund managers in such kind of markets.

Chapter 4

4.1 Introduction

Exchange Traded Funds (ETFs hereafter) constitute a relatively new financial innovation despite their 20-year presence in the financial markets. ETFs are a combination of open-end and close-end funds combining the advantages of both types of funds into one product. More specifically, an ETF is a fund, investing in a basket of stocks, whose aim is to replicate a benchmark index; nevertheless it can be traded as a stock itself intra-daily. The key features of the ETFs that made them so popular are their "creation and redemption process", tax effectiveness, low management fees, risk diversification and liquidity, which shall be discussed in detail later in this chapter. As Deville (2008) suggests, the characteristics of the ETFs make them particularly attractable to the rational investors (e.g. use as a hedging tool); however, Curcio *et al.* (2004) suggest that ETFs can be attractable to retail investors as well. Given that the retail investors are the prime candidates for noise trading [Barber *et al.* (2009)], the issue arising is what is the impact of the ETFs' introduction over market dynamics, in other words does the introduction of the ETFs promote market efficiency and depress noise trading?

This issue has not been addressed before in the literature and we will try to shed light on this by applying the established methodology of Sentana and Wadhwani (1992) which allows to test for a span of market dynamics, such as noise trading, return autocorrelation and volatility, by assuming two types of traders (rational and feedback). In order to do this, we use a sample of eight European countries and we also account for the current financial crisis. In addition, we test for the noise traders' migration hypothesis, i.e. whether noise traders migrate from the spot market to the ETF segment. Our research will be of particular interest for market regulators and policy makers as it will provide evidence whether ETFs could enhance the efficiency of the markets and contribute towards to their completeness. In addition, as our study is carried out under the premises of developed countries, our findings could have a beneficial impact for the emerging markets and markets in their infancy level as well. As far as it concerns the investment community, our findings could provide evidence whether the use of ETFs as an investment option could be beneficial for them as well.

The chapter is arranged as follows: section (4.2) provides the theoretical grounding and the findings of the relevant literature about noise trading, its causes and primary candidates for it. Section (4.3) provides an in depth description of the ETFs and its characteristics. Section (4.4) examines the relationship between ETFs and rational investors and whether the first ones are more appealing to the second ones, whereas section (4.5) examines the relationship between the ETFs and individual investors. Section (4.6) describes the data and methodology used in this research and section (4.7) presents our empirical findings. An additional discussion of the later is provided in section (4.8) whereas section (4.9) concludes.

4.2 Noise Trading

According to the Efficient Market Hypothesis of Fama (1970), investors are considered to be rational; the relative homogeneity of investors, in terms of rationality, is a prerequisite for the markets to be efficient. If irrational traders make their presence felt, rational arbitrageurs will enter the market and take advantage of the mispricing, driving prices back to their fundamental values. However, in the mid 1980s, a new term was introduced to describe those investors not strictly adhering to the rational paradigm, that of the noise trader (Kyle (1985); Black (1986). The term "noise" refers to the signals arriving in the market, which may not be real information, such as rumors, but are still treated by investors as if they were real information. Having said that, according to Black (1986), the presence of "noise" traders is essential in order for the markets to have substantial liquidity. Noise traders trade on non-fundamental information; however, noise trading can also be based upon fundamentals if the latter's processing is undertaken in a non-rational fashion. For example, Barberis *et al.* (1998) presented a model of investor sentiment illustrating how investors can form their beliefs about fundamentals in an irrational way. More specifically, the authors found that prices under-react to positive earnings announcements and overreact upon the arrival of good or bad earnings' news. What is more, Brav and Heaton (2002) suggested that investors can react irrationally either because they do not possess all the relevant information (rational structured uncertainty) or because, even if they do possess the right information, they cannot decide rationally due to the impact of biases and heuristics in their investing decisions (investors' irrationality).

Noise trading has been mainly associated with individual (retail) investors who may not have the quality of information large institutional investors or insiders may have. Barber *et al.* (2009) conclude that individual investors' trades may have an impact on stock prices as the authors suggest that their "noise" is systematic. Particularly, the authors suggest that the trades of individual investors are correlated and that these are mostly driven by various psychological biases such as the representativeness heuristic, limited attention, the disposition effect as well as common shifts in risk aversion. In support of the previously mentioned argument, there is a plethora of relative research regarding the trading of individual investors and how these make their investing decisions.

Odean (1998) studying ten thousand accounts of individual investors in the U.S found that the latter have the tendency to hold on to losing stocks and selling the winning ones (the disposition effect). The author suggests that whether the effect of this behavior upon stock prices is large or not, depends upon the actions of the more informed market participants, such as institutional investors. Kumar and Lee (2006) also analyzing the trades of individual investors over the period 1991-1996 in the U.S market found that these trades are correlated among each other and argued that investors' sentiment could possibly be an explanation for it. What is more, Dorn *et al.* (2008) examining the German individual investors for the 1998-2000 period found that the trades of the individual investors are correlated and that these correlated trades predict future returns. Finally, Barber and Odean (2008) showed that individual investors exhibit an attention grabbing behavior when trading on stocks, especially on the buy side. This is due to the fact that buy-decisions entail more difficulty than sell-ones in terms of stock-selection. When an investor has to decide upon buying a stock, his possible options have to be drawn out of a universe of hundreds or thousands of stocks. Conversely, when deciding which stock to sell, he only has to look at the stocks already in his portfolio.

All the above researches provide evidence in support of the view that individual investors are more prone to noise trading than institutional investors.

Having identified the prime candidates for noise trading, the question that arises at this point is how to measure noise trading. The latter can take place through various techniques, such as technical analysis, momentum trading or put it simply by using past returns. A proxy for modeling noise trading is feedback trading, a strategy based on past stock prices. Feedback trading can be positive or negative; in the first case investors buy/sell when prices rise/drop and in the second investors buy/sell when prices drop/rise.

Feedback trading can be motivated by technical analysis, i.e. the use of historical past prices, where investors, who have an informational disadvantage relative to their peers, believe that past stock prices contain information about the companies. There have been several studies regarding technical analysis and its profitability, most notably those by Brock *et al.* (1992), Antoniou *et al.* (1997) and Wong *et al.* (2003), which confirmed the profitability of technical analysis internationally.

In addition to technical analysis, other trading strategies such as momentum and contrarian trading have been associated with feedback trading. Particularly, momentum strategies (Jegadeesh and Titman (1993) are linked to positive feedback trading and suggest that it can be profitable for investors to buy past winners and sell past losers. On the other hand, contrarian strategies (Galariotis *et al.* (2007) are linked with negative feedback trading and suggest that investors could make profit by buying previous losers and sell past winners.

Apart from the technical analysis and the trading strategies, the sources of feedback trading can be traced through several biases and heuristics. More specifically, Barberis *et al.* (1998) associated the *representativeness heuristic* [Kahneman and Tversky (1973)] and the *conservatism bias* [Edwards (1968)] with feedback trading. In the first case, investors perceive price patterns as trends and ride on them whereas in the second one, investors are reluctant of updating their beliefs upon the arrival of new information in the market and this leads to the under-reaction of prices. What is more, negative feedback trading has been associated with the *disposition effect* [Shefrin and Statman (1985)], namely the tendency of investors to hold on to losing stocks and sell the winning ones. *Overconfidence* [Odean (1998)], a bias that causes investors to overvalue their own knowledge and skills is also associated to positive feedback trading. This is because the overvaluation of their own skills leads them to overreact to their own signals and this overreaction will persist the longer prices move in ("confirm") the direction of their own trades (i.e. confirm to them that their signals are correct), as this helps boost their overconfidence [Daniel *et al.* (2002)].

Furthermore, feedback trading could also take place due to informational reasons. More specifically, investors could engage in feedback trading strategies due to an informational disadvantage relative to their peers. Typical examples of the informational inferiority of some investors are the case of domestic vs. foreign investors as well as the case of investors investing in small firms. In the first case, foreign investors have an informational disadvantage compared to their domestic counterparts; as such it is possible that they might try to infer information about the stocks using their past prices. However, the problem of informational asymmetry between domestic and foreign investors has decayed throughout the years due to the technological advances that allow foreign investors to have access to similar information with their domestic counterparts. Today, it can only be the case for very small markets (emerging ones) that there is such a high informational asymmetry between foreign and domestic investors. Similarly, in the case of investors investing in small firms, since there is less information available on such kind of firms, investors will use past prices in order to gain information regarding these firms. However, the problem with this approach here is that small stocks tend to be subject to thin trading, so it is doubtful whether their prices (which exhibit frequent pockets of trading inactivity) can constitute a reliable tool to that end.

There has also been a quite large amount of empirical findings regarding feedback trading. One of the most important papers regarding feedback trading is considered to be that of Sentana and Wadhwani (1992), which examined the U.S and the U.K markets and found significant evidence in favor of positive feedback trading there. Additional research by Koutmos (1997) which examined the presence of feedback trading strategies in six developed countries found significant evidence of positive feedback trading. Conversely, Aguirre and Saidi (1999) examined the presence of feedback trading strategies in a span of developed and emerging markets, yet did not find significant evidence of feedback trading strategies; in case where feedback trading was found, it was negative feedback trading that was prevailing in the market rather than positive. Another research by Koutmos and Saidi (2001), examining feedback trading on the premises of emerging markets, found evidence of positive feedback trading during declining markets, whereas feedback trading was very weak during upward markets.

In addition to the above researches that examined feedback trading at the aggregate level, there has also been a vast amount of research examining the behavior of institutional investors. Lakonishok *et al.* (1992) examining a sample of U.S pension funds for the 1985-1989 period found little evidence of feedback trading, the latter being more evident in small sized firms. Another research by Wermers (1999) for the U.S. mutual fund industry revealed evidence of positive feedback trading in the case of growth funds, the latter typically investing in small capitalization stocks.

Choe *et al.* (1999) found evidence of positive feedback trading on behalf of foreign investors for the Korean market before the Asian crisis in 1997, whereas after the crisis positive feedback trading appeared to have weakened. Furthermore, Walter and Weber (2006) examining 60 mutual funds of the German market for the 1997-2002 period found the fund managers exhibited positive feedback trading behavior in the short run. Finally, Do *et al.* (2008) examining the Finish market for the 1995-2004 period found that foreign investors in Finland positive feedback trade more than their domestic counterparts.

4.3 Exchange Traded Funds

An Exchange Traded Fund (ETF hereafter) is a relatively new financial innovation that tracks a benchmark index, like an index fund. ETFs share several features in common with both the open-end funds (mutual funds) as well as the closed-end funds, as we shall later discuss. At the beginning, ETFs were financial instruments replicating equity indices; however, over the years we have born witness to the voluminous evolution of

ETFs tracking a variety of benchmarks including commodities, sectors, international markets, or even investing styles. The great acceptance of ETFs from investors outlines the gap they came and filled in with respect to the existing financial products. It is the special characteristics of the exchange traded funds and their ease of trade that made them so appealing to investors.

ETFs were introduced in Canada in the early 1990s; these were known as TIPs (Toronto Index Participation units) and they were tracing the Toronto 35 Index, with their main feature being their relatively low management fees. However, ETFs became widely known through the SPDRs (Standard & Poor's 500 Depositary Receipts, often referred as "spiders") which were introduced in the American Stock Exchange (AMEX) in 1993. A milestone in ETF history is considered the introduction of the Nasdaq-100 Index tracking Stock in 1999, an ETF later known as Cubes which became very popular after its launch. Since in the late 1990s the technology sector was at its peak and the NASDAQ accommodated the tech related stocks, this also played an important role in the development and spread of the particular ETF. Likewise, in Europe the first ETFs appeared in the U.K, German and Swedish markets in 2000, followed by those in the Euronext and the Swiss Stock Exchange in 2001. In 2002, ETFs were introduced in the stock markets of Finland and Italy, which were later followed by those in Iceland (2004), Norway (2005), Ireland (2005), Austria (2005) and Greece (2008). What is more, ETFs have been quite popular in emerging countries as well. To mention a few, the first ETF was introduced in South Africa in 2000, in Taiwan in 2003 whereas in Turkey it was no later than in 2005.

In simple words, an ETF is fund investing in a basket of stocks aiming at replicating a benchmark index; nevertheless it can be traded as a stock itself intra-daily. Some of the key features of the ETFs that made them so popular are their "creation and redemption process", tax effectiveness, low management fees, risk diversification and liquidity. First of all, unlike other mutual funds ETFs are traded in the stock exchange as any ordinary stock and can also be traded as ordinary stocks, which means they can be margin or even short traded. This characteristic makes ETFs attractive to a very large span of investors, be they institutional or smaller individual investors. Having said that, it is much easier for investors to invest in an ETF that invests in a basket of stocks than to monitor and invest in a number of stocks individually. As such, ETFs are considered a very important tool of portfolio diversification as well as a better hedging tool than futures since they have a lower cost than them and even smaller investors can use them to hedge their relatively small portfolios.

What is more, ETF shares (creation units) can be created or redeemed anytime by investors; the latter can be the authorized participants or market makers. Particularly these authorized traders can create ETF shares (creation units), often in batches of 50000 shares, by depositing the corresponding stocks of the basket and an additional amount of cash, whereas in the case of redeeming ETF shares, investors give their ETF units and receive the basket of stocks and an amount of cash. The cash amount in both cases represents the difference between the Net Asset Value and the value of the basket of stocks.

Since ETFs exchange their units with stocks and vice versa, in contrast with the common mutual funds, they do not have to keep a part of their assets in cash in order to cover any redemptions that may occur; as such, the full amount of money is always invested. Furthermore, in the case of the ETFs, any dividends acquired from the invested stocks are credited to their investors' account as opposed to the common mutual funds that reinvest the dividends automatically. Another feature of the ETFs is their low management fees. Since their basket of stocks tracks an index, there is no need for active management on behalf of their managers. As such, the cost of running an ETF is substantially lower compared to a closed end fund which requires a more active trading strategy. Furthermore, ETFs are also known for the tax effectiveness. Particularly, ETFs do not distribute large realized capital gains since they do not have to sell stocks in order to redeem their shares; this is done through their creation and redemption process. Additionally, ETFs are more transparent than conventional funds. The latter usually disclose their holdings quarterly whereas ETFs publish their stock baskets daily. As such, it is easier for investors to monitor their investments and there is greater transparency.

Finally, ETFs are found to be more price efficient than closed-end funds. This is due to the fact that ETFs are easier to trade and more frequently traded than the other funds and arbitrageurs can take advantage of any difference between the NAV and the ETF price.

However, the latter statement is a bit controversial, since there have been quite enough researches claiming the opposite. More specifically, numerous researchers have found that there are significant tracking errors in the ETFs; the tracking error is the difference between the performance of the ETF and its benchmark index [Shin and Soydemir (2010)]. One of the reasons for this phenomenon could be the previously mentioned passive management of the ETFs; the latter do not need a very active management on behalf of their managers as it is the case for the common mutual funds. As Gastineau

(2004) posits, a more aggressive management policy, such as this one followed by mutual fund managers, could lead ETF managers to (at least, a large extent) minimize the problem of tracking errors.

Evidence in support of the ETFs' pricing efficiency is provided by Lin *et al.* (2006) for the Taiwanese market. Particularly, the authors examined the only ETF in Taiwan, namely the Taiwan Top 50 Tracker fund (TTT), and found that it exhibited almost the same returns with the tracked Taiwan 50 Index. As such, according to their results, the specific ETF was a successful index-tracking tool. Further evidence in support of the ETFs' pricing efficiency is provide by the study of Kayali (2007) who examining the DJIST (Turkish ETF) found that it is price efficient and that any discounts or premia were disappearing in the second day of their occurrence.

On the other hand, the research by Ackert and Tian (2008) suggests that there are significant premia of the ETF prices relative to their Net Asset Values, especially in country funds[29], and attribute this mispricing to the limits of arbitrage. What is more, the authors suggest that the liquidity of the markets could be a possible explanation for this phenomenon, since they found that high liquidity in the U.S market was linked with lower premia, whereas in the case of emerging markets the low liquidity in the ETFs and their underlying spot markets was associated with higher premia. The authors suggest that this inverse effect of liquidity over the mispricing of the ETFs could be due to taxation and trading differences between the developed and emerging markets.

[29] The country ETFs were: Australia, Austria, Belgium, Canada, France, Germany, Italy, Japan, Netherlands, Singapore, Spain, Sweden, Switzerland, U.K, Brazil, Hong Kong, Malaysia, Mexico, South Africa, South Korea and Taiwan.

4.4 Exchange Traded Funds as Promoters of Rational Trading

Given the sophistication of rational investors we would expect that an advanced and innovative financial product such as the ETFs would attract more informed investors in the market and subsequently depress the effect of noise traders. Since ETFs provide a better diversification and hedging tool relative to other existing financial products, arbitrageurs would be very keen on using them. In fact, certain researches have showed that after the introduction of ETFs, the markets where these were introduced became more efficient and the mispricing less frequent. This phenomenon is attributed to the fact that the introduction of ETFs lowered arbitrage costs, as such more arbitrageurs came to the market and subsequently less arbitrage opportunities (less mispricing) became available. For example, Park and Switzer (1995) examined whether the introduction of the Toronto Index Participation Units (TIPS), the first ETF, had an impact on the Toronto 35 Index futures market, in terms of pricing efficiency. In order to test for this, the authors examined the trading volume and mispricing of the index futures pre and post the introduction of the TIPS. In the first case, that of trading volume, their results indicated that there was an increase in the demand for index futures and they attributed this phenomenon to the increased use of hedging and arbitrage. In the second case, that of mispricing, there was a significant decrease in the level of mispricing between the actual prices of index futures and their theoretical values. Similarly, another research by Switzer *et al.* (2000) examined the effect of the Standard and Poor's Depository Receipts (SPDRs) introduction on the S&P's future market, in terms of pricing efficiency. In line with the previous research mentioned, the authors found that the introduction of the SPDRs had a positive impact on the pricing efficiency of the underlying futures' market since the mispricing on these financial products had a significant, even though small, decrease after the introduction of the specific ETF. What is more, Kurov and Lasser (2002) also provided supporting evidence to the previous mentioned researches. Particularly, by examining the pricing efficiency of the NASDAQ-100 futures and the underlying index upon the introduction of the NASDAQ-100 Index Tracking Stock (Qubes), they found that indeed the pricing relationship between the futures market and the underlying spot index significantly improved after the introduction of the specific ETF. In addition, any mispricing in these markets was corrected faster after the introduction of the ETF, hence implying more effective hedging on behalf of the investors.

Another characteristic of ETFs that makes them attractive to rational investors is their capacity to simplify the stock selection process. More specifically, given the fact that a stock market is comprised by thousands of stocks or even a single index by some dozens or hundreds of them, investors by investing in an exchange traded fund have the opportunity to effectively diversify their portfolio without having to invest additional time and money by trading on multiple stocks; the latter, besides the invaluable time needed for the stock selection process also requires higher trading costs. This specific advantage of ETFs becomes more evident in the case of investing in foreign stock markets. Given the purported informational asymmetry between domestic and foreign investors, the introduction of ETFs provides foreign investors with a tool that allows them to hold a portfolio of stocks with relatively low trading costs and greater flexibility. For example, an investor investing in a foreign country not only faces an informational disadvantage but can also meet certain limitations and frictions, such as taxes, capital flow limitations and exchange rate risk. These, in conjunction with uncertainty, make the stock selection process for foreign investors more challenging; a solution to that could be the use of ETFs. The latter could minimize the research and monitoring cost, simplifying the stock selection process and additionally they could minimize the trading costs since it would much more cost effective to trade in a basket security rather than in a number of individual stocks.

Particularly, the trading from arbitrageurs would reduce any mispricing in the underlying spot markets; hence improve the pricing efficiency of the latter. Miffre (2007) examined 16 country-specific ETFs[30] and outlined the benefits of investing in such ETFs due to their special features. More specifically, the author emphasized on the ETFs' feature of short selling, tax advantage and low trading costs; these features provide superior portfolio diversification, in an international context, and have comparative advantages in relation to other index securities such as closed-end funds and index futures. Harper *et al.* (2006) also provide supporting evidence to the previous mentioned research. Particularly, the authors compared 29 closed-end funds of 14 countries and the underlying iShares ETFs for these countries; their results outlined two major advantages of the ETFs compared to the closed-end funds. First, ETFs exhibited higher mean returns than the closed-end funds of these countries and secondly that a less active investment strategy using ETFs was more profitable than a more active one using closed-end funds.

Rational investors are characterized by their ability to effectively hedge their portfolios; put it simple, they are involved in the use of various risk management techniques. The

[30] The authors examined 16 iShares ETFs from Barclays Global Investors. The examined markets were: Australia, Austria, Belgium, Canada, France, Germany, Italy, Hong Kong, Malaysia, Mexico, Singapore, the Netherlands, Spain, Sweden, Switzerland and the U.K.

options these investors have in order to effectively manage the risk of their portfolios span across a series of financial instruments such as options, swaps and futures. Having said that, another characteristic of ETFs that is of great importance for arbitrageurs is their hedging effectiveness. Highly related to the previous characteristic of the simplified selection process, ETFs constitute a relative cheap and easy-to-use hedging tool when compared to options and other similar products. For example, in the case of an investor who holds a portfolio of stocks of the S&P 500 index, it would be too costly for him to hedge a number of stocks in his portfolio. However, he could hedge his portfolio of stocks by using an ETF of the underlying index, without having to bear high trading costs or capital requirement as in the case of index futures where there is a certain margin requirement. What is more, in recent years, another type of ETFs has been introduced, namely the inverse ETF; the latter is specifically designed to provide an inverse multiple of the return (daily) of the underlying index; these can be -1x (-1 times the daily return),-2x (-2 times the daily return) or -3x (-3 times the daily return). Hill and Teller (2010) provide hedging examples using inverse ETFs and outline the advantages of the latter in terms of liquidity and monitoring. Nevertheless, according to the authors, the use of such financial instruments demands high managerial and monitoring skills. The latter can only be possessed by high-calibre investors with adequate skills and not by the individual investors. As such, compared to the existing hedging tools, ETFs enhanced investors' choices for hedging their portfolios by provide them lower trading and holding costs, more liquidity, tax efficiency and greater transparency.

The above mentioned characteristics of exchange traded funds make them quite appealing to rational investors. As such, in the case that ETFs succeed in attracting more rational investors into the markets they have been introduced, this should depress noise trading in these particular markets. Summarizing, the introduction of ETFs can increase the significance of rational investors in market trading due to three distinctive aspects of ETFs. First of all, it is their pricing efficiency; ETFs have been found to exhibit a low tracking error (that is the difference of the ETF price and the NAV). What is more, the introduction of the ETFs seems to have improved the pricing efficiency of the underlying spot markets in quite a few researches, as discussed above. Secondly, the ETFs can substantially simplify the stock selection process of investors and this is more evident in foreign country investments where investors have to surpass various frictions and restrictions. Thirdly, ETFs provide rational investors an additional tool for managing the risk of their portfolios more effectively and less costly. Despite the presence of these features, the introduction of ETFs may produce the opposite results, namely boost the significance of noise investors; this possibility is explored in the section below.

4.5 Exchange Traded Funds as Promoters of Noise Trading

Moving on to the case of noise traders, an ETF or a basket-security generally appears more attractive to them since they can achieve better diversification of their portfolio in a much cheaper and easier way than if they had to invest separately in the underlying assets of the basket-security. Gorton and Pennacchi (1993) in their theoretical model showed that the introduction of basket-securities, in a market without full disclosure of available information, has a positive impact on the expected utility of liquidity traders, providing a lower variance portfolio and less informational asymmetry. If this is the case and ETFs attract noise traders, due to their simplicity, we should expect that there should be substantial tracking errors and generally no improvement on pricing efficiency in the underlying markets. Before the introduction of the ETFs, individual investors could invest in open-ended and closed-ended funds; these two provided investors with a tool to diversify their investments, relatively easy and at a low cost. Mutual funds, by pooling funds from a span of different sources could offer their clients not only an additional diversification tool but access to markets that these investors would otherwise be less able to invest in. The introduction of the ETFs surpassed some obstacles/drawbacks of the mutual funds (by providing trading flexibility and tax efficiency) that made them even more attractive to the individual investors; in simple words, an ETF combines the characteristics of an open-ended fund with those of a closed-ended fund. Also, the key feature of an ETF is that it can be traded as a simple stock during the whole day by the investors. So, if the ETFs attract more noise traders, this would have a negative impact upon the pricing efficiency of the underlying spot markets; there are quite a few researches outlining the inefficiency of the ETF markets and the mispricing between them and the prices of the underlying markets.

Jares and Lavin (2004) examined the behavior of the Japan and Hong Kong iShares from 1996 till 2001. Their findings revealed significant premia and discounts between the NAV and the ETF returns. What is more, the authors suggested that these premia and discounts were predictable and could be exploited through various trading rules; for example, buy foreign ETF shares when the market price is smaller than the NAV, and sell the foreign ETF shares short when the market price is larger than the NAV. By applying these trading techniques, the authors came up with a return of 542.25% for the Japanese market and 12.119% for the Hong Kong market. As such, according to their study, the market of ETFs is not efficient in itself, at least in the case of foreign markets where the trading of ETFs does not occur simultaneously with the underlying market. Madura and Richie (2004) examined the overreaction hypothesis on a number of various U.S ETFs, including country and sector ETFs, for the period 1998-2002. Indeed, the authors found evidence of significant reversals on the ETF prices; the latter was more evident in country ETFs and in those that had extreme movements in their stock prices. Though, reversals on the ETF prices are weaker during after hours. The authors, conclude that arbitrageurs correct the mispricing caused by noise investors' overreaction. Furthermore, Shin and Soydemir (2010) examined 26 ETFs (out of them 20 were country ETFs and 6 were for the U.S market); their results indicated negative and significant tracking errors which to a great extent were ascribed to the exchange rate deviations. What is more, the ETFs of the Asian markets were found to exhibit momentum characteristics as their premia and discounts were related to past performance and their tracking errors were more persistent; something that was not the case for the U.S ETFs whose market appeared informational more efficient. As such, it appears that Asian markets are noisier than the U.S market and that trading techniques such as momentum trading, and the higher liquidity risk in these markets can induce mispricing and drive away prices from their fundamental values. So, the issue arising here is that if the market of ETFs is not price-efficient in itself, then we would expect that the introduction of these financial instruments would have a negative impact on the underlying markets, in terms of pricing efficiency.

An additional characteristic of the ETFs that makes them attractive to individual investors is the simplicity they offer. If ETFs can simplify the stock selection process for rational investors, this is amplified in the case of individual investors who do not have the skills or the means of their more sophisticated counterparts. Particularly, individual investors with their limited resources may face difficulties during the selection process of their investments. Having said that, the introduction of the ETFs has allowed investors to hold the whole index of a market in one go instead of searching the best stocks to invest in. The feature of the ETFs that allows investors to trade on them as if these were simple stocks gives them greater flexibility and familiarity. The latter was used by Huberman (2001) to demonstrate that investors were more prone to invest in companies geographically closed to them or domestic companies (which were more familiar to them) than in foreign ones. According to the author, companies that investors are more familiar with tend to be favored against those which are not that familiar; this familiarity could lead investors to be more confident on these stocks and give them the illusion that have better information or more control on them. In the case of ETFs, familiarity could be better explained from the following example. It is the case that the average investor cannot be familiar with all the constituent stocks of an index (i.e. S&P 500); some companies will have greater daily media coverage than others and usually even the investors knows all the constituent companies by name, it is hardly the case that he will have equal information for all of them. As such, by investing in an ETF, the investor would have the opportunity to invest in the specific basket of the index he is interested in.

The last statement about familiarity could be a possible source of *over-optimism* [Montier (2003)] and the *illusion of control* bias [Montier (2003)] on behalf of the noise traders. Particularly, the simplicity of the ETFs and its similar characteristics with those of a simple stock could make investors overestimate their capabilities and underestimate the underlying risk of the ETFs. As such, without the ETFs, it would be difficult for investors to invest in so many stocks in order to achieve an efficient replication of the underlying index. However, the simplicity of an ETF may give investors the illusion that they can have greater control of the underlying index than they really have; this in turn could make investors over-optimistic and overconfident about their skills. Now, given the fact that overconfident investors tend to trade more, the issue arising is that due to the ease with which investors can trade a single index through an ETF (this can be done through a single transaction), it can be that short term trading spirits proliferate among noise investors and the ETF market can become something of a speculative venue with knock on effects over the underlying basket's stocks at the spot segment. What is more, with the markets becoming more and more complex, investors are looking for tools to make their life easier, just as with the case of the heuristics' adoption. In fact, *the limited attention* bias may apply in the case of the ETFs (and the other basket securities as well) since by trading on a single ETF, investors do not have to monitor a large number of stocks with all the costs involved in both financial and time terms. It may be easy for investors to reach to a decision on which of their holding stocks they will sell, however choosing which stocks to buy among thousands of options is more difficult for them. As such, ETFs make the stock-selection process much faster and easier. And as in the case of rational investors discussed previously, this becomes more immense in the case of investing into foreign markets, where the trading costs are higher and monitoring the underlying stocks is too difficult for small individual investors.

Another heuristic, similar to the *familiarity bias* discussed previously, is the *recognition heuristic* [Boyd (2001)]. According to it, an investor when confronted with two available investment options, he will be in favor of the one that he recognizes the most. To make things clearer, let us elaborate on an example. Supposing that an investor wants to invest on the stock of S&P 500, it is hardly the case that he will know all the 500 constituent stocks of the index (especially the ones in the bottom of the list) and what is more the name of the companies would not be as highly recognizable as the S&P 500 Index itself. As such, an ETF linked to the S&P 500 Index would be more appealing to the investor since as it is more recognizable to him.

What is more, another bias that seems relevant to the attraction of retail investors by the ETFs is the *ambiguity aversion*. Retail investors often lack the necessary skills, experience and available sources of information and capital that their rational counterparts have. As such, building a portfolio to track the performance of a specific index could be difficult for a retail investor; hence he could be quite ambiguous about his investment choices. An ETF can be a useful tool for the inexperienced investor to follow the performance of a specific index removing any ambiguity from him, since he would not have to construct its own portfolio, rather he could choose the appropriate ETF.

So, the above mentioned characteristics make ETFs appealing to noise traders; hence if more noise traders trade in the market due to the introduction of the ETFs, this would have a negative impact on the pricing efficiency of the underlying markets. Certain researches, as discussed above, found significant tracking errors between the ETF prices and the NAV, thus implying that the markets of the ETFs are not always efficient and this can be due to certain behavioral biases such as overreaction. Additionally, the simplification of the stock selection process is more intense in the case of the individual investors rather than of the rational investors, given the lack of expertise and resources the former have. Additionally, certain psychological biases could boost the activity of noise traders on the ETF markets; *over-optimism*, *illusion of control*, *overconfidence* and the *limited attention bias* could be some of them. More specifically, the simplicity ETFs offer to investors could lead to the overestimation of their own skill and control they may think they have over the underlying index, hence this could eventually lead to the use of the ETFs as a tool, used for short term speculation; in this case, this could have a destabilizing effect on both the ETF and the underlying spot markets with noise trading driving away prices from their fundamental values. As such, it could be the case that the introduction of ETFs attracts more noise traders than rational investors.

4.6 Data and Methodology

Our sample is obtained from Bloomberg and Datastream and includes data of spot daily index prices for the period 2/1/1990 till 12/12/2011 from eight European countries (indices in the brackets), namely Belgium (BEL 20), Finland (OMXH25), France (CAC 40), Germany (DAX30), Netherlands (AEX), Sweden (OMXS30), Switzerland (SMI) and the U.K. (FTSE100). We used 2/1/1990 as our starting point as the availability of data from the Belgium market starts at this point of time. In addition, our sample includes the spot ETF daily prices and their starting dates varying according to each market's launch date of the ETFs; the ETFs selected for our study are the first ETFs introduced in each market, allowing us for a larger sample of observations. More specifically, the ETFs examined are LYXOR ETF BEL 20 (Belgium), SLG OMXH25 (Finland), LYXOR ETF CAC 40 (France), DAXEX (Germany), AEXT STREETTRACKS (Netherlands), XACT OMXS 30 (Sweden), XMTCH ON SMI (Switzerland) and iSHARES FTSE 100 (U.K.).

Our sample is divided into two sub-periods for each market, namely the one pre the introduction of the ETFs, starting for all markets on 2/1/1990, and the other post the introduction of the ETFs, ending for all markets on 12/12/2011. So, according to the introduction of ETFs in each market the sub-periods are formed as following: Belgium (2/1/1990-1/10/2002; 2/10/2002-12/12/2011), Finland (2/1/1990-10/2/2002; 11/2/2002-12/12/2011), France (2/1/1990-21/1/2001; 22/1/2001-12/12/2011), Germany (2/1/1990-2/1/2001; 3/1/20011-12/12/2001), Netherlands (2/1/1990-29/5/2001; 30/5/2001-12/12/2011), Sweden (2/1/1990-29/10/2000; 30/10/2000-12/12/2011), Switzerland (2/1/1990-14/3/2001; 15/3/2001-12/12/2011), U.K. (2/1/1990-27/4/2000; 28/4/2000-12/12/2011).

The methodology we are going to apply in our research is that of Sentana and Wadhwani (1992) which has been applied in numerous researches testing for feedback trading [Koutmos and Saidi (2001), Antoniou *et al.* (2005)]. The model assumes two types of traders, namely rational ones and noise traders or "feedback traders".

Sentana and Wadhwani (1992) calculated the demand for stocks of both rational and *feedback traders*.

The demand function of rational investors is the following:

$$Q_t = \frac{E_{t-1}(r_t) - \alpha}{\theta \sigma_t^2} \quad (1)$$

Where: Q_t , is the fraction of shares outstanding hold by rational traders, $E_{t-1}(r_t)$ is the expected return on period t, based on the information at the previous period, α is risk-free rate, θ is the measure of risk aversion and σ_t^2 is the coefficient of conditional variance at period t.

The demand for feedback traders is calculated by the following formula:

$$Y_t = \gamma r_{t-1} \qquad (2)$$

Where: Y_t is the demand of feedback traders, r_{t-1} is the returns of the previous period and γ distinguishes between positive feedback traders $(\gamma > 0)$ and negative feedback traders $(\gamma < 0)$.

In case of equilibrium in the market, this is expressed by

$$Q_t + Y_t = 1 \qquad (3)$$

If we substitute (1) and (2) into equation (3) we get:

$$E_{t-1}(r_t) = \alpha - \gamma r_{t-1} \theta \sigma_t^2 + \theta \sigma_t^2 \qquad (4)$$

Then if we set $r_t = E_{t-1}(r_t) + \varepsilon_t$, ε_t being a stochastic error term, and substitute into the above equation we get the following:

$$r_t = \alpha - \gamma r_{t-1} \theta \sigma_t^2 + \theta \sigma_t^2 + \varepsilon_t \qquad (5)$$

Where: r_t is the return at period t and ε_t is the error term. Now, in order to allow for autocorrelation, we apply the following specification as proposed by Sentana and Wadhwani (1992):

$$r_t = \alpha + \left(\phi_0 + \phi_1 \sigma_t^2\right) r_{t-1} + \theta \sigma_t^2 + \varepsilon_t \qquad (6)$$

Where: ϕ_0 captures any non-synchronous trading effects, $\phi_1 = -\theta \gamma$ indicates the presence of positive feedback trading when negative and the presence of negative feedback trading when positive. Moreover, the term $\gamma r_{t-1}\,\theta\;\sigma_t^2$, suggests that if positive feedback traders prevail in the market the autocorrelation will be negative, whereas if negative feedback traders prevail, then the autocorrelation will be positive. Now, in order to account for any asymmetries on feedback trading subject to market direction equation (6) can be modified as follows:

$$r_t = \alpha + \left(\phi_0 + \phi_1\sigma_t^2\right)r_{t-1} + \theta\sigma_t^2 + \phi_2\left|r_{t-1}\right| + \varepsilon_t \tag{7}$$

Where: If ϕ_2 is positive then positive feedback trading grows more after market declines than market upturns and the coefficient on r_{t-1} becomes:

$$\begin{array}{lll} \phi_0 + \phi_1\sigma_t^2 + \phi_2 & if & r_{t-1} \geq 0 \\ \phi_0 + \phi_1\sigma_t^2 - \phi_2 & if & r_{t-1} < 0 \end{array}$$

Now, in order to identify any significant difference in feedback trading over the two periods, pre and post the introduction of the ETFs, we apply the following specification proposed by Antoniou *et al.* (2005):

$$R_t = \alpha + \theta\sigma_t^2 + [\phi_{0,1}D_t + \phi_{0,2}(1-D_t)]R_{t-1} + [\phi_{1,1}D_t + \phi_{1,2}(1-D_t)]\sigma^2 R_{t-1} + \varepsilon_t \tag{8}$$

$$\sigma_t^2 = \beta_{0,1}D_t + \beta_{0,2}(1-D_t) + \beta_1\sigma_{t-1}^2 + \beta_2\varepsilon_{t-1}^2 + \delta S_{t-1}\varepsilon_{t-1}^2 \tag{9}$$

Where: D_t is the dummy variable that takes the value of one in the pre-ETF period and the value of zero in the post-ETF period.

What is more, since there is an ongoing credit crisis in the post-ETF period, we re-calculate the equations (8) and (9) for the post-ETF period, by setting D_t equal to one in the pre-crisis period and equal to zero in the post-crisis period.

To identify whether feedback traders have a longer memory in their demand than just one period, we introduce a second lag in equation (2) which takes the following form:

$$Y_t = \gamma_1 r_{t-1} + \gamma_2 r_{t-2} \tag{10}$$

Accordingly, equation (6) will become:

$$r_t = \alpha + \left(\phi_0 + \phi_1 \sigma_t^2\right) r_{t-1} + \left(\phi_3 + \phi_4 \sigma_t^2\right) r_{t-2} + \theta \sigma_t^2 + \varepsilon_t \tag{11}$$

Where: $\phi_1 = -\theta\, \gamma_1$ and $\phi_4 = -\theta\, \gamma_2$; when ϕ_1 and ϕ_4 are positive this would suggest the presence of negative feedback, whereas if these coefficients are negative this would suggest the presence of positive feedback trading. Similarly, if ϕ_0 is positive this would imply the presence of inefficiencies through a significant first order autocorrelation and if ϕ_3 is positive this would suggest the presence of market inefficiencies through a significant second order autocorrelation.

Finally, the conditional variance (σ_t^2) is specified as an Asymmetric GARCH process Glosten *et al.* (1993) to examine whether there is a link between the established volatility asymmetries and the feedback trading asymmetries calculated via equation (7):

$$\sigma_t^2 = \omega + \beta\, \varepsilon_{t-1}^2 + \gamma \sigma_{t-1}^2 + \delta S_{t-1} \varepsilon_{t-1}^2 \tag{12}$$

Where: δ measures the asymmetric responses of volatility on positive versus negative shocks, S_{t-1} is a variable that equals to one if the shock at period t-1 is negative and equals to zero if the shock at period t-1 is positive. If δ is positive and statistically significant this suggests that negative shocks increase volatility more that positive shocks do.

Table 4.1 provides the descriptive statistics for our data, namely the mean, standard deviation, skewness, kurtosis, the normality test (Jarque-Bera) and the Ljung-Box statistics for 10 lags. As one can infer from the table, the return-series appear to depart from normality as the skewness and kurtosis measures indicate and confirmed by the Jarque-Bera test. More specifically, the spot indices of Finland, Germany, Netherlands, Switzerland and the U.K appear to be significantly (1% level) negatively skewed, those of the Swedish market appear significantly (1% level) positively skewed, whereas those of Belgium and Paris are insignificantly skewed, positively and negatively respectively. Moreover, all eight series appear highly leptokurtic, whereas the significant (1% level) Jarque-Bera test-statistics confirm these departures from normality for all the spot indices examined. These departures from normality are also documented in the ETF series. Furthermore, the LB statistic is significant (5% level) in the all of the series but that of Finnish ETF series indicating that there are temporal dependencies in the first moments of the return series; market inefficiencies could be the reason for this phenomenon.

Table 4.1 - Descriptive Statistics

Panel A: Spot Market Returns

	BEL 20 (2/1/1990-12/12/2011)	**OMXH25 (2/1/2990-12/12/2011)**	**CAC 40 (2/1/1990-12/12/2011)**	**DAX 30 (2/1/1990-12/12/2011)**	**AEX (2/1/1990-12/12/2011)**	**OMXS 30 (2/1/1990-12/12/2011)**	**SMI (2/1/1990-12/12/2011)**	**FTSE 100 (2/1/1990-12/12/2011)**
μ	0.0069	0.0237	0.0080	0.0211	0.0140	0.0267	0.0206	0.0144
σ	1.17	1.54	1.41	1.46	1.37	1.51	1.19	1.14
S	0.0322	-0.1399**	-0.0209	-0.134777**	-0.149673**	0.157458**	-0.153008**	-0.1182**
E(K)	7.19452**	3428.451**	4.81715**	5.017958**	6.660763**	3.954705**	6.2505**	6.3200**
Jarque-Bera	12,346.012368**	2,823.066956**	5,536.728327**	6,024.840403**	10,606.3108**	3,755.030105**	9,343.5617**	9,543.1603**
LB(10)	76.663**	29.46*	49.374**	21.752*	71.265**	25.856*	63.736**	87.3580**
LB^2 (10)	3,620.314**	1,405.300**	2,600.058**	2,544.918**	4,615.734**	1,663.497**	3,419.23**	3,932.7120**

Panel B: ETF Returns

	LYXOR ETF BEL 20 (2/10/2002-12/12/2011)	**SLG OMXH25 (11/2/2002-12/12/2011)**	**LYXOR ETF CAC 40 (22/1/2001-12/12/2011)**	**DAX^{EX} (3/1/2001-12/12/2011)**	**AEXT STREETTRACKS (30/5/2001-12/12/2011)**	**XACT OMXS30 (30/10/2000-12/12/2011)**	**XMTCH ON SMI (15/3/2001-12/12/2011)**	**iSHARES FTSE 100 (28/4/2000-12/12/2011)**
μ	0.0158	0.0073	-0.0218	-0.0053	-0.0252	-0.0075	-0.0079	-0.0032
σ	1.22	1.61	1.57	1.60	1.63	1.67	1.31	1.36
S	-0.0123	2.5761**	0.0663	0.0317	-0.2178**	0.0476	-0.1428*	-0.6752**
E(K)	7.1359**	50.3621**	4.7329**	4.9762**	6.6765**	3.1183**	5.5128**	14.0484**
Jarque-Bera	5,070.9611**	26,8996.585**	2,652.8994**	2,944.1616**	5,023.1261**	1,176.1084**	3,557.7241**	25,030.7644**
LB(10)	22.033*	12.7170	52.835**	21.929*	53.57**	31.198**	44.224**	72.012**
LB^2 (10)	734.959**	5.1060	1,388.581**	1,262.31**	1,990.169**	762.728**	2,090.305**	1,326.713**

** denotes significance at the 1 percent level, * denotes significance at the 5 percent level; μ = mean, σ = standard deviation, S = skewness, E(K) = excess kurtosis, LB(10), LB^2 (10) = the Ljung- Box test-statistics for returns and squared returns for 10 lags. Dates in brackets refer to the sample window for each series. All spot indices bear 2/1/1990 as their start-date; ETF-series bear different start dates contingent upon the launch-date of each.

Nevertheless, this statistic cannot detect any sign reversals in autocorrelations caused by feedback trading, since it only documents dependencies in the first moments. As such, when we apply the LB statistic in the squared returns series, we get to see that there are higher moment dependencies, since the LB test in this case is also significant (1% level) in all cases but the Finnish ETF series and higher than the simple LB test on both the returns and ETF series.

4.7 Research Hypothesis

The relevant literature so far has presented evidence that the introduction of specific financial products (e.g. index futures, etc.) depressed the level of noise trading and had a beneficial impact over the efficiency of the markets these have been introduced to. ETFs have certain characteristics that make them attractive to both institutional investors (informed traders) and retail investors (these being the prime candidates for noise trading). However, given the fact that the introduction of similar products improved the efficiency of the markets these have been introduced to and the fact that the segment of the ETFs is dominated by institutional investors, we would expect that the introduction of the ETFs would depress the level of noise trading and improve the efficiency of the markets these are introduced to. As such, our hypotheses are formalized as following:

H_0: The introduction of the ETFs does not depress the level of noise trading.

H_1: The introduction of the ETFs depresses the level of noise trading.

4.8 Empirical Results

We begin our analysis with the findings of the equations (6) and (12) on spot indexes' prices during the pre and post ETF introduction; table 4.2 and table 4.3 present our findings. Starting with the coefficient ϕ_0, this indicates the presence of significant first order autocorrelation in the majority of the markets examined prior the introduction of the ETFs, as it is significant (5% level) in most of the cases, except those of the Netherlands and the U.K. However, in the sample period after the introduction of the ETFs, there is no evidence of first order autocorrelation as the coefficient ϕ_0 is insignificant in all markets. Hence, one can infer from this outcome that these six markets of our sample became more efficient after the introduction of the ETFs.

Furthermore, as we can see from the table which shows the pre ETF introduction period, the coefficient ϕ_1 indicating the presence of feedback trading is negative in most of the cases but the U.K. market. A negative and significant ϕ_1 coefficient implies the presence of positive feedback trading whereas a positive and significant coefficient implies negative feedback trading. As such in our case there is significant positive feedback trading in the markets of Belgium (5%level) and Finland (1% level). However, after the introduction of the ETFs in these two markets, there is no evidence of significant feedback trading as table 3.3 indicates. Regarding the conditional variance process as exhibited in eq.12, the coefficient γ is highly significant (1% level) in both pre and post ETF periods suggesting that volatility is persistent over the two periods. Further evidence to the above provides the measurement of the volatility's half life, calculated as $HL= \ln(0.5)/\ln(\beta+\gamma+\delta/2)$ [Harris and Pisedtasalasai (2006)]. The results from this test indicate that the effect of a volatility shock on the market lasts for a significant number of trading days[31]; what is more, the half life numbers are higher for the post ETF period (except in the U.K. market), indicating an increase on the volatility's persistence.

Regarding the β coefficient, this appears significantly (5% level) positive in all markets in the pre ETF periods, suggesting that volatility has increased due to the news arriving in the market over that period. Now, in the post ETF period, the β coefficient is insignificant in half of the markets, whereas in the other half is significantly (5% level) negative. Moving on to the coefficient δ, this is remains positive and highly significant (5% level) in all markets examined at periods, pre and post the introduction of the ETFs. This suggests that negative news have a greater impact upon market volatility rather than positive news. Supporting evidence to the previous finding provides the asymmetric ratio ($\beta+\delta/\delta$) which indicates that during the post ETF introduction period the asymmetric volatility is more pronounced (the higher the asymmetric ratio and the δ coefficient, the higher the asymmetric volatility).

Now, in order to control for possible asymmetries in feedback trading we will use the extension of the previous model used, as this was implemented by Sentana and Wadhwani (1992) and is expressed in equation (7). Tables 4.4 and 4.5 indicate the results pre and post the ETF introduction respectively. Again, in the pre-ETF period the ϕ_0 coefficient appears to be significant in five markets (Belgium, Finland, France, Sweden and Switzerland). However, in the post-ETF period these coefficients become insignificant. As previously, this signals an improvement in terms of market efficiency in these markets. Furthermore, the coefficient φ_1 is significant and negative in the markets

[31] Ranging from 7 trading days (Switzerland) to 92 (U.K.) in the pre ETF period and 40 trading days (Switzerland) to 75 trading days (Netherlands) in the post ETF period.

of Belgium and Finland, indicating the presence of negative feedback trading; though once again, these coefficients turn insignificant in the post ETF period. In addition, as the coefficient φ_2 is insignificant for all the markets examined at both sub-periods, we can say that there is no evidence of relationship between market direction and the feedback traders' behavior.

What is next is to examine the significance of the difference in feedback trading between the two periods, pre and post the introduction of the ETFs. In order to do this, we follow the specification of Antoniou *et al.* (2005) as indicated above in equations (8) and (9). The results are shown in table 4.5 and as we can see the coefficients φ_0 and φ_1 reveal similar outcomes to the previous models applied. More specifically, there is an improvement in terms of market efficiency for five markets of our sample as φ_0 is significant in the pre-ETF period and turns to insignificant in the post ETF period. Similarly, for the markets of Belgium and Finland, the coefficient φ_1, being significant and positive in the pre-ETF period, becomes insignificant in the post-ETF period. In addition, in all markets except that of Belgium, the volatility's level is smaller in the post-ETF period ($\beta_{0,1} > \beta_{0,2}$) and as our Wald-tests show, there is significant difference (5% level) in this coefficient's values between the pre and post ETF periods; the only exception here is the markets of Belgium and the Netherlands.

Our next step is to examine the robustness of our results by recalculating our model using different windows around the introduction of the ETFs; in our case we will use 2-year, 3-year and 4-year windows (that is 2 years before and 2 years after the introduction of the ETFs and so on). The results of this test are indicated in table 4.7. As we can see from the tables, the coefficient φ_0 appears to be significant for some markets. More specifically, in the pre-ETF period, the coefficient is significant for Belgium in all three time windows (2-3-4 years). Similarly, the coefficient for France is also significant for the 2- and 4-year window and the one for U.K market (3- and 4- year window). Nevertheless, the coefficient for these markets turns insignificant in the post ETF periods with this difference being significant (5% level).

Table 4. 2 - Maximum Likelihood Estimates of the Sentana and Wadwhani (1992) Model: Pre-ETF Spot Market Indices Daily Returns

Conditional Mean Equation: $r_t = \alpha + \left(\phi_0 + \phi_1 \sigma_t^2\right) r_{t-1} + \theta \sigma_t^2 + \varepsilon_t$

Conditional Variance Specification: $\sigma_t^2 = \omega + \beta\, \varepsilon_{t-1}^2 + \gamma \sigma_{t-1}^2 + \delta S_{t-1} \varepsilon_{t-1}^2$

Parameters	BEL 20 (2/1/1990 - 1/10/2002)	OMXH25 (2/1/1990 - 10/2/2002)	CAC 40 (2/1/1990 - 21/1/2001)	DAX 30 (2/1/1990 - 2/1/2001)	AEX (2/1/1990 - 29/5/2001)	OMXS30 (2/1/1990 - 29/10/2000)	SWISSMI (2/1/1990 - 14/3/2001)	FTSE 100 (2/1/1990 - 27/4/2000)
α	-0.0043 (0.0197)	0.0498 (0.0427)	-0.1085 (0.0493)*	-0.0038 (0.0380)	0.0153 (0.0262)	0.0625 (0.0355)	0.0008 (0.0328)	0.0035 (0.0293)
θ	0.0171 (0.0245)	-0.00750 (0.0205)	0.0996 (0.0361)	0.0356 (0.0275)	0.0347 (0.0277)	-0.0020 (0.0221)	0.0462 (0.0341)	0.0401 (0.0397)
φ_0	0.1812 (0.0239)**	0.2105 (0.0314)**	0.0782 (0.0384)*	0.0672 (0.0339)*	0.0331 (0.0288)	0.1242 (0.0303)**	0.1040 (0.0286)**	0.0581 (0.0369)
φ_1	-0.0268 (0.0121)*	-0.0291 (0.0084)**	-0.0158 (0.0186)	-0.0170 (0.0132)	-0.0050 (0.0146)	-0.0168 (0.0096)	-0.0209 (0.0137)	0.0016 (0.0324)
ω	0.0347 (0.0028)**	0.0877 (0.0093)**	0.0649 (0.0088)**	0.0458 (0.0057)**	0.0197 (0.0025)**	0.0473 (0.0080)**	0.0994 (0.0090)**	0.0062 (0.0016)**
γ	0.8442 (0.0111)**	0.8658 (0.0090)**	0.9018 (0.0114)**	0.8951 (0.0103)**	0.9082 (0.0084)**	0.8732 (0.0109)**	0.7832 (0.0191)**	0.9559 (0.0050)**
β	0.0573 (0.0099)**	0.0800 (0.0074)**	0.0145 (0.0086)**	0.0437 (0.0093)**	0.0474 (0.0078)**	0.0484 (0.0071)**	0.0322 (0.0115)**	0.0129 (0.0057)*
δ	0.1209 (0.0141)**	0.0387 (0.0118)*	0.0737 (0.0119)**	0.0586 (0.0112)**	0.0493 (0.0085)**	0.1117 (0.0139)**	0.1729 (0.0157)**	0.0474 (0.0082)**
(β +δ)/ β	3.1099	1.4838	6.0828	2.3410	2.0401	3.3079	6.3696	4.6744
Half Life	17.9	19.5	14.4	21.4	34.7	30.4	6.7	92.1

** denotes significance at the 1 percent level, * denotes significance at the 5 percent level. Parentheses include the standard errors of the estimates.

Table 4.3 - Maximum Likelihood Estimates of the Sentana and Wadhwani (1992) Model: Post-ETF Spot Market Indices Daily Returns

Conditional Mean Equation: $r_t = \alpha + \left(\phi_0 + \phi_1 \sigma_t^2\right) r_{t-1} + \theta \sigma_t^2 + \varepsilon_t$

Conditional Variance Specification: $\sigma_t^2 = \omega + \beta\, \varepsilon_{t-1}^2 + \gamma \sigma_{t-1}^2 + \delta S_{t-1} \varepsilon_{t-1}^2$

Parameters	BEL 20 (2/10/2002-12/12/2011)	OMXH25 (11/2/2002-12/12/2011)	CAC 40 (22/1/2001-12/12/2011)	DAX 30 (3/1/2001-12/12/2011)	AEX (30/5/2001-12/12/2011)	OMXS30 (30/10/2000-12/12/2011)	SWISSMI (15/3/2001-12/12/2011)	FTSE 100 (28/4/2000-12/12/2011)
α	0.0496 (0.0224)*	0.0329 (0.0286)	-0.0138 (0.0240)	0.0091 (0.0249)	0.0031 (0.0217)	0.0043 (0.0288)	0.0007 (0.0211)	-0.0042 (0.0198)
θ	(-0.0130) (0.0175)	-0.0023 (0.0176)	0.0058 (0.0135)	0.0039 (0.0130)	-0.0054 (0.0126)	0.0036 (0.0145)	0.0017 (0.0176)	0.0036 (0.0167)
φ_0	0.0079 (0.0262)	0.0506 (0.0305)	-0.0383 (0.0261)	-0.0108 (0.0270)	0.0183 (0.0259)	0.0043 (0.0288)	-0.0037 (0.0231)	-0.0408 (0.0241)
φ_1	0.0004 (0.0071)	-0.0057 (0.0088)	0.0002 (0.0062)	-0.0016 (0.0059)	-0.0050 (0.0051)	-0.0038 (0.0070)	0.0027 (0.0064)	-0.0022 (0.0074)
ω	0.0197 (0.0029)**	0.0190 (0.0032)**	0.0238 (0.0036)**	0.0265 (0.0037)**	0.0163 (0.0027)**	0.0224 (0.0037)**	0.0209 (0.0032)**	0.0161 (0.0024)**
γ	0.8901 (0.0076)**	0.9239 (0.0080)**	0.9180 (0.0076)**	0.9180 (0.0087)**	0.9265 (0.0070)**	0.9325 (0.0069)**	0.9017 (0.0084)**	0.9156 (0.0080)**
β	0.0092 (0.0083)	0.0143 (0.0086)	-0.0229 (0.0067)**	-0.0198 (0.0085)**	-0.0171 (0.0078)*	-0.0099 (0.0066)	-0.0142 (0.0071)*	-0.0097 (0.0081)
δ	0.1740 (0.0158)**	0.1008 (0.0125)**	0.1850 (0.0140)**	0.1747 (0.0135)**	0.1628 (0.0123)**	0.1340 (0.0118)**	0.1905 (0.0143)**	0.1590 (0.0120)**
(β +δ)/ β	19.9130	8.0490	-8.3434	-7.8232	-8.5205	-12.5354	-12.4155	-15.3918
Half Life	50.2	60.5	55.6	47.6	75.0	66.3	39.8	47.1

** denotes significance at the 1 percent level, * denotes significance at the 5 percent level. Parentheses include the standard errors of the estimates.

Table 4.4 - Maximum Likelihood Estimates of the Sentana and Wadhwani (1992) Model: Pre-ETF Spot Market Indices Daily Returns

Conditional Mean Equation: $r_t = \alpha + (\phi_0 + \phi_1 \sigma_t^2) r_{t-1} + \theta \sigma_t^2 + \phi_2 |r_{t-1}| + \varepsilon_t$

Conditional Variance Specification: $\sigma_t^2 = \omega + \beta\, \varepsilon_{t-1}^2 + \gamma \sigma_{t-1}^2 + \delta S_{t-1} \varepsilon_{t-1}^2$

Parameters	BEL 20 (2/1/1990 - 1/10/2002)	OMXH25 (2/1/1990 - 10/2/2002)	CAC 40 (2/1/1990 - 21/1/2001)	DAX 30 (2/1/1990 - 2/1/2001)	AEX (2/1/1990 - 29/5/2001)	OMXS30 (2/1/1990 - 29/10/2000)	SWISSMI (2/1/1990 - 14/3/2001)	FTSE 100 (2/1/1990 - 27/4/2000)
α	0.0024 (0.0205)	0.0486 (0.0431)	-0.1026 (0.0491)*	-0.0067 (0.0394)	0.0014 (0.0275)	0.0617 (0.0364)	0.0047 (0.0332)	0.0074 (0.0304)
θ	0.0322 (0.0284)	-0.0094 (0.0239)	0.1112 (0.0396)*	0.0306 (0.0303)	0.0091 (0.0313)	-0.0030 (0.0254)	0.0539 (0.0376)	0.0483 (0.0427)
φ_0	0.1870 (0.0242)**	0.2095 (0.0320)**	0.0837 (0.0392)*	0.0655 (0.0341)	0.0273 (0.0290)	0.1236 (0.0308)**	0.1079 (0.0293)**	0.0606 (0.0373)
φ_1	-0.0277 (0.0120)*	-0.0289 (0.0085)**	-0.0176 (0.0189)	-0.0165 (0.0133)	-0.0030 (0.0147)	-0.0167 (0.0096)	-0.0214 (0.0136)	0.0003 (0.0325)
φ_2	-0.0334 (0.0291)	0.0053 (0.0314)	-0.0259 (0.0328)	0.0124 (0.0358)	0.0583 (0.0323)	0.0028 (0.0327)	-0.0176 (0.0352)	-0.0159 (0.0332)
ω	0.0352 (0.0029)**	0.0877 (0.0095)**	0.0668 (0.0090)**	0.0453 (0.0056)**	0.0192 (0.0025)**	0.0472 (0.0081)**	0.1005 (0.0091)**	0.0063 (0.0016)**
γ	0.8422 (0.0112)**	0.8658 (0.0092)**	0.8994 (0.0116)**	0.8960 (0.0102)**	0.9096 (0.0084)**	0.8733 (0.0109)**	0.7810 (0.0193)**	0.9554 (0.0051)**
β	0.0572 (0.0099)**	0.0802 (0.0076)**	0.0152 (0.0088)	0.0434 (0.0093)**	0.0466 (0.0078)**	0.0484 (0.0072)**	0.0323 (0.0117)**	0.0132 (0.0058)*
δ	0.1243 (0.0143)**	0.0383 (0.0118)*	0.0745 (0.0121)**	0.0581 (0.0112)**	0.0487 (0.0083)**	0.1116 (0.0139)**	0.1749 (0.0162)**	0.0477 (0.0083)**
(β +δ)/ β	3.1731	1.4776	5.9013	2.3387	2.0451	3.3058	6.4149	4.6136
Half Life	17.7	19.5	14.0	21.6	35.3	30.5	6.6	91.5

** denotes significance at the 1 percent level, * denotes significance at the 5 percent level. Parentheses include the standard errors of the estimates.

Table 4.5 - Maximum Likelihood Estimates of the Sentana and Wadhwani (1992) Model: Post -ETF Spot Market Indices Daily Returns

Conditional Mean Equation: $r_t = \alpha + \left(\phi_0 + \phi_1 \sigma_t^2\right) r_{t-1} + \theta \sigma_t^2 + \phi_2 \left| r_{t-1} \right| + \varepsilon_t$

Conditional Variance Specification: $\sigma_t^2 = \omega + \beta\, \varepsilon_{t-1}^2 + \gamma \sigma_{t-1}^2 + \delta S_{t-1} \varepsilon_{t-1}^2$

Parameters	BEL 20 (2/10/2002-12/12/2011)	OMXH25 (11/2/2002-12/12/2011)	CAC 40 (22/1/2001-12/12/2011)	DAX 30 (3/1/2001-12/12/2011)	AEX (30/5/2001-12/12/2011)	OMXS30 (30/10/2000-12/12/2011)	SWISSMI (15/3/2001-12/12/2011)	FTSE 100 (28/4/2000-12/12/2011)
α	0.0482 (0.0248)	0.0477 (0.0318)	-0.0177 (0.0281)	0.0164 (0.0289)	0.0006 (0.0262)	0.0119 (0.0320)	-0.0015 (0.0244)	-0.0062 (0.0233)
θ	-0.0142 (0.0210)	0.0087 (0.0191)	0.0043 (0.0148)	0.0073 (0.0143)	-0.0065 (0.0139)	0.0079 (0.0159)	0.0000 (0.0196)	0.0022 (0.0182)
φ_0	0.0074 (0.0266)	0.0537 (0.0304)	-0.0391 (0.0262)	-0.0089 (0.0270)	0.0179 (0.0260)	0.0064 (0.0287)	-0.0044 (0.0235)	-0.0411 (0.0241)
φ_1	0.0004 (0.0071)	-0.0059 (0.0088)	0.0002 (0.0062)	-0.0017 (0.0059)	-0.0050 (0.0052)	-0.0040 (0.0069)	0.0028 (0.0064)	-0.0022 (0.0075)
φ_2	0.0041 (0.0355)	-0.0385 (0.0353)	0.0077 (0.0332)	-0.0155 (0.0334)	0.0055 (0.0332)	-0.0171 (0.0317)	0.0060 (0.0333)	0.0050 (0.0321)
ω	0.0197 (0.0029)**	0.0194 (0.0033)**	0.0238 (0.0036)**	0.0264 (0.0037)**	0.0163 (0.0027)**	0.0225 (0.0037)**	0.0209 (0.0032)**	0.0161 (0.0024)**
γ	0.8903 (0.0079)**	0.9225 (0.0082)**	0.9182 (0.0077)**	0.9177 (0.0087)**	0.9266 (0.0071)**	0.9320 (0.0069)**	0.9019 (0.0084)**	0.9158 (0.0081)**
β	0.0091 (0.0084)	0.0145 (0.0086)	-0.0232 (0.0067)**	-0.0194 (0.0085)**	-0.0173 (0.0079)**	-0.0097 (0.0066)	-0.0143 (0.0071)*	-0.0098 (0.0081)
δ	0.1739 (0.0160)	0.1026 (0.0128)**	0.1849 (0.0141)**	0.1746 (0.0135)**	0.1627 (0.0124)**	0.1345 (0.0119)**	0.1903 (0.0144)**	0.1588 (0.0121)**
(β +δ)/ β	20.1099	8.0759	-6.9698	-8.0000	-8.4046	-12.8660	-12.3077	-15.2041
Half Life	50.4	58.9	54.9	47.8	73.8	66.0	39.8	47.1

** denotes significance at the 1 percent level, * denotes significance at the 5 percent level. Parentheses include the standard errors of the estimates.

The only exception here is the Swedish market whose coefficient is significant in the post-ETF market, though its difference over the two periods is insignificant. Regarding the φ_1 coefficient, this appears insignificant in all markets and time windows with the only exception of the Swedish market where the coefficient is significant in the post ETF period, though its difference over the two periods is insignificant. As such, we can draw from the above results that feedback trading does not constitute an element of market dynamics in our sample countries.

Another test of robustness we apply is to split the post ETF period into pre and post crisis to gauge any effect of the ongoing credit crisis. As such, for any given series of our sample, we split the period from the ETF launch date till 31/8/2007 and from 1/9/2007 till 12/12/2011 and we rerun equations (8) and (9); the results are presented in table 4.8.

Table 4.6 - Maximum Likelihood Estimates of the Sentana and Wadhwani (1992) Model: Test for parameter changes in the Spot Market Indexes Daily Returns

Conditional Mean Equation: $r_t = \alpha + \theta\sigma_t^2 + [\phi_{0,1}D_t + \phi_{0,2}(1-D_t)]r_{t-1} + [\phi_{1,1}D_t + \phi_{1,2}(1-D_t)]\sigma^2 r_{t-1} + \varepsilon_t$

Conditional Variance Specification: $\sigma_t^2 = \beta_{0,1}D_t + \beta_{0,2}(1-D_t) + \beta\ \varepsilon_{t-1}^2 + \gamma\sigma_{t-1}^2 + \delta S_{t-1}\varepsilon_{t-1}^2$

Parameters	BEL 20	OMXH25	CAC 40	DAX 30	AEX	OMXS30	SWISSMI	FTSE 100
	0.0139	0.0531	-0.0246	0.0140	0.0199	0.0379	0.0048	0.0067
α	(0.0140)	(0.0241)*	(0.0211)	(0.0207)	(0.0159)	(0.0223)	(0.0175)	(0.0152)
	0.0055	-0.0123	0.0224	0.0112	0.0031	-0.0004	0.0195	0.0107
θ	(0.0138)	(0.0132)	(0.0132)	(0.0124)	(0.0120)	(0.0124)	(0.0160)	(0.0158)
	0.1750	0.2075	0.0837	0.0656	0.0486	0.1282	0.0968	0.0591
$\varphi_{0,1}$	(0.0229)**	(0.0294)**	(0.0350)*	(0.0324)*	(0.0280)	(0.0288)**	(0.0271)**	(0.0359)
	0.0056	0.0537	-0.0397	-0.0147	0.0158	-0.0001	-0.0094	-0.0469
$\varphi_{0,2}$	(0.0266)	(0.0307)	(0.0263)	(0.0277)	(0.0263)	(0.0297)	(0.0236)	(0.0241)
	-0.0234	-0.0275	-0.0146	-0.0135	-0.0083	0.0183	-0.0164	0.0080
$\varphi_{1,1}$	(0.0118)**	(0.0079)**	(0.0161)	(0.0122)	(0.0138)	(0.0100)	(0.0122)	(0.0306)
	0.0006	-0.0090	-0.0012	-0.0032	-0.0060	-0.0051	0.0016	-0.0023
$\varphi_{1,2}$	(0.0068)	(0.0086)	(0.0064)	(0.0061)	(0.0052)	(0.0069)	(0.0065)	(0.0076)
	0.0271	0.0500	0.0442	0.0400	0.0200	0.0347	0.0464	0.0151
$\beta_{0,1}$	(0.0016)**	(0.0053)**	(0.0040)**	(0.0035)**	(0.0018)**	(0.0040)**	(0.0031)**	(0.0019)**
	0.0278	0.0240	0.0267	0.0293	0.0172	0.0279	0.0305	0.0116
$\beta_{0.2}$	(0.0027)**	(0.0031)**	(0.0032)**	(0.0034)**	(0.0024)**	(0.0037)**	(0.0032)**	(0.0017)**
	0.8690	0.9047	0.9174	0.9052	0.9103	0.9049	0.8776	0.9240
γ	(0.0066)**	(0.0053)**	(0.0054)**	(0.0057)**	(0.0052)**	(0.0059)**	(0.0072)**	(0.0053)**
	0.0333	0.0492	-0.0013	0.0150	0.0246	0.0225	0.0059	0.0101
β	(0.0060)**	(0.0047)**	(0.0046)	(0.0047)**	(0.0042)**	(0.0046)**	(0.0054)	(0.0055)
	0.1448	0.0593	0.1226	0.1164	0.1007	0.1169	0.1625	0.1044
δ	(0.0102)**	(0.0077)**	(0.0084)**	(0.0081)**	(0.0067)**	(0.0083)**	(0.0091)**	(0.0078)**
(β+δ)/β	5.3483	2.2053	-93.3077	8.7600	5.0935	6.1956	28.5424	11.3366
Half Life	27.0	41.8	30.3	31.7	46.6	48.6	19.3	50.2
Wald tests statistics H$_0$: $\varphi_{0,1} = \varphi_{0,2}$	23.3092**	13.2654**	7.9303*	3.5511	0.7217	9.6152	8.8097*	6.0001*
H$_0$: $\varphi_{1,1} = \varphi_{1,2}$	3.2053	2.656312	0.6088	0.5725	0.0248	1.1810	1.8034	0.1089
H$_0$: $\beta_{0,1} = \beta_{0,2}$	0.1214	46.2358 **	44.5183**	17.873635**	2.2880	5.035845*	52.0386**	6.4387*

** denotes significance at the 1 percent level, * denotes significance at the 5 percent level. Parentheses include the standard errors of the estimates.
Wald-test statistics are represented here through their chi-square values.

Table 4.7: Maximum Likelihood Estimates of the Extended Sentana and Wadhwani (1992) Model: Tests for parameters changes using 2-/3-/4-year windows

Conditional Mean Equation: $r_t = \alpha + \theta\sigma_t^2 + [\phi_{0,1}D_t + \phi_{0,2}(1-D_t)]r_{t-1} + [\phi_{1,1}D_t + \phi_{1,2}(1-D_t)]\sigma^2 r_{t-1} + \varepsilon_t$ Conditional Variance Specification: $\sigma_t^2 = \beta_{0,1}D_t + \beta_{0,2}(1-D_t) + \beta\ \varepsilon_{t-1}^2 + \gamma\sigma_{t-1}^2 + \delta S_{t-1}\varepsilon_{t-1}^2$

Parameters		BEL 20	OMXH25	CAC 40	DAX 30	AEX	OMXS30	SWISSMI	FTSE 100
2-year windows		0.1326	0.1767	0.3320	0.1908	-0.0369	0.0841	-0.0434	0.1224
	$\varphi_{0,1}$	(0.0592)*	(0.1319)	(0.1293)*	(0.1485)	(0.1183)	(0.1060)	(0.1218)	(0.0842)
		-0.0739	0.0969	-0.0081	-0.0098	-0.0027	0.2543	-0.0201	-0.0288
	$\varphi_{0,2}$	(0.0639)	(0.1047)	(0.0759)	(0.0798)	(0.0760)	(0.1080)*	(0.0649)	(0.0665)
		-0.0005	-0.0262	-0.1254	-0.0602	0.0210	-0.0363	0.0434	-0.0109
	$\varphi_{1,1}$	(0.0205)	(0.0267)	(0.0667)	(0.0618)	(0.0611)	(0.0328)	(0.1022)	(0.0460)
		0.0108	-0.0124	-0.0018	-0.0040	-0.0019	-0.0413	0.0142	0.0154
	$\varphi_{1,2}$	(0.0150)	(0.0503)	(0.0165)	(0.0129)	(0.0102)	(0.0202)*	(0.0148)	(0.0358)
Wald tests	H_0: $\varphi_{0,1} = \varphi_{0,2}$	5.6306*	0.2229	4.9150*	1.4142	0.0587	1.2687	0.0277	2.1432
statistics	H_0: $\varphi_{1,1} = \varphi_{1,2}$	0.2064	0.0576	3.2370	0.7943	0.1378	0.0180	0.0792	0.2426
3-year windows		0.1591	-0.0110	0.1073	0.0419	-0.0053	0.0714	0.0170	0.1828
	$\varphi_{0,1}$	(0.0513)*	(0.0933)	(0.0707)	(0.0742)	(0.0596)	(0.0623)	(0.0518)	(0.0727)*
		-0.0181	0.0949	-0.0283	-0.0516	-0.0110	0.1793	-0.0645	-0.0541
	$\varphi_{0,2}$	(0.0490)	(0.0730)	(0.0652)	(0.0693)	(0.0604)	(0.0755)*	(0.0542)	(0.0533)
		-0.0067	0.0076	-0.0091	0.0046	0.0193	-0.0158	0.0113	-0.0311
	$\varphi_{1,1}$	(0.0180)	(0.0188)	(0.0262)	(0.0231)	(0.0190)	(0.0164)	(0.0183)	(0.0408)
		0.0016	-0.0202	-0.0012	-0.0011	-0.0036	-0.0309	0.0167	0.0028
	$\varphi_{1,2}$	(0.0130)	(0.0429)	(0.0147)	(0.0116)	(0.0091)	(0.0161)	(0.0142)	(0.0191)
Wald tests	H_0: $\varphi_{0,1} = \varphi_{0,2}$	6.1760*	0.808546	1.9647	0.8542	0.0044	1.1750	1.1769	6.9180*
statistics	H_0: $\varphi_{1,1} = \varphi_{1,2}$	0.1478	0.3589	0.0691	0.0507	1.2029	0.4110	0.0562	0.5883
4-year windows		0.1697	0.0122	0.1319	0.0806	0.0430	0.0540	0.0635	0.1508
	$\varphi_{0,1}$	(0.0461)**	(0.0687)	(0.0608)*	(0.0549)	(0.0539)	(0.0516)	(0.0480)	(0.0590)*
		-0.0019	0.0766	-0.0647	-0.0415	0.0208	0.0724	-0.0454	-0.0924
	$\varphi_{0,2}$	(0.0415)	(0.0601)	(0.0508)	(0.0540)	(0.0457)	(0.0567)	(0.0444)	(0.0493)
		-0.0082	0.0020	-0.0211	-0.0093	0.0025	-0.0121	-0.0003	-0.0300
	$\varphi_{1,1}$	(0.0177)	(0.0137)	(0.0217)	(0.0150)	(0.0171)	(0.0145)	(0.0170)	(0.0386)
		0.0065	-0.0125	0.0034	-0.0029	-0.0078	-0.0163	0.0098	0.0056
	$\varphi_{1,2}$	(0.0120)	(0.0398)	(0.0132)	(0.0103)	(0.0079)	(0.0137)	(0.0131)	(0.0183)
Wald tests	H_0: $\varphi_{0,1} = \varphi_{0,2}$	7.5660**	0.502729	6.1347*	2.5235	0.0981	0.0566	2.7858	10.0273**
statistics	H_0: $\varphi_{1,1} = \varphi_{1,2}$	0.0060	0.1220	0.9555	0.1245	0.3037	0.0439	0.2377	0.7069

** denotes significance at the 1 percent level, * denotes significance at the 5 percent level. Parentheses include the standard errors of the estimates. Wald-test statistics are represented here through their chi-square values.

As the results indicate the coefficients φ_0 and φ_1 are insignificant in both the pre and post ETF periods, suggesting that the current credit crisis did not have any impact on the insignificance of feedback trading and first order autocorrelation found previously in our tests for the post-ETF period. What is more, our results indicate that the level of volatility on average has increased due to the crisis for all the markets ($\beta_{0,2} > \beta_{0,1}$); more specifically, the rise of the volatility is significant (5% level) in the markets of Belgium, Finland, France, the Netherlands and the U.K, whereas in the other markets of our sample is insignificant. Finally, the persistence and asymmetries of the volatility found previously is maintained.

Now, in order to examine whether investors exhibit longer memory we re-calculate equations (9) and (12) by introducing a second lag in the demand function of feedback traders; Results for the pre and post-ETF periods are reported in tables 4.9 and 4.10. Particularly, in the markets of France, Germany, the Netherlands and the UK, the first order coefficients (ϕ_0 and ϕ_1) and the second order coefficients (ϕ_3 and ϕ_4) are found to be insignificant both in the pre and post-ETF periods. Belgium and Switzerland in the turn, exhibit significant ϕ_0 and ϕ_3 coefficients in the pre-ETF period, however these turn insignificant in the post-ETF period; hence signaling that the changes in market dynamics are due to improvement in market efficiency. Finland in its turn has significant ϕ_0 and ϕ_1 coefficients in the pre-ETF period, whereas in the post-ETF period, only the ϕ_0 coefficient remains significant; hence indicating that the reduction in noise trading leads to changes in market dynamics. Also, in the case of Sweden, both the ϕ_0 and ϕ_3 coefficients are significant in the pre-ETF period indicating significant inefficiencies, whereas the ϕ_4 coefficient is also significant. However, in the post-ETF period, only the ϕ_3 coefficient is significant, signaling that the change in market dynamics is due to the reduction of noise trading and market inefficiencies as well.

Finally, we examine the ETF series in order to test whether the decline in noise trading is due to the hypothesis that ETFs attract noise traders. Table 4.11 shows the results from the original model and as we can see that the ϕ_1 coefficient is insignificant for all the markets, hence suggesting that the hypothesis that the ETFs attract noise traders is rejected. What is more, the ϕ_0 coefficient is insignificant in all markets indicating that the ETF markets are characterized by efficiency. Summarizing the findings of our tests, we can draw the conclusion that the introduction of the ETFs can have a beneficiary effect in the markets introduced in terms of improving market efficiency. Particularly, our results suggest four main findings: a) ETF markets are not dominated by noise traders, b) ETFs improve the market efficiency of the markets being introduced in, c) ETFs appear to depress noise trading, and d) ETFs do have any impact upon market volatility.

Table 4.8 - Maximum Likelihood Estimates of the Sentana and Wadhwani (1992) Model: Test for parameter changes in the Post-ETF Spot Market Indexes Daily Returns pre versus post crisis

Conditional Mean Equation: $r_t = \alpha + \theta\sigma_t^2 + [\phi_{0,1}D_t + \phi_{0,2}(1-D_t)]r_{t-1} + [\phi_{1,1}D_t + \phi_{1,2}(1-D_t)]\sigma^2 r_{t-1} + \varepsilon_t$

Conditional Variance Specification: $\sigma_t^2 = \beta_{0,1}D_t + \beta_{0,2}(1-D_t) + \beta\,\varepsilon_{t-1}^2 + \gamma\sigma_{t-1}^2 + \delta S_{t-1}\varepsilon_{t-1}^2$

Parameters	BEL 20	OMXH25	CAC 40	DAX 30	AEX	OMXS30	SWISSMI	FTSE 100
	0.0487	0.0267	-0.0177	0.0074	-0.0005	0.0015	0.0011	-0.0133
α	(0.0225)*	(0.0289)	(0.0239)	(0.0250)	(0.0213)	(0.0289)	(0.0211)	(0.0192)
	0.0095	0.0009	0.0097	0.0054	-0.0004	0.0046	0.0030	0.0127
θ	(0.0178)	(0.0179)	(0.0135)	(0.0132)	(0.0126)	(0.0146)	(0.0177)	(0.0162)
	0.0128	0.0931	-0.0465	-0.0055	0.0251	0.0353	-0.0181	-0.0428
$\varphi_{0,1}$	(0.0375)	(0.0486)	(0.0353)	(0.0350)	(0.0330)	(0.0375)	(0.0315)	(0.0307)
	0.0238	-0.0019	-0.0144	-0.0071	0.0210	-0.0374	0.0230	-0.0234
$\varphi_{0,2}$	(0.0399)	(0.0526)	(0.0420)	(0.0439)	(0.0423)	(0.0493)	(0.0357)	(0.0425)
	-0.0177	-0.0204	0.0002	-0.0057	-0.0089	-0.0111	0.0042	-0.0067
$\varphi_{1,1}$	(0.0124)	(0.0291)	(0.0109)	(0.0084)	(0.0071)	(0.0110)	(0.0116)	(0.0146)
	0.0000	0.0012	-0.0016	0.0016	-0.0032	0.0023	0.0000	-0.0020
$\varphi_{1,2}$	(0.0085)	(0.0112)	(0.0073)	(0.0080)	(0.0069)	(0.0095)	(0.0074)	(0.0090)
	0.0229	0.0204	0.0247	0.0257	0.0168	0.0213	0.0207	0.0177
$\beta_{0,1}$	(0.0033)**	(0.0035)**	(0.0037)**	(0.0036)**	(0.0027)**	(0.0036)	(0.0031)**	(0.0025)**
	0.0513	0.0365	0.0415	0.0321	0.0290	0.0267	0.0253	0.0398
$\beta_{0,2}$	(0.0099)**	(0.0096)**	(0.0082)**	(0.0060)**	(0.0050)**	(0.0056)**	(0.0052)**	(0.0058)**
	0.8769	0.9204	0.9145	0.9170	0.9233	0.9338	0.9012	0.9143
γ	(0.0104)**	(0.0089)**	(0.0080)**	(0.0089)**	(0.0074)**	(0.0069)**	(0.0088)**	(0.0084)**
	0.0079	0.0130	-0.0259	-0.0202	-0.0202	-0.0110	-0.0149	-0.0242
β	(0.0090)	(0.0086)	(0.0062)**	(0.0085)*	(0.0082)*	(0.0067)	(0.0072)*	(0.0086)**
	0.1764	0.1005	0.1884	0.1751	0.1671	0.1322	0.1895	0.1721
δ	(0.0169)**	(0.0127)**	(0.0146)**	(0.0138)**	(0.0129)**	(0.0116)**	(0.0148)**	(0.0131)**
(β+δ)/β	23.3291	8.7308	-6.2741	-7.6683	-7.2723	-11.0182	-11.7181	-6.1116
Half Life	25.3	42.0	40.0	43.9	51.6	62.1	36.2	28.7
Wald H_0: $\varphi_{0,1} = \varphi_{0,2}$	0.0400	1.764607	0.3448	0.0008	0.0056	1.3904	0.7515	0.1379
tests H_0: $\varphi_{1,1} = \varphi_{1,2}$	1.4248	0.4885	0.0230	0.4382	0.3684	0.9152	0.1010	0.0775
statistics H_0: $\beta_{0,1} = \beta_{0,2}$	12.3482**	4.3937*	6.8175*	1.9546	9.9485*	1.7489	1.5009	23.9439**

** denotes significance at the 1 percent level, * denotes significance at the 5 percent level. Parentheses include the standard errors of the estimates. Wald-test statistics are represented here through their chi-square values.

Table 4.9 - Maximum Likelihood Estimates of the Sentana and Wadhwani (1992) Model: Controlling for higher-order feedback traders' demand (Pre-ETF)

Conditional Mean Equation: $r_t = \alpha + (\phi_0 + \phi_1\sigma_t^2)r_{t-1} + (\phi_3 + \phi_4\sigma_t^2)r_{t-2} + \theta\sigma_t^2 + \varepsilon_t$

Conditional Variance Specification: $\sigma_t^2 = \omega + \beta\,\varepsilon_{t-1}^2 + \gamma\sigma_{t-1}^2 + \delta S_{t-1}\varepsilon_{t-1}^2$

Parameters	BEL 20 (2/1/1990 - 1/10/2002)	OMXH25 (2/1/1990 - 10/2/2002)	CAC 40 (2/1/1990 - 21/1/2001)	DAX 30 (2/1/1990 - 2/1/2001)	AEX (2/1/1990 - 29/5/2001)	OMXS30 (2/1/1990 - 29/10/2000)	SWISSMI (2/1/1990 - 14/3/2001)	FTSE 100 (2/1/1990 - 27/4/2000)
α	-0.0053 (0.0200)	0.0563 (0.0428)	-0.1030 (0.0516)*	-0.0007 (0.0394)	0.0182 (0.0272)	0.0522 (0.0363)	0.0042 (0.0360)	0.0036 (0.0299)
θ	0.01452 (0.0252)	-0.0116 (0.0207)	0.0936 (0.0384)*	0.0298 (0.0290)	0.0297 (0.0297)	-0.0003 (0.0231)	0.0353 (0.0388)	0.0358 (0.0411)
φ_0	0.1671 (0.0247)**	0.2110 (0.0316)**	0.0708 (0.0383)	0.0640 (0.0338)	0.0290 (0.0295)	0.1192 (0.0305)**	0.0975 (0.0290)**	0.0535 (0.0370)
φ_1	-0.0194 (0.0126)	-0.0292 (0.0083)**	-0.0124 (0.0188)	-0.0170 (0.0133)	-0.0020 (0.0148)	-0.0152 (0.0098)	-0.0171 (0.0137)	0.0079 (0.0331)
φ_3	0.0581 (0.0265)*	0.0302 (0.0341)	0.0583 (0.0366)	0.0567 (0.0334)	0.0261 (0.0289)	0.0782 (0.0292)**	0.0586 (0.0279)*	0.0866 (0.0359)*
φ_4	-0.0257 (0.0136)	-0.0138 (0.0091)	-0.0283 (0.0179)	-0.0253 (0.0137)	-0.0266 (0.0156)	-0.0235 (0.0091)**	-0.0214 (0.0136)	-0.0976 (0.0337)**
ω	0.0345 (0.0028)**	0.0907 (0.0096)**	0.0630 (0.0087)**	0.0440 (0.0056)**	0.0195 (0.0025)**	0.0480 (0.0084)*	0.1019 (0.0092)**	0.0063 (0.0016)**
γ	0.8450 (0.0111)**	0.8629 (0.0093)**	0.9040 (0.0113)**	0.8992 (0.0101)**	0.9084 (0.0085)**	0.8718 (0.0115)	0.7761 (0.0194)**	0.9558 (0.0052)**
β	0.0558 (0.0099)**	0.0825 (0.0077)**	0.0140 (0.0087)	0.0412 (0.0090)**	0.0481 (0.0079)**	0.0473 (0.0072)**	0.0343 (0.0118)*	0.0125 (0.0057)*
δ	0.1223 (0.0143)**	0.0370 (0.0119)**	0.0728 (0.0119)**	0.0576 (0.0110)**	0.0477 (0.0085)**	0.1158 (0.0148)**	0.1792 (0.0165)**	0.0484 (0.0083)**
(β +δ)/ β	3.1918	1.4485	6.2000	2.3981	1.9917	3.4482	6.2245	4.8720
Half Life	17.9	18.9	14.9	22.2	34.9	29.8	6.6	92.1

** denotes significance at the 1 percent level, * denotes significance at the 5 percent level. Parentheses include the standard errors of the estimates.

Table 4.10 - Maximum Likelihood Estimates of the Sentana and Wadhwani (1992) Model: Controlling for higher-order feedback traders' demand (Post-ETF)

Conditional Mean Equation: $r_t = \alpha + \left(\phi_0 + \phi_1\sigma_t^2\right)r_{t-1} + \left(\phi_3 + \phi_4\sigma_t^2\right)r_{t-2} + \theta\sigma_t^2 + \varepsilon_t$

Conditional Variance Specification: $\sigma_t^2 = \omega + \beta\, \varepsilon_{t-1}^2 + \gamma\sigma_{t-1}^2 + \delta S_{t-1}\varepsilon_{t-1}^2$

Parameters	BEL 20 (2/10/2002-12/12/2011)	OMXH25 (11/2/2002-12/12/2011)	CAC 40 (22/1/2001-12/12/2011)	DAX 30 (3/1/2001-12/12/2011)	AEX (30/5/2001-12/12/2011)	OMXS30 (30/10/2000-12/12/2011)	SWISSMI (15/3/2001-12/12/2011)	FTSE 100 (28/4/2000-12/12/2011)
α	0.0501 (0.0230)*	0.0814 (0.0262)*	-0.0103 (0.0243)	0.0093 (0.0251)	0.0011 (0.0217)	0.0110 (0.0292)	0.0055 (0.0215)	-0.0013 (0.0202)
θ	-0.0165 (0.0187)	-0.0181 (0.0137)	0.0026 (0.0139)	0.0022 (0.0133)	-0.0062 (0.0128)	-0.0004 (0.0149)	-0.0027 (0.0182)	0.0002 (0.0175)
φ_0	0.0068 (0.0262)	0.0593 (0.0230)*	-0.0378 (0.0264)	-0.0104 (0.0271)	0.0173 (0.0259)	0.0047 (0.0288)	-0.0058 (0.0239)	-0.0409 (0.0246)
φ_1	0.0011 (0.0072)	-0.0080 (0.0060)	-0.0003 (0.0064)	-0.0017 (0.0061)	-0.0047 (0.0052)	-0.0042 (0.0070)	0.0037 (0.0077)	-0.0027 (0.0081)
φ_3	0.0194 (0.0258)	0.0217 (0.0243)	-0.0016 (0.0247)	0.0148 (0.0249)	0.0288 (0.0246)	-0.0135 (0.0260)*	-0.0104 (0.0249)	-0.0059 (0.0235)
φ_4	-0.0076 (0.0074)	-0.0083 (0.0061)	-0.0061 (0.0057)	-0.0049 (0.0053)	-0.0047 (0.0046)	-0.0070 (0.0067)	-0.0094 (0.0080)	-0.0097 (0.0075)
ω	0.0194 (0.0029)**	0.0209 (0.0031)**	0.0232 (0.0036)**	0.0261 (0.0037)**	0.0161 (0.0027)**	0.0213 (0.0037)**	0.0205 (0.0032)**	0.0157 (0.0024)**
γ	0.8913 (0.0076)**	0.9125 (0.0051)**	0.9191 (0.0076)**	0.9187 (0.0087)**	0.9279 (0.0070)**	0.9343 (0.0068)**	0.9025 (0.0083)**	0.9169 (0.0079)**
β	0.0086 (0.0083)	0.0526 (0.0060)**	-0.0221 (0.0068)**	-0.0195 (0.0085)**	-0.0189 (0.0078)*	-0.0093 (0.0066)	-0.0128 (0.0071)	-0.0091 (0.0081)
δ	0.1737 (0.0158)	0.0561 (0.0086)**	0.1813 (0.0137)**	0.1734 (0.0134)**	0.1640 (0.0125)**	0.1297 (0.0115)**	0.1864 (0.0141)**	0.1556 (0.0117)**
(β +δ)/ β	21.1977	2.0665	-7.2036	-7.8923	-7.6772	-12.9462	-13.5625	-16.0989
Half Life	52.0	100.8	55.8	48.8	76.7	67.9	40.2	47.8

** denotes significance at the 1 percent level, * denotes significance at the 5 percent level. Parentheses include the standard errors of the estimates.

Table 4.11 - Maximum Likelihood Estimates of the Sentana and Wadhwani (1992) Model: ETF Daily Returns

Conditional Mean Equation: $r_t = \alpha + \left(\phi_0 + \phi_1\sigma_t^2\right)r_{t-1} + \theta\sigma_t^2 + \varepsilon_t$

Conditional Variance Specification: $\sigma_t^2 = \omega + \beta\,\varepsilon_{t-1}^2 + \gamma\sigma_{t-1}^2 + \delta S_{t-1}\varepsilon_{t-1}^2$

Parameters	LYXOR ETF BEL 20 (2/10/2002-12/12/2011)	SLG OMXH25 (11/2/2002-12/12/2011)	LYXOR ETF CAC 40 (22/1/2001-12/12/2011	DAX^{EX} (3/1/2001-12/12/2011)	AEXT STREETTRACKS (30/5/2001-12/12/2011)	XACT OMXS30 (30/10/2000-12/12/2011)	XMTCH ON SMI (15/3/2001-12/12/2011)	iSHARES FTSE 100 (28/4/2000-12/12/2011)
α	0.0526 (0.0218)*	-0.1324 (0.0680)	-0.0041 (0.0252)	-0.0028 (0.0241)	0.0119 (0.0232)	0.0142 (0.0304)	0.0034 (0.0220)	-0.0022 (0.0204)
θ	-0.0133 (0.0205)	0.0593 (0.0288)*	0.0005 (0.0140)	0.0096 (0.0126)	-0.0140 (0.0131)	-0.0014 (0.0144)	0.0002 (0.0183)	0.0019 (0.0166)
φ_0	-0.0006 (0.0284)	0.0128 (0.0203)	-0.0413 (0.0263)	0.0062 (0.0271)	0.0064 (0.0253)	-0.0226 (0.0302)	-0.0139 (0.0240)	-0.0457 (0.0239)
φ_1	0.0082 (0.0098)	0.0000 (0.0156)	0.0008 (0.0064)	0.0008 (0.0060)	-0.0037 (0.0052)	-0.0017 (0.0077)	0.0028 (0.0072)	-0.0070 (0.0060)
ω	0.0176 (0.0027)**	0.1477 (0.1452)	0.0223 (0.0036)**	0.0267 (0.0030)**	0.0144 (0.0027)**	0.0170 (0.0031)**	0.0193 (0.0028)**	0.0162 (0.0024)**
γ	0.8972 (0.0083)**	0.8989 (0.0351)**	0.9189 (0.0077)**	0.9217 (0.0076)**	0.9300 (0.0073)**	0.9465 (0.0058)**	0.9118 (0.0079)**	0.9161 (0.0071)**
β	0.0062 (0.0080)	-0.0012 (0.0012)	-0.0184 (0.0071)**	-0.0280 (0.0078)**	0.0170 (0.0082)*	-0.0101 (0.0055)	-0.0157 (0.0071)*	-0.0028 (0.0076)
δ	0.1636 (0.0148)**	0.0886 (0.0276)**	0.1753 (0.0139)**	0.1820 (0.0130)**	0.1590 (0.0117)**	0.1104 (0.0100)**	0.1722 (0.0143)**	0.1442 (0.0110)**
(β +δ)/ β	27.3871	-72.8333	-8.5272	-5.5000	10.3529	-9.9307	-9.9682	-50.5000
Half Life	46.5	11.6	58.1	45.0	-26.5	82.2	38.6	47.1

** denotes significance at the 1 percent level, * denotes significance at the 5 percent level. Parentheses include the standard errors of the estimates.

4.9 Further Discussion of the Results

Let us now try to produce a synthesis of our results from tables 4.1-4.11. If there is one thing that is reflected through our results, it is the rather scant presence of feedback trading in European markets, both in their spot and ETF segments. The above indicate the prevalence of rational investors and the absence of significant feedback traders in these markets. It is interesting to further note that any presence of significant feedback trading is confined to the pre-ETF period, with almost no evidence of significant feedback trading being detected post-ETF. These findings suggest that the advent of ETFs in European markets led to the depression of any existing pre-ETF feedback trading significance, something we get to notice in the cases of Belgium and Finland. A possible explanation for this is that ETFs are dominated by rational investors and that their launch endowed rational traders with the opportunity to curtail noise trading. This is further corroborated through our results from the ETF-series, which further allow us to refute the possibility of noise traders migrating to the ETF-segment following the launch of ETFs. This is a particularly encouraging finding, both for the investment community as well as for the regulatory authorities. As far as investors are concerned, the absence of noise traders from the ETF-segment implies greater efficiency in their pricing and reduced risk, both of which are particularly important considering the fact that rational investors tend to employ ETFs for risk management purposes. On the other hand, the insignificance of noise trading should be welcome for regulators and policymakers alike, since it indicates that this prolifically popular financial innovation has succeeded in constituting another channel of rational trading towards the market, thus rendering markets more complete.

The beneficial impact of ETFs over market dynamics is further suggested through the reduction of predictability traits in the return-generation process. As our results have indicated, the significance of the first-order autocorrelations of returns is confined to the pre-ETF period, with overall evidence of predictability appear extremely scant post-ETF even when second-order lags are taken into account. The overall picture is that the efficiency of European markets grew following the introduction of ETFs. Although one may find hard to assert whether this was exclusively due to their launch, the fact that they are found to be dominated by rational investors certainly confirms their contribution to enhancing market efficiency itself. If noise investors help induce mispricing and rational investors can counter this through the use of ETFs as one route, then our results provide evidence in favor of ETFs improving pricing at the spot segment.

If rational investors dominate ETFs (and reduce noise trading post-ETF at the spot level where it was found to be significant pre-ETF) and if efficiency improves post-ETF and given that rational investors trade on the basis of information, the above combined would imply an increase in the flow of information to the spot-segment through rational trades in the ETF-market. In view of that and in line with Ross (1989) this would be expected to translate in a rise in volatility post-ETF; however, this is not what we witness. The significant drop in the average volatility level post-ETF is an interesting finding here and may be taken to imply that the lower costs associated with ETF-trading ended up attracting more rational investors to the ETF-segment who, in turn, helped dampen spot volatility through improved risk management induced by the addition of ETFs in their arsenal of investment choices.

In addition, the ongoing credit financial crisis that started in the late 2007 appears to have no impact over our results. More specifically, when accounting for the impact of the financial crisis, both the first-order return autocorrelation and feedback trading remain insignificant in the post ETF period. What is more, there appears to be a slight increase in the levels of volatility in some markets; particularly, in the cases of Belgium, Finland, France, the Netherlands and the U.K., there is a significant rise in the average level of volatility (at 5% level), whereas in the rest of the markets examined is insignificant.

Summarizing our findings, we believe that there are important implications for both the market regulators and the investors. Particularly, given the fact that our sample consisted of developed markets, our findings can be of great importance to the regulatory authorities of emerging or relatively new established markets as the launch of ETFs could essentially contribute towards the completion of these markets and the attraction of sophisticated investors. Since the launch of the ETFs in the developed markets enhanced their pricing efficiency and depressed the levels of noise trading, this could be amplified under the premises of the non developed markets. As it concerns the investors' side and how these could benefit from the use of the ETFs, there are important implications as well. Our findings indicate that the ETF segment is characterized by pricing efficiency and the absence of noise trading; hence, this enhances confidence among the investment community regarding these financial products and makes them more appealing to them. Having said that, it is the case that the ETFs are products whose trading volume is dominated by the institutional investors; thus making them less prone to mispricing. Finally, since the use of the ETFs have no destabilizing effect on the spot prices, in fact the opposite is true, these products can be successfully used as hedging tools on behalf of the investors.

4.10 Conclusion

Noise trading has been found to play a significant role against the completeness of the markets and the efficiency of their prices. As such, it is important for both the market regulators and the investing community to try to identify ways to depress the effect of noise trading upon the pricing efficiency of the markets. Since the establishment of the stock markets and their development throughout the years, there has been a plethora of financial instruments, out of which investors can choose the ones that best fit to their risk and return preferences. The role of these instruments is twofold; first they offer investors an alternative investing option, sometimes unique according to each instrument's characteristics and secondly, they can contribute towards the depression of noise trading in the markets making asset prices more efficient. Research has identified the beneficial effect the introduction of some financial instruments had towards the efficiency of the markets where these have been introduced [Antoniou *et al.* (2005), Chau *et al.* (2008)]. The gap we identified and tried to examine in this chapter was the impact of the introduction of the Exchange Traded Funds over the levels of noise trading. In order to do so, we used data from a span of developed markets, more specifically eight European markets, and we employed the established methodology of Sentana and Wadhwani (1992) that assumes two types of traders, namely rational and feedback trader.

The results of our empirical analysis outline the impact the introduction of the Exchange Traded Funds had over the market dynamics, in terms of noise trading, efficiency and volatility. More specifically, our findings suggest two important implications regarding the impact of ETFs' introduction over noise trading. Firstly, the ETFs are found to depress noise trading since in all the markets of our sample the significance of feedback trading appeared to dissipate after the launch of the ETFs. Secondly, the segment of the ETFs appears to be in the hands of rational investors; our results indicated no evidence of feedback trading strategies in the segment of the ETFs. As such, ETFs are less prone to noise trader risk, hence more efficiently priced, and can be considered as a very useful and safe tool for risk- and portfolio management purposes.

What is more, ETFs appear to have a beneficiary impact on the overall efficiency of the markets these have been introduced to. More specifically, in the majority of the markets examined in our sample there is evidence of first-order autocorrelation in the pre-ETF period, this implying predictability on the stock prices. However, this predictability appears to diminish after the launch of the ETFs in these markets. This suggests that ETFs promote efficiency on the spot markets and provides supporting evidence to previous researches such as those of Switzer *et al.* (2000) and Kurov and Lasser (2002) which found that the introduction of the ETFs contributed to the improvement of the efficiency of the markets where these were introduced. Furthermore, the introduction of the ETFs appears to have no significant impact over the volatility of the market, since volatility is highly persistent and asymmetric in both the pre and post ETF periods.

Concluding, we believe that our results bear important implications for both the market regulators and the investors. In the first case, since our sample consisted of developed markets, our results can be of great importance to the regulatory authorities of relatively new established or emerging markets as the launch of ETFs could essentially increase the informational efficiency of these markets and contribute to their further completion. Since the introduction of the Exchanged Traded Funds in the developed markets can have a beneficial role improving their pricing efficiency and depressing the levels of noise trading, this could be amplified under the premises of the non developed markets. As it concerns the investment community, our findings suggest that the ETF segment is characterized by pricing efficiency and the absence of noise trading; hence, these characteristics enhance the confidence of the investment community regarding ETFs and the latter become more appealing to the investors. Having said that, it is the case that the trading volume of the ETFs is dominated by the institutional investors; thus making them less prone to mispricing. Finally, since the ETFs have found to bear no destabilizing effect on the spot prices (on the contrary, they have the opposite effect), these products can be successfully used as hedging tools on behalf of the investment community.

Chapter 5

5.1 Introduction

The endeavor to identifying whether institutional investors herd intentionally or not, is of key interest to academics, investors and regulators alike. In academic terms, a wealth of empirical studies [see the excellent review by Hirshleifer and Teoh (2003)] has confirmed the presence of herding among fund managers internationally, without however assessing empirically the extent to which this herding is due to intent. From the investors' viewpoint, establishing intent behind fund managers' herding can help investors decipher between "leaders" and "followers" in the investments' industry and entrust their savings with those funds whose managers are of high ability (as opposed to those who resort to imitation to conceal their low competence). Finally, regulators have every interest in identifying the factors leading fund managers to herd intentionally in order to devise measures aiming at reducing their impact; this is because any herding tendencies on behalf of fund managers can give rise to destabilizing outcomes and amplify systemic risk [Goodhart *et al.* (1998)] given funds' dominance in equity turnover internationally.

Holmes *et al.* (2011) were the first to raise the issue of herding intent in the empirical dimension by drawing upon the documented motives in the literature underlying institutional herding, which they classified into intentional (information-related; career-related) and unintentional (relative homogeneity; characteristic trading). They then employed a series of market states (based on variables, such as, for example, market performance and market volatility) and put forward a series of hypotheses linking the various states with fund managers' propensity to herd intentionally. In essence, their research rested upon the notion that if fund managers herd intentionally, their herding should exhibit differences in its significance between periods characterized by varying conditions. If fund managers herd spuriously, their herding would be expected to be significant irrespective of the market states accounted for. Estimating institutional herding at the market level conditional upon different market states in the context of the Portuguese stock exchange, they showed that fund managers there did not herd indiscriminately but rather that their herding grew in significance when the market underwent specific conditions (i.e. that they herded intentionally).

Our present chapter extends the approach proposed by Holmes *et al.* (2011) by investigating whether institutional investors herd intentionally at the sector level. Fund managers have been found to herd significantly when investing in different industries [e.g.Voronkova and Bohl (2005); Choi and Sias (2009) ; Chen *et al.* (2012)], yet no study to date has concluded whether their herding is the result of intent or is spurious in nature. A key feature of our work is that we assess the presence of intent in sector herding on the premises of variables (returns; volatility; volume; concentration of trading) using both their market and sector expressions to gauge whether herding intent at the sector level is more relevant to conditions prevailing in a sector or the market as a whole. The rationale here is that sector conditions reflect states of a sector's environment not necessarily similar to those of the market. It is possible, for example, that, while the market is rising for a given time-window, a sector exhibits a particularly negative performance during the same window, due to adverse industry-specific fundamentals, be they domestic or global.

If this is the case, that sector's institutional herding estimates for periods of positive (negative) market performance will differ from the estimates obtained for periods of positive (negative) sector performance[32] and lead us to generate different inferences with regards to fund managers' herding intent. This approach allows us, therefore, to control for the impact of different possible environmental states (market as well as sector ones) over institutional herding and their relation to the intent underlying it.

We test for institutional herding intent at the sector level drawing upon a unique database of quarterly portfolio holdings of Spanish mutual funds for the period 06/1995-09/2008. Our results indicate that Spanish fund managers herd significantly at the overall market level, with the significance of their herding identified with certain sectors (Consumer Services; Industrials; Technology) for the full sample-period. Controlling for a variety of market and sector states, we denote that their herding exhibits clear signs of intent for a series of industries including Basic Materials, Consumer Goods, Consumer Services, Financials and Industrials. Technology as a sector is characterized by significant institutional herding irrespective of the environmental states tested for, indicating that intent is absent in fund managers' herding there, while some sectors (Healthcare; Oil & Gas; Utilities) exhibit no herding at all.

The next section will present initially an overview of herd behavior in terms of motivations, both intentional and unintentional and will then proceed to discuss the specific issues related to sector herding. Section 3 will introduce the data employed in

[32] For the obvious reason that the market-states herding estimates will be based on a different period compared to the sector-states herding estimates.

this chapter, delineate the empirical design and present some descriptive statistics. Section 4 presents and discusses the results and section 5 concludes.

5.2 Literature Review

5.2.1 Definition and Sources

According to Hwang and Salmon (2004) herding occurs when investors choose to mimic their peers' actions disregarding their own beliefs and informational sets. In addition, Bikhchandani and Sharma (2001) identified two kinds of herding, namely "*spurious*" and "*intentional*"; the first one arises when investors act in the same way due to their similar reaction to commonly perceived information or market conditions and the latter when investors intentionally disregard their own beliefs and choose to copy other investors' actions.

Possible sources of *spurious* herding include characteristic trading and the relative homogeneity of investment professionals. More specifically, characteristic trading, the term being first introduced by Falkenstein (1996), involves institutional investors trading in stocks with specific characteristics; these could be size, past returns (momentum or contrarian trading), or industry. As such, the selection of stocks with similar characteristics may lead to similar trading behavior on behalf of the fund managers. The latter may also engage in similar trading behavior due to their common background; typically, investment professionals share common educational and professional skills that may lead them to trade similarly. For example, most of the fund managers are graduates from business schools or holders of various accredited professional certificates; hence they may use the same evaluation techniques or tools to form their own trading strategies. This relative homogeneity on the educational background of the fund managers along with their performance-based assessment may drive them into parallel trading behavior; however this kind of behavior would not be the product of intent.

Moving on to *intentional* herding, this could be the result of the informational asymmetry among the investors. It is usually the case that not all the investors, be they professionals or not, have the same access to information. So, some fund managers may decide to copy the actions of their peers which are considered to be better informed than they are. In addition, fund managers may herd on others' actions even if they themselves possess information; particularly, if they believe that some of their peers have better information than they do, they may choose to disregard their own informational sets and herd on the others' trades. The decision of some fund managers to follow the trades of their peers may lead to a pattern of correlated trading among the investors. As such, the informational asymmetry among the investment professionals may be a possible source of herd behavior and it was defined by Banerjee (1992) and Bikhchandani *et al.* (1992) as *informational cascading*; the latter can have great implications on the efficiency of the stock markets. More specifically, since fund managers may choose to disregard their own information and trade on their peers' informational sets, the latter reflected through their actions, this could mean that not all the information is conveyed to the market. However, what should be the case in an efficient market is that all available information should be reflected on the stock prices; Hirshleifer and Teoh (2003) posited that this phenomenon causes *informational blockages* since not all the available information is conveyed to the market. There is a plethora of empirical evidence supporting the theory of *informational cascades*. Calvo and Mendoza (1997) and Calvo and Mendoza (2000) examined portfolio managers' diversification strategies and found evidence of *informational cascading*; more specifically, the authors found that managers would prefer to herd on their peers' actions rather than trying to acquire their own information. In order to support their argument, the researchers used the example of the Mexican crisis in 1994 where countries with similar characteristics such as Brazil, Chile and Mexico were impacted by investors' herding. More specifically, instead of examining each country's specific fundamentals, investors assumed that every country similar to Mexico, i.e. the Latin countries, would follow; as such after the devaluation of the Mexican Peso, these countries' currencies were also severely devaluated.

Apart from the informational reasons discussed above, another potential source of intentional herding is professional reasons which are derived by the principal-agency problem between fund managers and their employers/clients. More specifically, it could be the case that fund managers may choose to follow the market consensus in order to protect their interests, even though this could be against their clients' best interest. Fund managers are evaluated according to their performance and in comparison to their peers' performance; if things are bad in the market then a fund manager having a poor performance is not that bad if everyone else performed poorly as well. In that case "bad luck" or adverse market conditions could be blamed rather than him. Furthermore, as Scharfstein and Stein (1990) argued, it could be the case that less experienced or less capable managers would choose to herd on the actions of their peers that are considered as good or experienced in order to upgrade their status to that of the good ones.

Moreover, even the good managers have an incentive to herd in order for them to protect their good status; the cost of bad performance when acting alone is greater than the gain from it. Finally, several studies such as those by Trueman (1994), Graham (1999) and Welch (2000) provide evidence that analysts would herd on their good peers and the market consensus and attributed this phenomenon to reputational incentives.

5.2.2 Sector Herding

After discussing the different kinds of herding and their possible sources, we now move on to the crux of this study, namely industry herding. The importance of the specific elements that characterize each industry and differentiate it from the rest has been notably identified by the investors over the last years, both practically and theoretically. For example, it is quite often the case that a single industry can affect the whole market either upwards or downwards; the rise of the technology sector in the 1990s that boosted the rest of the stocks worldwide is a well documented example of the significance that industries can have on market returns. Similarly, but on the downward side, the recent collapse of Lehman Brothers and a number of other banks as well had a great impact on financial markets worldwide. These two notable examples of the importance of sectors for the investment community and particularly the technology sector are what gave rise to a particular investment style, namely the sector investment style. The creation of financial products, mostly mutual funds, which invest in specific sectors, has been quite popular over the last decades. In addition, in their groundbreaking paper about style investing, Barberis and Shleifer (2003) also include sector investing as a style. Moreover, there has been a plethora of research papers studying trading strategies in various sectors. Moskowitz and Grinblatt (1999) examined the presence of industry momentum in the U.S market. Particularly, the authors composed twenty value-weighted portfolios for the period 1963-1995 and they found that industry momentum strategies were more profitable than momentum strategies based on individual stocks; in fact, it was found that most of the profitability of individual stock momentum returns was explain by the industry momentum profitability. Furthermore, O'Neal (2000) using a sample of 31 sector mutual funds for the 1989-1999 period found evidence of momentum profits in the industry level. More specifically, especially in the 12-month period, the portfolios of mutual funds that exhibited higher returns during the past were found to outperform those portfolios that consisted of mutual funds that performed poorly. Another study by Swinkels (2002) examined the presence of industry momentum in the markets of Europe, Japan and the U.S.; his findings revealed evidence of industry momentum in the European and the U.S markets, yet not in the Japanese one. More recently, Ji and Giannikos (2010) examined the presence of industry momentum in a span of countries worldwide. Particularly, the authors using data for 35 countries during the period 1970-2006 found significant evidence of industry momentum in most of the sample countries, especially during the month of January.

The above studies indicate that investors do invest in sectors; however we will now try to understand the underlying reasons that lead investors to invest according to the industry classification of the stocks. Moskowitz and Grinblatt (1999) suggested several reasons why this could be the case; one of the them, was that there are sectors in the economy that are “hot” and “cold”, like the case with the biotechnology and internet firms, leading investors to herd into and out of these sectors; hence creating persistent returns. In addition, the authors also suggested some behavioral reasons in their effort to explain this phenomenon; one of them could be the presence of the overconfidence and self-attribution biases [both presented in the Daniel *et al.* (1998) model] on behalf of the investors. Particularly, as it may be more difficult for investors to update and evaluate new information about the industries they already invest in, investors may be more overconfident or exhibit more self-attribution bias in certain industries of the market, hence creating mispricing in these industries. Similarly, based on the theory of Barberis *et al.* (1998), industry momentum could be the product of the conservatism bias and the representativeness heuristic. In the first case, investors, upon the arrival of new information in the market, may be reluctant to update their beliefs about certain industries, thus leading to the under-reaction of prices. In the case of the representativeness heuristic, investors may become very optimistic in the presence of repetitive good news (or pessimistic in the case of bad news); hence industry-focused investors may extrapolate this news for the whole industry causing return reversals in these industries. More specifically, in the latter case, the overreaction of investors to specific news and their extrapolation to the whole industry causes prices to deviate from their fair values, though in the long run these revert to their fair values. Furthermore, Hong *et al.* (2000) found evidence of stronger momentum effect in small firms with low coverage from the analysts and this could be due to slower information transmission into this kind of firms. So, it could be the case that information is not dispersed equally among the firms of the same industry. First the information affects the larger firms and then it is spread among the smaller ones as investors may interpret the information as representative for the whole industry; hence, this could result into momentum effects with smaller firms following the larger ones.

Apart from the behavioral reasons stated above, Berk *et al.* (1999) suggested that systematic risk is responsible for the firms' growth options and this could lead to momentum effect on their returns. Moreover, it is more likely that firms in the same industry face similar growth opportunities, hence there is greater possibility for them to exhibit momentum returns. Finally, Moskowitz and Grinblatt (1999) outline the importance of sector investing through the high correlation among the firms belonging in the same industry in terms of similar regulatory and corporate environment, responses to macroeconomic news and supply and demand variations.

So far we discussed whether investors engage in sector/industry investing and the underlying reasons for it. Now, we will examine whether investors herd at the industry level and if they do, whether their herd behavior is driven by intent or not. Early research by Lakonishok *et al.* (1992) found no evidence that institutional investors herd more on the stocks of specific industries than others. More specifically, the authors, using quarterly data on 769 U.S equity funds for the period 1985-1989, found that the mutual funds of their sample did not herd more on the stocks of a particular industry. However, another research by Sharma *et al.* (2006), which examined the case of the internet bubble in the U.S market found different results. The authors, examining a sample of 430 technology firms and their institutional holdings for the period 1998-2001, found that institutions as a group did herd in and out of the internet stocks. The above mentioned studies examined whether institutional investors herd more on individual stocks of specific industries; however, the study by Choi and Sias (2009) examined whether institutional investors herd across industries (i.e. whether institutional investors follow each other into and out of specific industries). The authors, using quarterly data of U.S institutions for the period 1983-2005, found strong evidence that institutional investors herd into and out of the same industries.

Choi and Sias (2009) suggested various reasons why institutional investors may industry herd. First of all, according to the authors, this could be due to the underlying investors' flows; retail investors' flows from certain funds to others may be able to explain institutional industry herding. More specifically, if there is an increasing number of investors choosing to invest in a specific mutual fund, then the other fund managers may interpret this as a signal of informational or skill superiority (if many investors keep investing in a specific fund, then the fund manager must be good); hence, the other fund managers may herd on his actions. Another reason why institutions herd at the industry level could be momentum-related; institutional investors may be attracted by industries with high past returns and pull out from industries with low past returns. Furthermore, if fund managers herd due to professional/reputational reasons, it could be the case that it is more likely for them to follow similarly classified funds. Choi and Sias (2009) also suggested that institutional industry herding could be due to herding into size and Book-to-Market styles; it is very often the case that stocks in the same industry share similar market capitalization and B/M ratios. For example, the technology sector is dominated by stocks with low B/M ratios; so if institutional investors follow a low B/M investment style, then they may appear to industry herd, whereas in reality they could herd due to the B/M style they follow (e.g. a low B/M ratio indicates growth strategies). Finally, Choi and Sias (2009) suggested that investigative herding could drive institutional industry herding; institutional investors may trade on correlated signals at different times, thus this could be the source of their herd behavior. After testing for all the above mentioned possible reasons, Choi and Sias (2009) concluded that the correlated signals explanation is more likely to explain the phenomenon of institutional industry herding.

Our study examines the presence of industry herding on the premises of the Spanish mutual funds' market. What is more, building upon Holmes *et al.* (2011), we aim to shed light on whether institutional industry herding in the Spanish market is intentional or not and whether any evidence of intent is due to market- or industry-specific conditions. Holmes *et al.* (2011), using monthly data of Portuguese mutual funds for the period 1998-2005, found significant evidence of herding and concluded that this was due to intent on behalf of fund managers. More specifically, after testing for several market conditions (such as market direction and market volatility), they attributed the intent of fund managers to herd to professional reasons. We take this approach a step further and examine whether the intent of fund managers to herd at the industry level is the result of market or industry conditions.

At this stage, we will try to analyze why we would expect industry conditions to affect institutional investors' intent to herd at the sector level more than market conditions. First of all, industry conditions are more representative of the fundamentals of an industry's constituent stocks; it could be the case that a particular sector of the economy has better growth opportunities than the rest of the economy, and vice versa. So, industry specific news should have a greater effect upon the decision of fund managers to herd into and out of an industry. What is more, the type of information that affects the entire market has primarily to do with macroeconomic variables, hence it is easy for fund managers (and investors generally) to acquire and interpret this kind of information. On the other hand, industry or firm-specific information is not always widely available to all investors and it often requires high processing skills in order to correctly interpret them. As such, fund managers that do not possess the required skills to analyze the information may be more willing to follow the actions of their peers; hence, this could imply more intent on their herd behavior. Finally, most of the analysts make industry recommendations (e.g. overweight or underweight a specific industry); hence, fund managers in order to protect their professional/reputational interests may decide to herd following the consensus of the market.

5.3 Data - Methodology

Our study uses quarterly portfolio holdings of Spanish mutual funds covering the December 1995 - September 2008 period which was obtained from the Spanish Securities Markets Commission; our sample consists of 1543 mutual funds and 245 stocks. More specifically, what our sample consists of is the code and the name of the fund, its description, the code and the name of the assets and the number of stocks each fund holds for every quarter of our sample period.

In order to identify any possible signs of herd behavior on behalf of mutual fund managers we employ the methodology proposed by Sias (2004). Accordingly, the first thing to do is to calculate the fraction of institutions of each security that are buyers for it every quarter. The author named that ratio the "raw fraction of institutions buying" for security *k* at quarter *t*:

$$Raw\Delta_{k,t} = \frac{No.of\ institutions\ Buying_{k,t}}{No.of\ institutions\ Buying_{k,t} + No.of\ institutions\ Selling_{k,t}} \tag{1}$$

Afterwards, he assumed this ratio and standardized it as follows:

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

where, $\overline{Raw\Delta_t}$ is the cross-sectional average raw fraction of institutions buying in quarter t and $\sigma(Raw\Delta_{k,t})$ is the cross-sectional standard deviation of the raw fraction of institutions buying in quarter *t*. In order to gauge the existence of herding, Sias assumed institutional demand to follow an autoregressive process of order one (AR-1) as follows:

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

The autocorrelation coefficient (β_t) here indicates the quarter-on-quarter cross-sectional correlation between institutional demand in quarter t and the previous quarter (t-1), given that both sides of equation (3) are standardized and there is only one independent variable on the right-hand side of the equation. The next step is the decomposition of this correlation between institutional demand this quarter and institutional demand the previous quarter into two components, namely one showing whether the correlation observed is due to institutional investors following "their own trades" and another one showing whether the correlation observed is due to institutional investors following "the trades of others". So, the slope coefficient of the above equation is decomposed as follows:

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

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

where $N_{k,t}$ is the number of investors trading security *k* in quarter *t* and $D_{n,k,t}$ is a dummy variable taking the value of one when trader *n* is a buyer of security *k* in quarter *t* and zero when trader *n* is a seller of security *k* in quarter *t*. Likewise, $N_{k,t-1}$ is the number of investors trading security *k* in quarter *t*-1 and $D_{n,k,t-1}$ is a dummy variable equal to one when trader *n* is a buyer of security *k* in quarter *t*-1 and zero when trader *n* is a seller of security *k* in quarter *t*-1. $D_{m,k,t-1}$ is a dummy variable that equals one when investor m (m≠n) is a buyer of security *k* in quarter *t*-1 and zero when investor m (m≠n) is a seller of security *k* in quarter *t*-1.

The first term on the right-hand side of equation (4) is the portion of the correlation attributable to investors following their own trades. If it is positive, then institutional investors tend to follow their own trades over adjacent quarters. Otherwise, if investors' transactions in quarter *t* are independent of their own transactions in the previous quarter, the first term will be zero. In case the term is negative, then investors reverse their transactions of the previous quarter. The second term on the right-hand side equation (4) is the portion of the correlation attributable to institutional investors following other investors. If it is positive, then institutional investors tend to follow each other over adjacent quarters. If investors buy (sell) the securities that other investors sell (buy) over the previous quarter, the term will be negative. Finally, if investors' trades are independent of other investors', the term will be zero.

Table 5.1 presents some descriptive statistics regarding Spanish funds' holdings both for the full sample (market level) as well as each individual sector.

Table 5.1 - Descriptive Statistics

	Total Market	Basic Materials	Consumer Goods	Consumer Services	Financials	Healthcare	Industrials	Oil & Gas	Technology	Utilities
No. of Stocks	245	23	33	28	65	10	54	6	6	20
No. of Funds	1543	1003	874	1189	1241	839	1176	1235	967	1409
No. of Quarter-holdings positions	647045	36512	25472	75717	148810	12804	123648	41477	19394	151915
No. of Stock-Quarters	15190	1426	2046	1708	4030	620	3348	372	242	1240

Average No of active stocks per quarter traded by ≥1 fund	Jun 1995-Sep 2008	1995	1996	1997	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008
Total Market	79,87	36,83	40,62	66,78	82,07	100,11	94,16	81,54	81,30	77,28	85,34	94,77	96,09	98,02	83,20
Basic Materials	15,64	15,67	15,50	16,25	18,50	18,50	17,00	17,00	15,50	14,75	14,25	14,25	13,75	14,00	14,00
Consumer Goods	19,07	20,00	17,50	21,25	24,00	23,75	21,00	20,50	18,50	17,00	17,00	16,75	17,00	16,50	16,25
Consumer Services	12,38	6,00	7,50	9,50	11,25	12,50	15,00	16,50	15,75	15,00	14,50	13,50	12,00	12,00	12,25
Financials	34,19	30,67	33,00	33,25	37,25	38,00	34,25	34,00	33,75	33,50	33,00	31,00	33,25	37,50	36,25
Healthcare	4,66	3,00	3,25	4,00	4,00	4,00	4,00	4,00	4,00	4,00	4,00	4,50	5,75	7,75	9,00
Industrials	31,40	33,67	33,25	36,25	35,50	37,25	33,50	31,75	31,75	29,75	27,75	28,75	28,00	25,75	26,75
Oil & Gas	3,80	2,67	3,25	4,00	3,25	3,00	3,25	4,00	4,00	4,00	4,00	4,00	4,00	4,75	5,00
Technology	3,54	1,33	1,00	1,00	1,75	3,50	5,00	5,00	4,75	4,50	5,00	4,75	4,00	4,00	4,00
Utilities	11,25	14,00	14,50	14,50	15,00	14,50	9,00	8,50	9,00	9,00	9,00	9,00	9,50	10,25	11,75

Average No of active funds per stock per quarter traded by ≥1 fund	Jun 1995-Sep 2008	1995	1996	1997	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008
Total Market	136,55	128,00	129,75	141,00	151,50	156,00	143,00	142,25	138,00	132,25	128,50	126,50	127,25	132,50	135,25
Basic Materials	43,04	26,87	23,55	50,75	52,05	55,89	50,75	38,81	29,95	25,29	32,69	48,97	64,45	58,70	43,89
Consumer Goods	25,89	14,19	14,42	27,17	31,99	33,43	25,38	21,50	20,92	21,29	24,88	32,92	32,38	34,06	27,98
Consumer Services	113,60	54,92	53,74	114,54	123,38	156,70	139,60	107,63	103,66	110,15	130,15	150,52	135,31	119,48	90,69
Financials	38,14	21,83	21,04	42,35	50,74	56,86	35,89	24,10	34,15	34,16	39,88	52,07	51,88	43,08	25,87
Healthcare	40,33	2,67	3,13	19,88	31,19	32,69	64,44	64,00	56,31	45,88	40,56	35,55	42,19	65,00	61,17
Industrials	46,15	37,01	36,77	48,71	69,68	82,02	46,15	25,12	28,83	29,00	33,78	48,81	56,56	55,40	48,22
Oil & Gas	182,24	71,50	81,13	116,56	161,75	269,58	198,50	221,19	197,50	195,25	210,06	233,63	229,75	189,27	175,70
Technology	94,24	16,83	54,00	137,25	61,96	109,33	166,65	151,40	119,03	96,80	64,35	68,00	101,81	97,19	74,81
Utilities	248,49	89,86	117,28	159,08	198,30	217,13	345,25	317,22	303,58	317,17	318,19	312,47	273,55	271,27	238,49

The total number of active funds is 1543 and the total number of stocks they invest in at any point during our sample period is 245. In addition, the average number of stocks traded actively by at least one fund is 79.87 for the whole period, peaking in 1999 to 100.11 and declining to 83.20 at the end of our sample period (September 2008). Likewise, the average number of active funds per stock for the whole period is 136.55, reaching a peak in 1999 with a number of 156 and falling to 135.25 at the end of our sample period. The pattern witnessed above tracks the course of the Spanish stock market (which peaked in early 2000 only to crash later following the burst of the Dot Com bubble in the spring of year 2000 in the US) and is encountered in most of our sample sectors as well.

In order to examine whether institutional investors in Spain herd intentionally or unintentionally at the sector-level we will follow the same approach with Holmes *et al.* (2011) which accounts for different market states; in our case we take into consideration the returns, volatility, volume and concentration, both for the total market and each sector. If the herd behavior of fund managers is unintentional then we would expect to trace no effect on its significance over different market conditions. However, if herding is indeed intentional then different market conditions would have an effect on the significance of herding.

Starting with **market/sector returns**, as Holmes *et al.* (2011) suggested, intentional herding on behalf of fund managers should be more prominent during periods of negative returns (down markets). The authors' argument is in line with the findings of Scharfstein and Stein (1990) which relate fund managers' herding with career and reputational reasons. The concept here involves the presence of both "good" and "bad" fund managers in the market; since it is more likely for managers to generate losses during bearish markets, bad managers may herd on the actions of their more experienced peers in order to share the blame with them. Put it simple, if everyone in the market has performed similarly poorly, it is very difficult for the assessors of the fund managers to distinguish between good and bad managers, i.e. tell between those who performed poorly because of their bad skills and those who performed poorly because of the adverse market conditions. In addition, intentional herding could be the case even during bullish markets. Again, the fear of underperformance relative to the other fund managers and their assessment by their employers/clients may drive “bad” fund managers to follow their more successful peers. As such, if institutional herding is intentional, we would expect to find a relationship between market/sector returns and herding, i.e. difference in the levels of herding between bearish and bullish markets. However, if herding among fund managers is unintentional (spurious), we would not expect to find any difference in the significance of herding under different market conditions.

In order to test for the effect of market returns over herding we use the quarter-end closing prices of the Madrid Stock Exchange General Price Index[33] and estimate its quarterly log-differenced returns; then we rank them in ascending order. After that, since we have already calculated the β_t coefficient and split it into the two sub-coefficients (namely the one showing funds following their own trades and the other showing funds following others’ trades), we divide these series into two parts upon the condition on whether the market had positive or negative returns in each quarter. In addition, we rank the time series once again in ascending order and we split them in three parts, namely high returns, mid returns and low returns and examine the significance of herding on these three categories. Similarly, we follow the same

[33] The data on the Madrid Stock Exchange General Price Index and the sector indices have been obtained from Thomson DataStream.

procedure for each of the sector indices[34]; by using their quarter-end closing prices, we calculate the quarterly log-differenced returns for each sector and rank them in ascending order. After that, we again split the series of the β_t coefficient and its two sub-coefficients, calculated for each sector, into two parts, one with positive sector returns and one with negative sector returns. Furthermore, after we rank again the series in ascending order according to sector returns, we split the series into high, mid and low returns.

The next factor we consider in order to test for herding intent is **market/sector volatility**. During periods of high turbulence, hence of higher volatility, what prevails in the market is uncertainty; that means that it is harder for fund managers to assess and interpret correctly the available information. As such, it may be more convenient for them to follow the consensus of the market and herd on the trades of the other fund managers. However, according to Ross (1989) high levels of volatility lead to more informational disclosure to the market, thus fund managers may have less incentives to copy the actions of their peers as they possess more information to trade on. This is more so the case since fund managers are the prime candidates for "rational", sophisticated investors in the market (Barber and Odean, 2009), since they bear the capacity to process large amounts of information. Nevertheless, fund managers may also herd during calm periods; this is due to the fact that in such periods it might be easier for the "bad managers" to visualize the trades of the "good" managers. So, if there is a relationship between fund managers' herd behavior and market/sector volatility this could be evidence of intent. On the other hand, if there is

[34] The sector indices along with their Datastream mnemonics in the parentheses used are: Basic Materials (BMATRES), Consumer Goods (CNSMGES), Consumer Services (CNSMSES), Financials (FINANES), Healthcare (HLTHCES), Industrials (INDUSES), Oil & Gas (OILGSES), Technology (TECNOES) and Utilities (UTILSES).

no intent in the herd behavior of fund managers there should be no effect on the significance of herding between periods of high and low volatility.

In order to extract market volatility we use daily closing prices of the Madrid Stock Exchange General Price Index, and calculate its quarterly volatility using the approach of Schwert (1989). Afterwards, we calculate the first difference between the values from one quarter to the next and then split the beta and its two components. We then rank these differences where the positive ones correspond to "increase" quarters and the negative ones to "decrease" quarters. After ranking the volatility values in ascending order, we split the β_t coefficient and its two sub-coefficients into those quarters where market volatility has increased and those quarters where market volatility has decreased. The next step is to rank the quarterly volatility values in ascending order and split the series of the β_t coefficient and its two sub-coefficients in equal three parts, namely high, mid and low volatility periods. Similarly, we follow the same approach to calculate each sector's volatility. By using the sector indices' daily prices we calculate the quarterly volatility for each and then split the series of the β_t coefficient and its two sub-coefficients into two parts, namely whether there is an increase of volatility over two quarters or a decline. In addition, we rank the quarterly volatility values in ascending order and split the series of the β_t coefficient and its two sub-coefficients into three parts, namely high, mid and low sector volatility periods.

The next factor we take into consideration when we account for herding intent is **market/sector volume**. High trading volume minimizes liquidity risk, thus informed investors such as fund managers can more easily trade on their information. The increased trading activity of the fund managers makes the trades of the "good" fund managers more visible to their peers, so it is easier for "bad" managers to copy the actions of their peers. Conversely, in periods of low trading volume, fund managers may also engage in herd behavior intentionally. In this case, where there is low trading volume, this may be an obstacle for fund managers to trade on the stocks they wish to (either buy or sell their own stocks); as such, trading on stocks that their peers trade, ensures that their orders have more chances of being executed. Consequently, if there is intent on behalf of fund managers to herd, we would expect to find a relationship between herding and different levels of trading volume. However, if there is no intent in herding, there will be no difference in the significance of herding between high and low volume periods.

In order to gauge the effect of market volume on the level of herding, we use daily volume observations of the Madrid Stock Exchange General Price Index in order to calculate the market volume for each quarter (we aggregate the daily volume observations each quarter) and then we rank the quarterly figures of volume in ascending order. Afterwards, we calculate the first difference between the values from one quarter to the next and then split the beta and its two components. We then rank these differences where the positive ones correspond to "increase" quarters and the negative ones to "decrease" quarter. Then, we split the β_t coefficient and its two sub-coefficients into those quarters where market volume has increased and those quarters where market volume has decreased. The next step is to rank the quarterly volume values in ascending order and split the series of the β_t coefficient and its two sub-coefficients in equal three parts, namely high, mid and low market volume periods. A similar approach we follow when we account for the effect of sector volume over the level of herding. By using daily volume figures for each of the sectors we calculate quarterly volume figures and then rank them in ascending order. Then, for each sector we split the series of β_t coefficient and its two sub-coefficients into two parts, the one where sector volume has increased over the quarters and the other one where sector volume has decreased. In addition, we rank the quarterly sector volume values in ascending order and split the series of the β_t coefficient and its two sub-coefficients into three parts, namely high, mid and low sector volume periods.

The final factor we take into consideration in order to examine whether fund managers in the Spanish market herd intentionally is **market/sector concentration**. Highly concentrated markets are typified by the domination of a few big companies in their volume. On the contrary, the volume of less concentrated markets is spread along a large number of stocks. Typically, we would expect that the higher the concentration of a market, the more the fund managers would engage in herding; the intuition behind that is similar to the case of volume discussed previously. High market concentration implies that there is a limited number of stocks that investors could trade feasibly on. As such, we would expect that if there was intent in herding on behalf of fund managers that would be higher in periods of high market/sector concentration than in periods of low market/sector concentration.

In order to calculate market/sector concentration, we use the Herfindahl-Hirschman index which is the sum of the squared shares of each stock in total market/sector sales; in our case the market/sector share of a stock is substituted by its share in the total market/sector volume and takes the following form:

$$HHI = \sum_{i=1}^{N} {s_i}^2 \qquad (5)$$

Where

$$s_i = \frac{aggregate\ market/sector\ volume\ of\ stock\ i\ in\ quarter\ t}{sum\ of\ aggregate\ marktet/sector\ volumes\ of\ all\ N\ stocks\ in\ quarter\ t} \qquad (6)$$

In order to calculate market/sector concentration we use daily market/sector volume data on all listed stocks, be they active, dead or suspended. Now, for each of the stocks we calculate its quarterly volume by summing each quarter's daily market/sector volume of each stock. Afterwards, we calculate the sum of the quarterly market volumes for all market/sector stocks in quarter *t* and divide each stock's quarterly market/sector volume by that sum and acquiring each stock's share in the total market/sector volume for the quarter. In addition, we calculate the first difference between the values from one quarter to the next and then split the beta and its two components. We then rank these differences where the positive ones correspond to "increase" quarters and the negative ones to "decrease" quarter. After this procedure we split the series of β_t coefficient and its two sub-coefficients, for the market and for each sector, into two parts, the one where market/sector concentration has increased over the quarters and the one where market/sector concentration has decreased. Finally, we rank the quarterly market/sector concentration values in ascending order and split the series of the β_t coefficient and its two sub-coefficients into three parts, namely high, mid and low market/sector concentration periods.

5.4 Research Hypothesis

There has been very little attention devoted to the empirical identification of intent underlying herding in the Finance literature so far. The only research, to our knowledge, is that by Holmes *et al.* (2011) which suggested that if institutional herding is intentional, its significance will exhibit variations between different states of the market. However, if the propensity of fund managers to herd at the market level varied across different market conditions, we would expect the same to hold at the industry level as well; in addition we would expect that both market and sector conditions should be relevant. That is because sector conditions are more representative of the activity surrounding an industry and should be more relevant to the investment decisions of fund managers relative to that sector.

More formally, we distinguish between two hypotheses:

H_0: institutional industry herding is spurious (i.e. it does not depend on market/sector conditions).

H_1: institutional industry herding is intentional (i.e. it depends on market/sector conditions).

5.5 Empirical Results

In this section we present the results of our empirical analysis, starting with the results for herding from equations 3 and 4, for the whole market and the industries (table 5.2). Particularly, we can see that the β_t coefficient for the whole market is positive and significant at the 5 percent level with a value of 0.0426; this means that the institutional demand in the current quarter is highly dependent on the institutional demand of the previous quarter.

Table 5.2 - Test of Herding

The table presents the results from equation (3) and (4):

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

Market	Average Coefficient (β)	Funds following their own trades	Funds following the others' trades	Average R^2
All Sectors	**0,0426 (0.0206)***	-0,0112 (0.2005)	**0,0538 (0.0001)****	0,0181
Basic Materials	0,0017 (0.9687)	-0,0425 (0.0525)	0,0442 (0.2619)	0,0987
Consumer Goods	0,0220 (0.5967)	-0,0484 (0.2430)	0,0704 (0.1456)	0,0867
Consumer Services	0,1052 (0.0658)	-0,0439 (0.0694)	**0,1492 (0.0045)***	0,1673
Financials	0,0376 (0.2466)	0,0004 (0.9820)	0,0372 (0.0612)	0,0525
Healthcare	0,0324 (0.6894)	0,0724 (0.1416)	-0,0400 (0.6113)	0,3318
Industrials	0,0572 (0.0560)	-0,0062 (0.6878)	**0,0634 (0.0121)***	0,0463
Oil & Gas	-0,0527 (0.5697)	-0,0021 (0.9446)	-0,0505 (0.5813)	0,4401
Technology	**0,7775 (0.0000)****	**-0,1013 (0,0146)***	**0,8788 (0.0000)****	0,4275
Utilities	0,0601 (0.2755)	0,0105 (0.4736)	0,0496 (0.3559)	0,1538

*indicates significance at the 5 percent level and **indicates significance at the 1 percent level. The p-values are shown in the brackets.

The partition of the β_t coefficient reveals that the quarter-on-quarter dependence of institutional demand is mostly due to institutions following other institutions (herding). More specifically, the sub-coefficient that indicates institutions following themselves is -0.0112 (insignificant) and the sub-coefficient that indicates institutions following each other is 0.0538 (significant at the 1 percent level); hence, the demand of Spanish funds for stocks quarter-on-quarter is mainly due to herding. Looking under the lenses of industry classification, we find weak evidence of herding behavior in all sectors but that of technology. More specifically, there is scarce evidence of herding for Consumer Services and Industrials; however, herding becomes more evident in the Technology sector where it is highly significant (1 percent level).

We now move to examine whether it is the market or sector conditions that have a greater impact on the levels of herding. We start with the market conditions and particularly the direction of the market; table 5.3 indicates the findings for the whole market and the industry sectors for the β_t coefficient and its two sub-coefficients.

Table 5.3 - Tests for herding conditional upon market returns (Positive-Negative)

Market	Average Coefficient (β)		Funds following their own trades		Funds following the others' trades		Average R^2	
	Positive Market Returns	Negative Market Returns	Positive Market Returns	Negative Market Returns	Positive Market Returns	Negative Market Returns	Positive Market Returns	Negative Market Returns
All Sectors	0,0196 (0.3971)	**0,0794 (0.0086)***	-0,0183 (0.1107)	0,0001 (0.9904)	**0,0380 (0.0302)***	**0,0792 (0.0003)****	0,0167	0,0200
Basic Materials	-0,0401 (0.5065)	0,0687 (0.3055)	-0,0580 (0.0751)	-0,0177 (0.4622)	0,0179 (0.7080)	0,0864 (0.2178)	0,1028	0,0877
Consumer Goods	0,0537 (0.2976)	-0,0287 (0.6924)	-0,0533 (0.4133)	-0,0404 (0.1948)	0,1070 (0.1350)	0,0118 (0.8267)	0,0810	0,0960
Consumer Services	0,1478 (0.0605)	0,0371 (0.6490)	-0,0198 (0.4023)	-0,0825 (0.1063)	**0,1676 (0.0259)***	0,1196 (0.0840)	0,1908	0,1299
Financials	-0,00716 (0.8628)	**0,1094 (0.0369)***	-0,0237 (0.3359)	0,0392 (0.2342)	0,0166 (0.5258)	**0,0702 (0.0224)***	0,0499	0,0567
Healthcare	-0,0021 (0.9840)	0,0878 (0.4708)	0,0964 (0.1842)	0,0341 (0.5512)	-0,0986 (0.3485)	0,0537 (0.6546)	0,3651	0,3319
Industrials	0,0403 (0.3200)	0,0841 (0.0586)	-0,0004 (0.9832)	-0,0154 (0.4785)	0,0408 (0.2461)	**0,0995 (0.0040)***	0,0517	0,0379
Oil & Gas	0,0839 (0.5030)	**-0,2714 (0.0397)***	0,0169 (0.7371)	**-0,0328 (0.0140)***	0,0669 (0.5952)	-0,2386 (0.0601)	0,4885	0,3627
Technology	**0,8350 (0.0002)****	**0,6962 (0.0047)***	-0,0908 (0.0630)	-0,1162 (0.1233)	**0,9258 (0.0001)****	**0,8125 (0.0056)***	0,4068	0,4569
Utilities	0,0232 (0.7325)	0,1193 (0.2150)	0,0160 (0.4324)	0,0017 (0.9321)	0,0071 (0.9185)	0,1175 (0.1679)	0,1295	0,1928

*indicates significance at the 5 percent level and **indicates significance at the 1 percent level. The p-values are shown in the brackets.

Starting with the whole market, the quarter-on-quarter institutional demand is higher and significant (5 percent level) during quarters of negative market returns. The partitioning of the β_t coefficient reveals some interesting facts. Even though the coefficient, indicating funds following the trades of others, is significant during positive (5 percent level) market returns, it is during negative market returns that it becomes significantly higher (significant at the 1 percent level); what is more, the herding coefficient has a value of 0.0792, which means that it accounts for 99.7 percent of the quarter-on-quarter institutional demand, which is quite impressive. What is next is to examine whether there is a change in the significance of herding level during high, mid and low market returns. As table 5.4 shows, there is evidence of herding during mid and low market returns (both significant at 5 percent level), however the overall institutional demand over quarters is insignificant at all three levels.

When it comes to the sector level during positive or negative market returns (table 5.3), we can see that there is mixed evidence of herding. Particularly, the quarter-on-quarter institutional demand is significant (5 percent level) during negative market returns for Financials and Oil & Gas companies while for the Technology sector it is significant during both positive (1 percent level) and negative (5 percent level) market returns. Similarly, the herding coefficient for the Technology sector is significant during both positive (1 percent level) and negative (5 percent level) market returns. In addition, the herding coefficient is also significant (5 percent level) during negative returns for Financials, accounting for 64% of the institutional demand over the quarters.

Table 5.4 - Tests for herding conditional upon market returns (High-Mid-Low)

Market	Average Coefficient (β)			Funds following their own trades			Funds following the others' trades			Average R^2		
	High Market Returns	Mid Market Returns	Low Market Returns	High Market Returns	Mid Market Returns	Low Market Returns	High Market Returns	Mid Market Returns	Low Market Returns	High Market Returns	Mid Market Returns	Low Market Returns
All Sectors	0,0110 (0.7507)	0,0544 (0.0814)	0,0617 (0.0526)	-0,0105 (0.0545)	-0.0198 (0.1302)	-0,0027 (0.8661)	0,0216 (0.3856)	**0,0742 (0.0028)***	**0,0645 (0.0041)***	0,0194	0,0168	0,0181
Basic Materials	0,0044 (0.9648)	-0,0380 (0.5369)	0,0411 (0.5730)	-0,0246 (0.5732)	-0,1003 (0.0255)	0,0008 (0.9668)	0,0291 (0.7101)	0,0622 (0.3456)	0,0403 (0.5445)	0,1470	0,0601	0,0861
Consumer Goods	0,0359 (0.6281)	0,1010 (0.1457)	-0,0754 (0.3231)	0,0153 (0.7218)	-0,1096 (0.3246)	-0,0473 (0.1440)	0,0206 (0.6550)	0,2106 (0.0851)	-0,0281 (0.6211)	0,0835	1,1022	0,0938
Consumer Services	0,0547 (0.6459)	0,0511 (0.4994)	**0,2131 (0.0454)***	-0,0921 (0.1732)	-0,0131 (0.1904)	-0,0283 (0.3762)	0,1468 (0.1812)	0,0642 (0.1812)	**0,2415 (0.0112)***	0,2244	0,1008	0,1810
Financials	-0,0213 (0.7271)	0,0359 (0.5332)	0,0984 (0.0630)	-0,0262 (0.4400)	-0,0047 (0.8971)	0,0326 (0.3301)	0,0049 (0.8953)	0,0407 (0.2402)	**0,0658 (0.0481)***	0,0559	0,0519	0,0497
Healthcare	-0,0557 (0.7441)	0,0434 (0.7106)	0,1089 (0.4480)	0,1061 (0.3623)	0,0586 (0.4498)	0,0534 (0.3862)	-0,1619 (0.2915)	-0,0151 (0.9035)	0,0555 (0.6931)	0,4458	0,2299	0,3260
Industrials	0,0734 (0,1816)	0,0200 (0,7071)	0,0803 (0.1168)	0,0062 (0.8604)	-0,0109 (0.5960)	-0,0136 (0.5924)	0,0672 (0.1195)	0,0309 (0.5397)	**0,0093 (0.0166)***	0,0517	0,0459	0,0416
Oil & Gas	0,0345 (0.8403)	0,0258 (0.8809)	-0,2231 (0.1276)	0,0659 (0.4797)	-0,0425 (0.0747)	-0,0276 (0,0520)	-0,0314 (0.8546)	0,0683 (0.6894)	-0,1955 (0.1684)	0,4430	0,5114	0,3617
Technology	**0,9726 (0.0066)***	**0,8415 (0.0093)***	**0,5085 (0.0000)****	-0,0227 (0.5870)	**-0,1673 (0.0286)***	-0,1038 (0.2584)	**0,9953 (0.0077)***	**1,0089 (0.0059)***	**0,6123 (0.0009)****	0,4145	0,4752	0,3857
Utilities	0,0229 (0.8240)	0,0571 (0.4971)	0,1006 (0.3499)	0,0093 (0.7825)	0,0265 (0.2249)	-0,0051 (0.8130)	0,0136 (0.9005)	0,0305 (0.7024)	0,1057 (0.2761)	0,1362	0,1232	0,2039

*indicates significance at the 5 percent level and **indicates significance at the 1 percent level. The p-values are shown in the brackets.

Furthermore, in the case of Oil & Gas, it is not the herding coefficient that is significant during negative returns but the one indicating institutions following themselves; as such, in this case the quarter-on-quarter institutional demand is mostly due to institutions following their own trades rather than herding on each other. Finally, there is some evidence of herding in the Consumer Services and the Industrials (significant at the 5 percent level) during positive and negative market returns respectively; however, overall the institutional demand over the quarters is insignificant for both cases.

When we partition the coefficients according to high, mid and low market returns (table 5.4) we get to see that the Technology sector once again is dominated by high quarter-on-quarter institutional demand and herding in all three market states. Particularly, during high and mid market returns, the institutional demand over quarters and the herding coefficient are both significant at the 5 percent level, whereas during low market returns these two indicators become even more significant at the 1 percent level. With respect to the other sectors, Consumer Services exhibit significant (5 percent level) quarter-on-quarter institutional demand and herding during low market returns, whereas there is some evidence of significant herding (5 percent level) for Financials and Industrials during low returns; however in both cases the overall institutional demand over quarters is insignificant.

The next market state we examine is volatility. Table 5.5 reports our findings for the whole market and the industries as well. Starting with the results at the aggregate market level, these indicate that there is significant (5 percent level) quarter-on-quarter institutional demand during positive market volatility quarters; the partitioning of the β_t coefficient reveals evidence of herding during periods of both positive and negative volatility, however herding is more significant (1 percent level) during periods of positive market volatility (i.e. when market volatility has increased over two quarters).

Table 5.5 - Tests for herding conditional upon market volatility (Positive-Negative)

Market	Average Coefficient (β)		Funds following their own trades		Funds following the others' trades		Average R²	
	Positive Market Volatility	Negative Market Volatility	Positive Market Volatility	Negative Market Volatility	Positive Market Volatility	Negative Market Volatility	Positive Market Volatility	Negative Market Volatility
All Sectors	**0,0598 (0.0132)***	0,0400 (0.1783)	-0,0068 (0.5864)	-0,0139 (0.3089)	**0,0666 (0.0001)****	**0,0539 (0.0219)***	0,0190	0,0172
Basic Materials	0,0018 (0.9740)	0,0016 (0.9810)	**-0,0812 (0.0149)***	-0,0067 (0.8160)	0,0830 (0.1472)	0,0083 (0.88030	0,0751	0,1060
Consumer Goods	0,0524 (0.4123)	-0,0060 (0.9132)	-0,1003 (0.2147)	-0,0003 (0.9905)	0,1527 (0.0936)	-0,0057 (0.8869)	0,0987	0,0757
Consumer Services	0,1382 (0.0939)	0,0747 (0.3589)	-0,0826 (0.0747)	-0,0080 (0.6633)	**0,2209 (0.0029)***	0,0827 (0.2735)	0,1725	0,1627
Financials	0,0656 (0.1907)	0,0118 (0.7840)	0,0195 (0.5256)	-0,0172 (0.5014	0,0460 (0.1110)	0,0291 (0.3021)	0,0601	0,0455
Healthcare	0,0779 (0.5213)	-0,0096 (0.9308)	0,0787 (0.3865)	0,0666 (0.1573)	-0,0007 (0.9947)	-0,0763 (0.5098)	0,3504	0,3147
industrials	0,0459 (0.3631)	-0,0100 (0.0543)	0,0075 (0.3700)	0,0133 (0.8079)	0,1284 (0.1272)	**-0,0233 (0.0378)***	0,0613	0,0326
Oil & Gas	0,0176 (0.8837)	-0,1179 (0.4068)	0,0121 (0.8512)	-0,0153 (0.2604)	0,0055 (0.9650)	-0,1025 (0.4481)	0,3508	0,5228
Technology	**0,9125 (0.0047)***	**0,6297 (0.0013)***	-0,1020 (0.1739)	-0,1059 (0.0819)	**1,0145 (0.0060)***	**0,7357 (0.0006)****	0,4069	0,4052
Utilities	0,1360 (0.1334)	-0,1528 (0.8798)	0,4544 (0.6536)	0,5582 (0.5815)	1,5786 (0.1275)	-0,3435 (0.7340)	0,1898	0,1205

*indicates significance at the 5 percent level and **indicates significance at the 1 percent level. The p-values are shown in the brackets.

When partitioning the β_t coefficient according to periods of high, mid and low market volatility (table 5.6) we get to see that there is no evidence of significant quarter-on-quarter institutional demand, or herding during all market volatility states.

Table 5.6 - Tests for herding conditional upon market volatility (High-Mid-Low)

Market	Average Coefficient (β)			Funds following their own trades			Funds following the others' trades			Average R²		
	High Market Volatility	Mid Market Volatility	Low Market Volatility	High Market Volatility	Mid Market Volatility	Low Market Volatility	High Market Volatility	Mid Market Volatility	Low Market Volatility	High Market Volatility	Mid Market Volatility	Low Market Volatility
All Sectors	-0,0002 (0.9973)	0,1550 (0.1867)	0,0202 (0.8291)	-0,0215 (0.2775)	0,0349 (0.1273)	0,0168 (0.6139)	0,0213 (0.7479)	0,1200 (0.2835)	0,0033 (0.9732)	0,0827	0,2282	0,1462
Basic Materials	-0,0400 (0.5781)	0,0853 (0.3267)	-0,0449 (0.5618)	-0,0272 (0.3190)	-0,0611 (0.2085)	-0,0380 (0.3019)	-0,0127 (0.8720)	**0,1465 (0.0285)***	-0,0069 (0.9089)	0,0795	0,1243	0,0857
Consumer Goods	0,0171 (0.8434)	0,0165 (0.7719)	0,0328 (0.6745)	-0,0337 (0.3004)	-0,0956 (0.3897)	-0,0130 (0.7713)	0,0509 (0.4538)	0,1121 (0.3501)	0,0458 (0.3496)	0,1172	0,0535	0,0915
Consumer Services	0,1019 (0.1556)	0,1156 (0.2278)	0,0975 (0.4555)	-0,0278 (0.3491)	-0,0263 (0.4180)	-0,0786 (0.1958)	0,1298 (0.0767)	0,1419 (0.0976)	0,1762 (0.1371)	0,1011	0,1600	0,2416
Financials	0,1085 (0.0755)	0,0073 (0.8858)	-0,0010 (0.9866)	0,0458 (0.2921)	-0,0279 (0.2896)	-0,0149 (0.6519)	**0,0626 (0.0137)***	0,0353 (0.3469)	0,0138 (0.7335)	0,0640	0,0405	0,0538
Healthcare	0,0847 (0.4590)	0,0469 (0.7730)	-0,0352 (0.8140)	0,0512 (0.3200)	0,1150 (0.3587)	0,0486 (0.4285)	0,0335 (0.7819)	-0,0680 (0.6641)	-0,0839 (0.5443)	0,2069	0,4391	0,3434
industrials	**0,1160 (0.0136)***	0,0226 (0.7246)	0,0349 (0.4191)	0,0050 (0.7759)	-0,0162 (0.6235)	-0,0068 (0.8117)	**0,1110 (0.0081)***	0,0388 (0.4258)	0,0388 (0.3234)	0,0369	0,0671	0,0339
Oil & Gas	**-0,2783 (0.0361)***	0,0845 (0.6018)	0,0275 (0.8845)	**-0,0281 (0.0123)***	0,0368 (0.6804)	-0,0175 (0.4474)	-0,2501 (0.0531)	0,0476 (0.7840)	0,0450 (0.7977)	0,3167	0,4386	0,5651
Technology	**0,5660 (0.0000)****	**0,7402 (0.0040)***	**0,9365 (0.0386)***	0,0114 (0.8315)	-0,2244 (0.0577)	-0,0999 (0.0567)	**0,5546 (0.0002)****	**0,9647 (0.0026)***	**1,0364 (0.0331)***	0,3351	0,4571	0,4256
Utilities	-0,0002 (0.9973)	0,1550 (0.1867)	0,0205 (0.8291)	-0,0215 (0.2775)	0,0349 (0.1273)	0,0168 (0.6139)	0,0213 (0.7479)	0,1200 (0.2835)	0,0033 (0.9732)	0,0827	0,2282	0,1462

*indicates significance at the 5 percent level and **indicates significance at the 1 percent level. The p-values are shown in the brackets.

At the sector level, it is only the Technology sector that exhibits significant (5 percent level) quarter-on-quarter institutional demand during periods of both positive and negative market volatility. Similarly, there is significant level of herding during periods of positive and negative market volatility at the 5 and 1 percent levels respectively. Regarding the other sectors, there is some evidence of significant herding (5 percent level) for Consumer Services and Industrials during periods of positive and negative market volatility respectively; however in both cases the institutional demand over quarters is overall insignificant.

When partitioning the β_t coefficient according to periods of high, mid and low market volatility, there is mixed evidence of herding at the sector level. Particularly, the Technology sector exhibits once more significant quarter-on-quarter institutional demand and herding at all three market volatility states (at the 1 percent level during periods of high market volatility and at the 5 percent level during periods of mid and low market volatility). With respect to the other sectors, the Industrials and Oil & Gas industries exhibit significant (5 percent level) institutional demand over the quarters during periods of high market volatility. However, it is only in the Industrials' sector where the herding component is significant (5 percent level); in the case of the Oil & Gas sector it is the coefficient indicating institutions following each other that is significant (5 percent level) during periods of high market volatility. Finally, some evidence of significant herding is exhibited in the Basic Materials' sector (5 percent level) during periods of mid market volatility and in the Financials' sector (5 percent level) during periods of high market volatility; however in both cases the overall institutional demand over quarters is insignificant.

The next market state we are examining is that of market volume; table 5.7 illustrates our results for the aggregate market and the sectors during periods of increasing/decreasing market volume. As we can see, at the aggregate market level, the coefficient of herding is significant (5 percent level) during both periods of increasing and decreasing market volume; however in both cases the overall quarter-on-quarter institutional demand is insignificant. When partitioning the β_t coefficient according to periods of high, mid and low market volume (table 5.8), we get to see that the institutional demand over the quarters at the aggregate market level is significant (5 percent level); however there is no significant evidence of herding.

Table 5.7 - Tests for herding conditional upon market volume (Positive-Negative)

Market	Average Coefficient (β)		Funds following their own trades		Funds following the others' trades		Average R^2	
	Positive Market Volume	Negative Market Volume	Positive Market Volume	Negative Market Volume	Positive Market Volume	Negative Market Volume	Positive Market Volume	Negative Market Volume
All Sectors	0,0457 (0.0649)	0,0389 (0.2112)	-0,0088 (0.4608)	-0,0197 (0.1552)	**0,0545 (0.0021)***	**0,0586 (0.0173)***	0,0190	0,0167
Basic Materials	-0,0435 (0.4732)	0,0635 (0.3471)	-0,0489 (0.1062)	-0,0338 (0.2989)	0,0053 (0.9172)	0,0973 (0.1201)	0,1002	0,0926
Consumer Goods	0,0539 (0.3494)	-0,0214 (0.7265)	-0,0606 (0.3841)	-0,0316 (0.2594)	0,1146 (0.1316)	0,0102 (0.8385)	0,0955	0,0748
Consumer Services	**0,1825 (0.0135)***	-0,0001 (0.9985)	-0,0145 (0.5349)	-0,0840 (0.0798)	**0,1971 (0.0075)***	0,0838 (0.2680)	0,1524	0,1879
Financials	0,0340 (0.4296)	0,0426 (0.4062)	-0,0006 (0.9811)	0,0019 (0.9438)	0,0347 (0.1892)	0,0407 (0.1936)	0,0519	0,0534
Healthcare	-0,0075 (0.9487)	0,0869 (0.4353)	0,1184 (0.1334)	0,0098 (0.8337)	-0,1259 (0.3038)	0,0771 (0.3594)	0,3857	0,2585
industrials	0,0555 (0.2136)	0,0594 (0.1167)	-0,0013 (0.9531)	-0,0128 (0.4942)	0,0569 (0.0986)	0,0722 (0.0590)	0,0585	0,0298
Oil & Gas	0,0746 (0.5338)	-0,2264 (0.1222)	0,0284 (0.5898)	**-0,0439 (0.0200)***	0,0462 (0.6985)	-0,1825 (0.2098)	0,4213	0,4612
Technology	**0,6925 (0.0001)****	**0,8861 (0.0037)***	-0,0838 (0.0732)	-0,1238 (0.1018)	**0,7763 (0.0001)****	**1,009 (0.0028)***	0,4206	0,4365
Utilities	0,0428 (0.5394)	0,0838 (0.3623)	-0,0055 (0.7525)	0,0325 (0.2035)	0,0484 (0.4735)	0,0512 (0.5707)	0,1228	0,1961

*indicates significance at the 5 percent level and **indicates significance at the 1 percent level.
The p-values are shown in the brackets.

At the sector level, we get to see that the Technology sector appears to have significant quarter-on-quarter institutional demand and herding during both periods of increasing and decreasing market volume (1 percent and 5 percent levels respectively). In addition, the Consumer Services sector also exhibits significant evidence of institutional demand over the quarters and herding (both at the 5 percent level) during periods of increasing market volume.

Table 5.8 - Tests for herding conditional upon market volume (High-Mid-Low)

Market	Average Coefficient (β)			Funds following their own trades			Funds following the others' trades			Average R²		
	High Market Volume	Mid Market Volume	Low Market Volume	High Market Volume	Mid Market Volume	Low Market Volume	High Market Volume	Mid Market Volume	Low Market Volume	High Market Volume	Mid Market Volume	Low Market Volume
All Sectors	-0,0697 (0.3361)	-0,0305 (0.6634)	**0,1696 (0.0206)***	-0,0689 (0.0614)	-0,0026 (0.9276)	-0,0763 (0.5292)	-0,0008 (0.9866)	-0,0279 (0.6188)	0,2459 (0.0505)	0,0843	0,0816	0,0946
Basic Materials	0,0655 (0.4802)	-0,0337 (0.6384)	-0,0244 (0.7405)	-0,0997 (0.0646)	-0,0019 (0.9542)	-0,0282 (0.1525)	**0,1653 (0.0500)***	-0,0317 (0.5515)	0,0037 (0.9548)	0,1293	0,0835	0,0791
Consumer Goods	-0,0697 (0.3361)	-0,0305 (0.6634)	**0,1696 (0.0206)***	-0,0689 (0.0614)	-0,0026 (0.9276)	-0,0763 (0.5292)	-0,0008 (0.9866)	-0,0279 (0.6188)	0,2459 (0.0505)	0,0843	0,0816	0,0946
Consumer Services	**0,2359 (0.0271)***	0,0289 (0.6930)	0,0553 (0.6426)	-0,0291 (0.3622)	-0,0109 (0.2971)	-0,0936 (0.1653)	**0,2651 (0.0050)***	0,0399 (0.5755)	0,1490 (0.1757)	0,1856	0,0961	0,2247
Financials	-0,0064 (0.9141)	0,0597 (0.3192)	0,0584 (0.2740)	-0,0164 (0.6459)	0,0081 (0.8273)	0,0091 (0.7731)	0,0100 (0.7719)	0,0515 (0.1428)	0,0493 (0.1746)	0,0555	0,0575	0,0443
Healthcare	0,0687 (0.5680)	0,0151 (0.9156)	0,0144 (0.9313)	0,0415 (0.2136)	0,1190 (0.0663)	0,0541 (0.6886)	0,0272 (0.7827)	-0,1039 (0.5224)	-0,0396 (0.7891)	0,2267	0,3362	0,4325
industrials	0,0518 (0,3339)	0,0728 (0.1569)	0,0459 (0.4052)	0,0083 (0.7762)	0,0112 (0.6832)	-0,0392 (0.1085)	0,0434 (0.4022)	0,0616 (0.0785)	0,0852 (0.0726)	0,0451	0,0435	0,0507
Oil & Gas	0,0650 (0.7123)	-0,0991 (0.4397)	-0,1213 (0.5187)	-0,0113 (0.2232)	-0,0145 (0.0907)	0,0201 (0.8373)	0,0763 (0.6587)	-0,0845 (0.5008)	-0,1414 (0.4511)	0,4993	0,2797	0,5508
Technology	**0,6911 (0.0035)***	**0,5421 (0,0000)****	**1,1354 (0.0120)***	-0,0565 (0.1023)	-0,0729 (0.3358)	-0,1790 (0.0627)	**0,7476 (0.0031)***	**0,6151 (0.0001)****	**1,3144 (0.0082)***	0,3940	0,3560	0,5487
Utilities	0,0416 (0.6809)	0,0704 (0.4264)	0,0678 (0.5220)	0,0043 (0.8695)	0,0439 (0.1140)	-0,0186 (0.4086)	0,0372 (0.7131)	0,0264 (0.7789)	0,0865 (0.3461)	0,1695	0,1307	0,1626

*indicates significance at the 5 percent level and **indicates significance at the 1 percent level.
The p-values are shown in the brackets.

When accounting for periods of high, mid and low market volume, the Technology sector appears to have significant quarter-on-quarter institutional demand and herding at all three states (at the 5 percent level at high and low levels and the 1 percent level at mid levels of market volume). In addition, the Consumer Services sector also exhibits significant institutional demand over the quarters and herding during periods of high market volume (both significant at the 5 percent level). The Consumer Goods sector in its turn appears to have significant (5 percent level) quarter-on-quarter institutional demand during periods of low market volume; however, there is no evidence of significant herding in any of the market volume levels. Finally, there is some evidence of herding in the Basic Materials sector which is significant (5 percent level) during periods of high market volume; nevertheless, the overall quarter-on-quarter institutional demand is insignificant.

The last market state that we are examining is that of market concentration; table 5.9 illustrates the results for both the aggregate market and the industries as well during periods of increasing and decreasing market concentration. As we can see, at the aggregate market level, there is significant level of herding (1 percent level) during periods of high market concentration; however the overall quarter-on-quarter institutional demand is insignificant.

Table 5.9 - Tests for herding conditional upon market Concentration (Positive-Negative)

Market	Average Coefficient (β)		Funds following their own trades		Funds following the others' trades		Average R²	
	Positive Market Concentration	Negative Market Concentration	Positive Market Concentration	Negative Market Concentration	Positive Market Concentration	Negative Market Concentration	Positive Market Concentration	Negative Market Concentration
All Sectors	0,0420 (0.0641)	0,0347 (0.2793)	-0,0145 (0.2028)	-0,0083 (0.5749)	**0,0565 (0.0004)****	0,0428 (0.0901)	0,0165	0,0203
Basic Materials	-0,0337 (0.5822)	0,0541 (0.4156)	**-0,0621 (0.0369)***	-0,0135 (0.6777)	0,0284 (0.5782)	0,0676 (0.2923)	0,1041	0,0866
Consumer Goods	0,0174 (0.7629)	0,0288 (0.6341)	-0,0745 (0.2707)	-0,0097 (0,7158)	0,0920 (0.2143)	0,0386 (0.4595)	0,0978	0,0704
Consumer Services	0,1455 (0.0559)	0,0457 (0.6063)	-0,0307 (0.1894)	-0,0634 (0.2058)	**0,1762 (0.0169)***	0,1092 (0.1458)	0,1587	0,1801
Financials	0,0377 (0.3189)	0,0375 (0.5300)	0,0048 (0.8454)	-0,0061 (0.8540)	0,0328 (0.1651)	0,0436 (0.2229)	0,0422	0,0677
Healthcare	0,0521 (0.6349)	0,0033 (0.9785)	0,1181 (0.1196)	0,0049 (0.9211)	-0,066 (0.5751)	-0,00164 (0.9860)	0,3549	0,2979
industrials	0,0545 (0.1942)	0,0611 (0.1506)	-0,0060 (0.7697)	-0,0064 (0.7886)	0,0605 (0.0518)	0,0676 (0.1239)	0,0552	0,0334
Oil & Gas	0,0089 (0.9408)	-0,1438 (0.3342)	0,0265 (0.6036)	**-0,0445 (0.0252)***	-0,0175 (0.8839)	-0,0993 (0.4992)	0,4387	0,4422
Technology	**0,7106 (0,0006)****	**0,8718 (0.0017)***	**-0,1052 (0.0457)***	-0,0958 (0.1710)	**0,8159 (0.0005)****	**0,9677 (0.0013)***	0,4105	0,4516
Utilities	0,0721 (0.2879)	0,0425 (0.6578)	0,0016 (0.9253)	0,0237 (0.3797)	0,0705 (0.2866)	0,0187 (0.8405)	0,1219	0,2009

*indicates significance at the 5 percent level and **indicates significance at the 1 percent level. The p-values are shown in the brackets.

When partitioning the β_t coefficient according to periods of high, mid and low periods of market concentration (table 5.10), we can see that, at the aggregate market level, there is significant quarter-on-quarter institutional demand and herding during periods of high and low market concentration, both significant at the 5 percent level.

Table 5.10 - Tests for herding conditional upon market concentration (High-Mid-Low)

Market	Average Coefficient (β)			Funds following their own trades			Funds following the others' trades			Average R²		
	High Market Con/tion	Mid Market Con/tion	Low Market Con/tion	High Market Con/tion	Mid Market Con/tion	Low Market Con/tion	High Market Con/tion	Mid Market Con/tion	Low Market Con/tion	High Market Con/tion	Mid Market Con/tion	Low Market Con/tion
All Sectors	**0,0613 (0.0284)***	0,0023 (0.9483)	**0,0667 (0.0452)***	-0,0098 (0.4117)	-0,0243 (0.1351)	0,0013 (0.9422)	**0,0711 (0.0022)***	0,0266 (0.2887)	**0,0654 (0.0071)***	0,0146	0,0192	0,0203
Basic Materials	0,1019 (0.2357)	-0,0708 (0.3123)	-0,0216 (0.7911)	-0,0101 (0.7166)	-0,0491 (0.3071)	-0,0679 (0.0641)	0,1120 (0.2180)	-0,0217 (0.6883)	0,0464 (0.4438)	0,1142	0,0752	0,1029
Consumer Goods	0,0238 (0.7680)	0,0589 (0.3068)	-0,0187 (0.8227)	-0,0071 (0.8060)	-0,0888 (0.4291)	-0,0469 (0.2893)	0,0310 (0.6315)	0,1477 (0.2203)	0,0282 (0.5734)	0,0995	0,0550	0,1075
Consumer Services	0,0940 (0.2908)	0,1708 (0.0922)	0,0472 (0.6769)	-0,0044 (0.9025)	-0,0508 (0.0545)	-0,0762 (0.2096)	0,0984 (0.2393)	**0,2216 (0.0270)***	0,1234 (0.1966)	0,1540	0,1597	0,1889
Financials	0,0247 (0.6311)	-0,0425 (0.4994)	**0,1356 (0.0114)***	-0,0098 (0.7796)	-0,0260 (0.4513)	0,0387 (0.2727)	0,0344 (0.1843)	-0,0165 (0.6795)	**0,0969 (0.0060)***	0,0406	0,0596	0,0570
Healthcare	0,1492 (0.3072)	0,0476 (0.7448)	-0,1004 (0.4687)	0,0466 (0.5256)	0,0286 (0.6920)	0,1448 (0.1988)	0,1026 (0.4312)	0,0191 (0.8970)	-0,2451 (0.0683)	0,3424	0,3521	0,3000
Industrials	0,0704 (0.1496)	-0,0270 (0.6405)	**0,1332 (0.0053)***	-0,0204 (0.4504)	-0,0207 (0.4477)	0,0233 (0.3995)	**0,0908 (0.0184)***	-0,0063 (0.8883)	**0,1099 (0.0220)***	0,0352	0,0544	0,0490
Oil & Gas	-0,1650 (0.3308)	0,0354 (0.8163)	-0,0338 (0.8452)	0,0478 (0.6085)	-0,0180 (0.3169)	-0,0354 (0.1455)	-0,2127 (0.2362)	0,0534 (0.7183)	0,0015 (0.9924)	0,4624	0,3986	0,4618
Technology	**0,6581 (0.0050)***	**1,1242 (0.0043)***	**0,4970 (0.0000)****	-0,0968 (0.0826)	**-0,1352 (0.0464)***	-0,0669 (0.4847)	**0,7548 (0.0030)***	**1,2594 (0.0033)***	**0,5639 (0.0017)***	0,3792	0,5167	0,3730
Utilities	0,1789 (0.0620)	0,0924 (0.3388)	-0,0926 (0.3387)	-0,0050 (0.8125)	0,0575 (0.0997)	-0,0236 (0.1073)	**0,1839 (0.0345)***	0,0348 (0.7340)	-0,0690 (0.4485)	0,1398	0,1541	0,1676

*indicates significance at the 5 percent level and **indicates significance at the 1 percent level. The p-values are shown in the brackets.

At the sector level, we get to see that the Technology industry exhibits strong institutional demand over the quarters at all states of market concentration (significant at the 5 percent level for high and mid levels of market concentration and at the 1 percent level for the low level of market concentration). In addition, the coefficient indicating institutions following themselves is significant (5 percent level) for the mid level of market concentration. The herding coefficient in its turn is always significant (at the 5 percent level) at all three market concentration levels. Moving to the Consumer Services sector, there is some evidence of herding (significant at the 5 percent level) for the mid level of market concentration; however, the overall quarter-on-quarter institutional demand is insignificant at all levels of market concentration. The Financials sector in turn exhibits significant (5 percent level) institutional demand over the quarters for low levels of market concentration, accompanied by significant (5 percent level) evidence of herding at the same level of market concentration. In addition, the Industrials sector appears to have significant (5 percent level) quarter-on-quarter institutional demand for low levels of market concentration and the coefficient indicating herding is significant (5 percent level) at the low and high levels of market concentration. Finally, there is some significant (5 percent level) evidence of herding in the Utilities sector at the high level of market concentration; nevertheless the institutional demand over the quarters is insignificant at all market concentration levels.

So far, we have examined the impact that different market states have on the significance of herding at both the market and the sector level. Now we will examine whether the sector-specific expressions of the same states have an impact over the significance of sector herding or not. Again, we will start with the direction of sector-returns, i.e. whether herding is more significant when each sector has had positive or negative returns over the quarters (table 5.11 shows the results for each sector). As we can see, there is significant evidence of quarter-on-quarter institutional demand in four out of the nine sectors examined, namely Consumer Services, Financials, Industrials and Technology. Starting with Consumer Services, we get to see that the institutional demand over the quarters, and herding as well, is significant (5 percent level) during quarters of negative sector returns. Compared to the results when testing for the market returns, the sector now exhibits significant quarter-on-quarter institutional demand, something that was not the case when accounting for market returns; in that case there was only some evidence of significant herding during positive market returns. The Financials sector also exhibits significant (5 percent level) institutional demand over the quarters during negative sector returns, but this time it is both the coefficients (institutions following themselves and institutions following each other) that are significant (5 percent level) during negative sector returns; in the case of market returns, it was only the coefficient indicating institutions following each other that was significant.

Table 5.11 - Tests for herding conditional upon sector returns (Positive-Negative)

Market	Average Coefficient (β)		Funds following their own trades		Funds following the others' trades		Average R^2	
	Positive Sector Returns	Negative Sector Returns	Positive Sector Returns	Negative Sector Returns	Positive Sector Returns	Negative Sector Returns	Positive Sector Returns	Negative Sector Returns
Basic Materials	-0,0231 (0.7080)	0,0450 (0.4708)	-0,0471 (0.1434)	-0,0346 (0.1427)	0,0240 (0.6201)	0,0796 (0.2576)	0,1132	0,0689
Consumer Goods	-0,0033 (0.9482)	0,0455 (0.4942)	-0,0878 (0.2746)	-0,0120 (0.7045)	0,0845 (0.3440)	0,0575 (0.2136)	0,0592	0,1123
Consumer Services	0,0666 (0.4250)	**0,1540 (0.0475)***	-0,0462 (0.2288)	-0,0411 (0.1296)	0,1128 (0.1263)	**0,1951 (0.0112)***	0,1887	0,1405
Financials	-0,0142 (0.7274)	**0,1207 (0.0224)***	-0,0337 (0.1665)	**0,0550 (0,0922)***	0,0194 (0,4782)	**0,0657 (0,0191)***	0,0491	0,0581
Healthcare	0,0390 (0.7169)	0,0210 (0.8674)	0,0773 (0.2601)	0,0641 (0.3379)	-0,0383 (0.6875)	-0,0430 (0.7647)	0,3618	0,2799
Industrials	0,0341 (0.3717)	**0,0974 (0.0490)***	0,0021 (0.9219)	-0,0206 (0.3627)	0,0320 (0.3218)	**0,1179 (0.0034)***	0,0461	0,0469
Oil & Gas	0,0039 (0.9734)	-0,1511 (0.3308)	0,0169 (0.7287)	**-0,0352 (0.0479)***	-0,0129 (0.9136)	-0,1159 (0.4320)	0,4417	0,4373
Technology	**0,9857 (0.0004)****	**0,5978 (0.0020)***	-0,0724 (0.1742)	**-0,1264 (0.0473)***	**1,0581 (0.0004)****	**0,7241 (0,001)***	0,4341	0,4079
Utilities	0,0752 (0.2834)	0,0342 (0.7137)	0,0133 (0.5038)	0,0058 (0.7910)	0,0618 (0.3930)	0,0285 (0.7226)	0,1459	0,1676

*indicates significance at the 5 percent level and **indicates significance at the 1 percent level. The p-values are shown in the brackets.

The Industrials sector appears to have significant (5 percent level) institutional demand over the quarters and herding during negative sector returns. Accounting for market returns, the specific sector exhibited significant herding during negative market returns, though the overall quarter-on-quarter institutional demand was insignificant. The inverse picture surfaces for Oil & Gas; particularly it now appears only the coefficient indicating institutions following themselves to be significant (5 percent level) during negative sector returns, whereas when accounting for market returns it was both the coefficients indicating quarter-on-quarter institutional demand and institutions following themselves that were significant during negative market returns. Finally, the Technology sector appears to have significant quarter-on-quarter demand and herding during both positive and negative sector returns (at 1 percent and 5 percent levels respectively); the results here are quite similar to those when accounting for market returns.

When partitioning the β_t coefficient according to periods of high, mid and low sector returns, we get to see that only the Technology sector exhibits significant institutional demand over the quarters (at the 5 percent level for high and low levels and at the 1 percent level for the mid level) during all levels of sector returns; similarly the herding coefficient is also significant (5 percent level) at all levels of sector returns. The Industrial sector exhibits significant evidence of herding (5 percent level) during periods of low sector returns, though the quarter-on-quarter institutional demand is insignificant at all levels of sector returns; exactly the same results we got when accounting for market returns. Finally, in the Consumer Services sector we see that both the coefficient indicating institutions following themselves and institutions following each other are significant (5 percent level) during periods of mid sector returns, though the overall institutional demand over quarters is insignificant at all levels of sector returns. On the contrary, when accounting for market returns, both the quarter-on-quarter institutional demand and herding were significant (5 percent level) during periods of low market returns.

Table 5.12 - Tests for herding conditional upon sector returns (High-Mid-Low)

Market	Average Coefficient (β)			Funds following their own trades			Funds following the others' trades			Average R^2		
	High Sector Returns	Mid Sector Returns	Low Sector Returns	High Sector Returns	Mid Sector Returns	Low Sector Returns	High Sector Returns	Mid Sector Returns	Low Sector Returns	High Sector Returns	Mid Sector Returns	Low Sector Returns
Basic Materials	-0,0665 (0.4696)	0,0559 (0.4929)	0,0127 (0.8381)	-0,0489 (0.3180)	-0,0534 (0.2060)	-0,0247 (0.2006)	-0,0176 (0.8275)	0,1092 (0.0982)	0,0374 (0.5454)	0,1228	0,1077	0,0600
Consumer Goods	0,0213 (0.7605)	0,0088 (0.8902)	0,0369 (0.6777)	-0,1169 (0.3212)	-0,0267 (0.4262)	-0,0029 (0.9452)	0,1382 (0.2899)	0,0355 (0.3973)	0,0398 (0.5348)	0,0768	0,0674	0,1172
Consumer Services	0,0604 (0.6039)	0,1506 (0.1016)	0,1022 (0.2918)	-0,0411 (0.5129)	**-0,0733 (0.0270)***	-0,0157 (0.5185)	0,1015 (0.2689)	**0,2239 (0.0229)***	0,1178 (0.1899)	0,1909	0,1718	0,1391
Financials	-0,0189 (0.7551)	0,0520 (0.3807)	0,0823 (0.1512)	-0,0178 (0.5932)	-0,0172 (0.6495)	0,0448 (0.2318)	-0,0011 (0.9779)	0,0691 (0.0664)	0,0375 (0.1701)	0,0541	0,0518	0,0517
Healthcare	-0,0033 (0.9833)	0,0494 (0.7364)	0,0503 (0.6977)	0,1298 (0.3242)	0,0598 (0.2425)	0,0285 (0.6417)	-0,1331 (0.3461)	-0,0104 (0.9442)	0,0218 (0.8646)	0,3779	0,3535	0,2630
Industrials	0,0332 (0.5825)	0,0495 (0.2783)	0,0893 (0.0953)	0,0236 (0.4867)	-0,0132 (0.5579)	-0,02879 (0.2449)	0,0096 (0.8514)	0,0627 (0.0948)	**0,1180 (0.0074)***	0,0557	0,0354	0,0487
Oil & Gas	0,0639 (0.7274)	-0,0663 (0.6672)	-0,1550 (0.3223)	0,0656 (0.4849)	-0,0321 (0.0630)	-0,0383 (0.0544)	-0,0017 (0.9926)	-0,0343 (0.8277)	-0,1167 (0.4270)	0,5254	0,4015	0,3957
Technology	**0,9419 (0.0084)***	**0,6935 (0.0007)****	**0,7101 (0.0279)***	-0,0359 (0.3902)	-0,0726 (0.3320)	**-0,2000 (0.0309)***	**0,9778 (0.0088)***	**0,7661 (0.0012)***	**0,9101 (0.0167)***	0,3886	0,4635	0,4250
Utilities	0,0627 (0.5698)	0,0804 (0.3162)	0,0363 (0.7280)	0,0164 (0.5854)	0,0106 (0.6632)	0,0047 (0.8467)	0,0463 (0.6925)	0,0698 (0.3765)	0,0316 (0.7243)	0,1601	0,1168	0,1866

*indicates significance at the 5 percent level and **indicates significance at the 1 percent level. The p-values are shown in the brackets.

The next state we examine at the sector level is volatility; table 5.13 illustrates our results. Similarly to the results accounting for market volatility, the Technology sector exhibits significant quarter-on-quarter institutional demand and herding during both periods of increasing and decreasing volatility (both significant at the 1 percent level during increasing periods and the 5 percent level during decreasing periods of sector volatility).

Table 5.13 - Tests for herding conditional upon sector volatility (Positive-Negative)

Market	Average Coefficient (β)		Funds following their own trades		Funds following the others' trades		Average R^2	
	Positive Sector Volatility	Negative Sector Volatility	Positive Sector Volatility	Negative Sector Volatility	Positive Sector Volatility	Negative Sector Volatility	Positive Sector Volatility	Negative Sector Volatility
Basic Materials	-0,0698 (0.0515)	-0,0173 (0.5165)	0,0404 (0.4811)	0,0479 (0.3926)	0,0404 (0.4811)	0,0479 (0.3926)	0,0869	0,1064
Consumer Goods	0,0693 (0.3619)	-0,0099 (0.8388)	-0,0974 (0.3223)	-0,0152 (0.5171)	0,1667 (0.1150)	0,0053 (0.8925)	0,1140	0,0683
Consumer Services	0,1472 (0.1017)	0,0564 (0.4111)	-0,0717 (0.08330	-0,0116 (0.5854)	**0,2188 (0.0080)***	0,0680 (0,2767)	0,2041	0,1246
Financials	0,0848 (0.1270)	0,0003 (0.9938)	0,0331 (0.2943)	-0,0254 (0.3146)	0,0518 (0.1119)	0,0257 (0.3095)	0,0688	0,0396
Healthcare	0,0419 (0.7087)	0,0231 (0.8489)	0,0751 (0.3651)	0,0698 (0.2130)	-0,0333 (0.7579)	-0,0467 (0.6917)	0,3084	0,3554
Industrials	0,0214 (0.6331)	**0,0930 (0.0211)***	-0,0250 (0.2121)	0,0126 (0.5975)	0,0464 (0.2006)	**0,0804 (0.0261)***	0,0472	0,0456
Oil & Gas	0,0333 (0.8064)	-0,1264 (0.3295)	-0,0417 (0.0594)	0,0317 (0.5667)	0,0750 (0.5667)	-0,1582 (0.2222)	0,4144	0,4622
Technology	**0,5600 (0.0102)***	**0,8670 (0.0006)****	-0,0996 (0.16720	-0,1074 (0.0848)	**0,6596 (0.0092)***	**0,9744 (0.0005)****	0,3339	0,4518
Utilities	0,0258 (0.0974)	0,7159 (0.2666)	**0,0126 (0.0084)***	0,4701 (0.7352)	0,0132 (0,0890)	0,8428 (0,3091)	0,1357	0,1734

*indicates significance at the 5 percent level and **indicates significance at the 1 percent level. The p-values are shown in the brackets.

The Industrials sector in turn exhibits significant (5 percent level) institutional demand over quarters during periods of decreasing sector volatility and the herding coefficient also appears to be significant (5 percent level) during periods of decreasing sector volatility; as we can see, contrary to the results when accounting for market volatility, here the coefficient indicating the quarter-on-quarter institutional demand is significant. On the other hand, the results for the Consumer Services sector are similar to those reported for market volatility; particularly, the herding coefficient is significant (5 percent level) during periods of increasing sector volatility, though the overall quarter-on-quarter institutional demand over quarters is insignificant. Finally, the Utilities sector here exhibits evidence of institutions following their own trades (significant at the 5 percent level) during periods of increasing sector volatility; however, the institutional demand over quarters is insignificant at both periods of increasing and decreasing sector volatility.

The results from partitioning the β_t coefficient according to periods of high, mid and low sector volatility are illustrated in table 5.14.

Table 5.14 - Tests for herding conditional upon sector volatility (High-Mid-Low)

Market	Average Coefficient (β)			Funds following their own trades			Funds following the others' trades			Average R^2		
	High Sector Volatility	Mid Sector Volatility	Low Sector Volatility	High Sector Volatility	Mid Sector Volatility	Low Sector Volatility	High Sector Volatility	Mid Sector Volatility	Low Sector Volatility	High Sector Volatility	Mid Sector Volatility	Low Sector Volatility
Basic Materials	-0,0015 (0.9816)	-0,0056 (0.9490)	0,0128 (0.8795)	-0,0305 (0.2125)	-0,0710 (0.1013)	-0,0245 (0.58770	0,0290 (0.7007)	0,0654 (0.3890)	0,0373 (0.5181)	0,0704	0,1137	0,1060
Consumer Goods	0,1443 (0.0856)	-0,0318 (0.6129)	-0,0431 (0.5458)	-0,0894 (0.4596)	-0,0319 (0.2696)	-0,0249 (0.5191)	0,2337 (0.0681)	0,0000 (0.9993)	-0,0181 (0.7212)	0,1191	0,0632	0,0794
Consumer Services	0,1345 (0.0536)	0,1320 (0.1937)	0,0477 (0.7055)	-0,0148 (0.5851)	-0,0509 (0.1857)	-0,0657 (0.2589)	**0,1494** **(0.0432)***	**0,1828** **(0.0470)***	0,1134 (0.3130)	0,1067	0,1571	0,2389
Financials	0,0763 (0.2415)	0,0209 (0.6354)	0,0168 (0.7913)	0,0175 (0.7060)	-0,0083 (0.7180)	-0,0073 (0.8273)	0,0589 (0.0691)	0,0292 (0.3324)	0,0241 (0.5747)	0,0674	0,0308	0,0607
Healthcare	-0,0089 (0.9352)	0,0013 (0.9932)	0,1068 (0.5140)	0,0911 (0.12440	0,0561 (0.6373)	0,0711 (0.3003)	-0,1001 (0.49550)	-0,0548 (0.7082)	0,0357 (0.7757)	0,1898	0,3846	0,4182
Industrials	**0,1054** **(0.0199)***	0,0695 (0.2668)	-0,0040 (0.9328)	-0,0192 (0.3599)	0,0087 (0.7273)	-0,0090 (0.79680	**0,1246** **(0.0025)***	0,0608 (0.2513)	0,0050 (0.8866)	0,0351	0,0654	0,0376
Oil & Gas	-0,0634 (0.6752)	0,0041 (0.9800)	-0,1023 (0.5684)	**-0,0240** **(0.0267)***	0,0327 (0.7153)	-0,0172 (0.4560)	-0,0393 (0.7901)	-0,0286 (0.8701)	-0,0850 (0.6075)	0,3602	0,4470	0,5127
Technology	**0,4795** **(0.0008)****	**0,9554** **(0.0123)***	**0,8080** **(0.0204)***	-0,0052 (0.8969)	-0,0247 (0.5710)	**-0,2831** **(0.0207)***	**0,4847** **(0.0004)****	**0,9801** **(0.0136)***	**1,0911** **(0.0103)***	0,2808	0,3985	0,5384
Utilities	0,0241 (0.7790)	0,1085 (0.3264)	0,0452 (0.6356)	-0,0173 (0.4047)	0,0129 (0.4877)	0,0359 (0.3187)	0,0413 (0.5847)	0,0956 (0.3780)	0,0093 (0.9248)	0,1247	0,1862	0,1487

*indicates significance at the 5 percent level and **indicates significance at the 1 percent level.
The p-values are shown in the brackets.

Once more, the Technology Sector exhibits significant quarter-on-quarter institutional demand at all periods of sector volatility (at the 1 percent level during periods of high volatility and the 5 percent level during periods of mid and low sector volatility). The sector exhibits similar significance at the levels of herding; what is more, the coefficient indicating institutions following themselves is also significant (5 percent level) during periods of low sector volatility. These findings are similar to those accounting for market volatility. In addition, the Industrials sector exhibits similar results with those found when accounting for market volatility. Particularly, the quarter-on-quarter institutional demand and herding are both significant (5 percent level) during periods of high sector volatility. In the Consumer Services sector we notice that there is evidence of significant herding (5 percent level) during periods of high and mid sector volatility, though the institutional demand over quarters is insignificant; in the case of market volatility, there was no evidence of significant herding. Finally, in the Oil & Gas sector, the coefficient indicating institutions following themselves is significant (5 percent level) during periods of high sector volatility; however the quarter-on-quarter institutional demand is insignificant during all periods of sector volatility.

The next state examined is sector volume. As we can see in table 5.15, the Technology sector once more exhibits significant (1 percent level) institutional demand over quarters both during periods of increasing and decreasing sector volume. What is more, the coefficient indicating institutions following themselves is also significant (5 percent level) during periods of decreasing sector volume. Regarding the herding coefficient, the latter appears highly significant (1 percent level) during both periods of increasing and decreasing sector volume. The Consumer Services sector exhibits significant (5 percent level) herding during periods of increasing sector volume, though the institutional demand over quarters is insignificant (in the case of market volume the latter was significant). Moving on to the Industrials sector, both the coefficient indicating institutions following themselves and the herding coefficient appear significant (5 percent level) during periods of decreasing sector volume, though the institutional demand over quarters is once more insignificant. The Oil & Gas sector and the Utilities Sector exhibit significant (5 percent level) coefficients indicating institutions following themselves during periods of decreasing and increasing sector volume respectively.

Table 5.15 - Tests for herding conditional upon Sector volume (Positive-Negative)

Market	Average Coefficient (β)		Funds following their own trades		Funds following the others' trades		Average R^2	
	Positive Sector Volume	Negative Sector Volume	Positive Sector Volume	Negative Sector Volume	Positive Sector Volume	Negative Sector Volume	Positive Sector Volume	Negative Sector Volume
Basic Materials	-0,0309 (0.6976)	0,0297 (0.5522)	-0,0545 (0.1508)	-0,0323 (0.2061)	0,0236 (0.7131)	0,0620 (0.2156)	0,1344	0,0650
Consumer Goods	0,0840 (0.2469)	-0,0270 (0.5781)	-0,0612 (0.4995)	-0,0383 (0.1087)	0,1452 (0.1453)	0,0112 (0.7649)	0,1145	0,0648
Consumer Services	0,1126 (0.1266)	0,0945 (0.3155)	-0,0555 (0.1119)	-0,0269 (0.4007)	0,1681 **(0.0134)***	0,1214 (0.1614)	0,1598	0,1785
Financials	0,0200 (0.6233)	0,0638 (0.2482)	-0,0051 (0.8494)	0,0086 (0.7705)	0,0251 (0.3142)	0,0552 (0.1015)	0,0469	0,0608
Healthcare	-0,0272 (0.8174)	0,0969 (0.3957)	0,0540 (0.4664)	0,0924 (0.1639)	-0,0812 (0.4563)	0,0045 (0.9692)	0,3500	0,3123
Industrials	0,0672 (0.1414)	0,0455 (0.2371)	0,0216 (0.3589)	**-0,0386 (0.0417)***	0,0457 (0.2022)	**0,0841 (0.0208)***	0,0567	0,0344
Oil & Gas	-0,0506 (0.6893)	-0,0550 (0.6949)	0,0319 (0.5875)	**-0,0390 (0.0202)***	-0,0825 (0.5121)	-0,0161 (0.9071)	0,4133	0,4691
Technology	**0,6455 (0.0003)****	**0,8808 (0.0007)****	-0,0437 (0.2293)	**-0,1465 (0.0333)***	**0,6892 (0.0003)****	**1,0273 (0.0005)****	0,4331	0,4232
Utilities	0,0286 (0.1033)	0,6475 (0.3076)	**0,0027 (0.0213)***	0,8859 (0.3830)	0,0259 (0.0820)	0,6557 (0.4211)	0,1107	0,2126

*indicates significance at the 5 percent level and **indicates significance at the 1 percent level. The p-values are shown in the brackets.

What is next is the illustration of the results according to periods of high, mid and low sector volume (table 5.16). Once more, the Technology sector exhibits significant institutional demand and herding during all periods of sector volume (at the 5 percent level during periods of high and low sector volume and at the 1 percent level during periods of mid volume).

Table 5.16 - Tests for herding conditional upon sector volume (High-Mid-Low)

Market	Average Coefficient (β)			Funds following their own trades			Funds following the others' trades			Average R^2		
	High Sector Volume	Mid Sector Volume	Low Sector Volume	High Sector Volume	Mid Sector Volume	Low Sector Volume	High Sector Volume	Mid Sector Volume	Low Sector Volume	High Sector Volume	Mid Sector Volume	Low Sector Volume
Basic Materials	0,0655 (0.4802)	-0,0337 (0.6384)	-0,0245 (0.7405)	-0,0998 (0.0646)	-0,0020 (0.9542)	-0,0283 (0.1525)	**0,1653** **(0.0500)***	-0,0317 (0.5515)	0,0038 (0.9548)	0,1293	0,0835	0,0791
Consumer Goods	**0,1906** **(0.0268)***	**-0,1305** **(0.0382)***	0,0151 (0.8025)	-0,0830 (0.4973)	**-0,0689** **(0.0127)***	0,0078 (0.8164)	**0,2736** **(0.0327)***	-0,0617 (0.2179)	0,0073 (0.8694)	0,1307	0,0719	0,0585
Consumer Services	**0,2362** **(0.0266)***	0,0403 (0.6000)	0,0431 (0.7125)	-0,0170 (0.5086)	-0,0237 (0.2512)	-0,0922 (0.1725)	**0,2532** **(0.0092)***	0,0641 (0.3775)	0,1354 (0.2097)	0,1873	0,1100	0,2083
Financials	-0,0246 (0.7030)	0,0509 (0.3519)	0,0860 (0.1045)	-0,0195 (0.5924)	-0,0141 (0.7164)	0,0358 (0.2037)	-0,0050 (0.8946)	**0,0650** **(0.0354)***	0,0502 (0.1686)	0,0641	0,0483	0,0454
Healthcare	0,0510 (0.6004)	0,1245 (0.4136)	-0,0836 (0.6256)	-0,0061 (0.8716)	0,0811 (0.1214)	0,1419 (0.3075)	0,0571 (0.4758)	0,0434 (0.7772)	-0,2255 (0.1708)	0,1506	0,3879	0,4539
Industrials	0,0378 (0.4866)	0,0629 (0.2118)	0,0706 (0.2047)	-0,0072 (0.8488)	0,0198 (0.2770)	-0,0327 (0.1532)	0,0450 (0.3361)	0,0431 (0.2966)	**0,1033** **(0.0263)***	0,0442	0,0422	0,0530
Oil & Gas	0,0423 (0.8066)	-0,0046 (0.9702)	-0,1987 (0.3049)	-0,0096 (0.2801)	0,0671 (0.4339)	**-0,0681** **(0.0389)***	0,0519 (0.7600)	-0,0718 (0.5941)	-0,1305 (0.4784)	0,4783	0,2567	0,5960
Technology	**0,6911** **(0.0035)***	**0,5422** **(0.0000)****	**1,1355** **(0.0120)***	-0,565 (0.1023)	-0,0729 (0.3358)	-0,1790 (0.0627)	**0,476** **(0.0031)***	**0,6151** **(0.0001)****	**1,3145** **(0.0082)***	0,3940	0,3516	0,5487
Utilities	-0,0282 (0.7736)	0,1222 (0.1785)	0,0829 (0.4304)	0,0026 (0.9239)	0,0401 (0.1401)	-0,0128 (0.5738)	-0,0308 (0.7575)	0,0821 (0.3884)	0,0957 (0.2937)	0,1586	0,1420	0,1616

*indicates significance at the 5 percent level and **indicates significance at the 1 percent level.
The p-values are shown in the brackets.

The Consumer Goods sector exhibits significant (5 percent level) evidence of quarter-on-quarter institutional demand during periods of high and mid sector volume, though the coefficient indicating funds following others is only significant (5 percent level) during periods of high sector volume, whereas the coefficient indicating institutions following their own trades is significant (5 percent level) during periods of mid sector volume. Significant herding at the 5 percent level is documented for the Consumer Services during periods of mid sector volume, the Financials Sector during mid levels of sector volume and the Industrials sector during mid levels of sector volume; however, in all cases, the institutional demand over quarters is insignificant at all levels of sector volume. Finally, the coefficient indicating institutions following themselves in the Oil & Gas sector is significant at the 5 percent level during periods of low sector volume, though once more the institutional demand over quarters is insignificant.

The last state examined is sector concentration; table 5.17 illustrates our findings. Particularly, we get to see that the Technology sector is the only sector that exhibits significant (1 percent level) quarter-on-quarter institutional demand during periods of increasing and decreasing periods of sector concentration. The coefficient indicating institutions following themselves is significant (5 percent level) during periods of decreasing sector concentration, whereas herding is significant (1 percent level) during both periods of increasing and decreasing sector concentration.

Table 5.17 - Tests for herding conditional upon Sector Concentration (Positive-Negative)

Market	Average Coefficient (β)		Funds following their own trades		Funds following the others' trades		Average R^2	
	Positive Sector Conc/tion	Negative Sector Conc/tion	Positive Sector Conc/tion	Negative Sector Conc/tion	Positive Sector Conc/tion	Negative Sector Conc/tion	Positive Sector Conc/tion	Negative Sector Conc/tion
Basic Materials	-0,0417 (0.5986)	0,0390 (0.4372)	-0,0563 (0.1462)	-0,0307 (0.2114)	0,0146 (0.8167)	0,0697 (0.1709)	0,1338	0,0655
Consumer Goods	0,0840 (0.2469)	-0,0270 (0.5781)	-0,0612 (0.4995)	-0,0383 (0.1087)	0,1452 (0.1453)	0,0112 (0.7649)	0,1145	0,0648
Consumer Services	0,0871 (0.2196)	0,1301 (0.1819)	-0,0641 (0.0708)	-0,0164 (0.60160	**0,1512 (0.0235)***	0,1465 (0.0965)	0,1441	0,1991
Financials	0,0173 (0.6660)	0,0703 (0.2159)	-0,0085 (0.7461)	0,0148 (0.6262)	0,0258 (0.2879)	0,0555 (0.1145)	0,0473	0,0609
Healthcare	-0,0661 (0.5676)	0,1310 (0.2577)	0,0215 (0.7990)	**0,1235 (0.0196)***	-0,0876 (0,4072)	0,0076 (0,9496)	0,3271	0,3367
Industrials	0,0755 (0.0946)	0,0342 (0.3696)	0,0249 (0.2785)	**-0,0454 (0.0153)***	0,0506 (0.1490)	**0,0796 (0.0334)***	0,0596	0,0297
Oil & Gas	0,0022 (0.9859)	-0,1120 (0.4381)	0,0322 (0.5837)	**-0,0393 (0.0190)***	-0,0301 (0.8045)	-0,0727 (0.6097)	0,3832	0,5016
Technology	**0,6455 (0.0003)****	**0,8808 (0.0007)****	-0,0437 (0.2293)	**-0,1465 (0,0333)***	**0,6892 (0.0003)****	**1,0273 (0.0005)****	0,4331	0,4232
Utilities	0,0016 (0.9787)	0,1341 (0.1819)	0,0013 (0.9461)	0,0223 (0.3492)	0,0003 (0.9954)	0,1118 (0.2669)	0,0966	0,2259

*indicates significance at the 5 percent level and **indicates significance at the 1 percent level. The p-values are shown in the brackets.

Furthermore, significant herding (5 percent level) is reflected in the Consumer Services sector during periods of increasing sector concentration and the Industrial sector during periods of decreasing sector concentration. The latter sector also exhibits significant (5 percent level) evidence of institutions following themselves during periods of decreasing sector concentration. Finally, the coefficient indicating institutions following themselves is significant (5 percent level) in the Healthcare and the Oil & Gas sectors during periods of decreasing sector concentration.

What is next, is the illustration of the results according to periods of high, mid and low sector concentration (table 5.18).

Table 5.18 - Tests for herding conditional upon sector Concentration (High-Mid-Low)

Market	Average Coefficient (β)			Funds following their own trades			Funds following the others' trades			Average R²		
	High Sector Conc/tion	Mid Sector Conc/tion	Low Sector Conc/tion	High Sector Conc/tion	Mid Sector Conc/tion	Low Sector Conc/tion	High Sector Conc/tion	Mid Sector Conc/tion	Low Sector Conc/tion	High Sector Conc/tion	Mid Sector Conc/tion	Low Sector Conc/tion
Basic Materials	0,0269 (0.7774)	-0,0681 (0.3274)	0,0507 (0.4874)	-0,0817 (0.0542)	-0,0632 (0.0723)	0,0186 (0.6199)	0,1086 (0.2016)	-0,0049 (0.9423)	0,0321 (0.5496)	0,1275	0,0849	0,0794
Consumer Goods	**0,1652 (0.0425)***	-0,0951 (0.1839)	0,0031 (0.9596)	-0,0981 (0.4216)	**-0,0570 (0.0487)***	0,0104 (0.7529)	**0,2632 (0.0355)***	-0,0381 (0.5237)	-0,0073 (0.8615)	0,1134	0,0873	0,0596
Consumer Services	0,1688 (0.0992)	0,1040 (0.2219)	0,0431 (0.7125)	-0,0319 (0.3198)	-0,0097 (0.3273)	-0,0922 (0.1725)	**0,2007 (0.0248)***	0,1137 (0.1758)	0,1354 (0.2097)	0,1582	0,1375	0,2083
Financials	-0,0246 (0.7030)	0,0497 (0.3626)	0,0872 (0.0998)	-0,0195 (0.5924)	-0,0087 (0.8204)	0,0301 (0.2989)	-0,0050 (0.8946)	**0,0584 (0.0490)***	0,0571 (0.1290)	0,0641	0,0479	0,0458
Healthcare	0,0974 (0.3456)	-0,0156 (0.9162)	0,0184 (0.9154)	-0,0009 (0.9812)	0,1114 (0.0901)	0,1046 (0.4314)	0,0983 (0.2583)	-0,1270 (0.4476)	-0,0862 (0.5585)	0,1727	0,3613	0,4599
Industrials	0,0400 (0.4760)	0,0387 (0.4345)	0,0940 (0.0832)	-0,0014 (0.9671)	0,0146 (0.5372)	-0,0331 (0.1536)	0,0414 (0.3990)	0,0241 (0.5460)	**0,1271 (0.0037)***	0,0503	0,0367	0,0527
Oil & Gas	0,0891 (0.5833)	-0,0544 (0.6917)	-0,1927 (0.3153)	-0,0098 (0.2688)	0,0741 (0.3845)	**-0,0753 (0.0245)***	0,0989 (0.5342)	-0,1285 (0.3865)	-0,1174 (0.5151)	0,4276	0,3153	0,5848
Technology	**0,8837 (0.0159)***	**0,8171 (0.0024)***	**0,6257 (0.0083)***	-0,0641 (0.2298)	-0,0664 (0.3990)	**-0,1790 (0.0320)***	**0,9478 (0.0204)***	**0,8835 (0.0025)***	**0,8047 (0.0039)***	0,4183	0,4819	0,3741
Utilities	-0,0209 (0.8310)	0,1153 (0.2064)	0,0829 (0.4304)	-0,0117 (0.6480)	0,0537 (0.0554)	-0,0128 (0.5738)	-0,0092 (0.9261)	0,0616 (0.5242)	0,0957 (0.2937)	0,1582	0,1423	0,1616

*indicates significance at the 5 percent level and **indicates significance at the 1 percent level. The p-values are shown in the brackets.

As we can see, the Technology sector exhibits significant (1 percent level) quarter-on-quarter institutional demand and herding during all periods of sector concentration; the coefficient indicating institutions following themselves is also significant (5 percent level) during periods of low sector concentration. The Consumer Goods sector also exhibits significant (5 percent level) quarter-on-quarter institutional demand and herding during periods of high sector concentration; what is more, the coefficient indicating institutions following themselves is also significant (5 percent level) during periods of mid sector concentration. Here, we should notice that in the case of market concentration, this sector did not exhibit significant institutional demand over quarters. On the contrary, it was the Consumer Services sector when accounting for market concentration that exhibited significant quarter-on-quarter institutional demand; however, in the case of sector concentration, this sector does not exhibit significant institutional demand over the quarters but only some evidence of herding (significant at the 5 percent level) during periods of high sector concentration. Furthermore, we also find significant (5 percent level) evidence of herding in the Financials sector during periods of mid sector concentration and the Industrials sector during periods of low sector concentration; in addition, the coefficient indicating institution following themselves is significant (5 percent level) in the Oil & Gas sector during periods of low sector concentration. However, in all three previous sectors there is significant evidence of institutional demand over quarters.

5.6 Further discussion of the results

In this section we will provide a synthesis of our results from tables 5.1-5.18 and further attack the question whether industry herding in the Spanish stock market on behalf of the fund managers is more reflected through market or sector conditions. So far, the only research, to our knowledge, that examined the intent of fund managers to herd is that of Holmes *et al.* (2011), under the premises of the Portuguese market.

Table 5.19 - Conditions affecting Institutional Industry Herding

	Market Conditions affecting Institutional Industry Herding																			
	Market Returns					**Market Volatility**					**Market Volume**					**Market Concentration**				
Sector	**(+)ve**	**(-)ve**	**High**	**Mid**	**Low**	**(+)ve**	**(-)ve**	**High**	**Mid**	**Low**	**(+)ve**	**(-)ve**	**High**	**Mid**	**Low**	**(+)ve**	**(-)ve**	**High**	**Mid**	**Low**
Basic Materials		-	-	-	-	-	-	-	√	-	-	-	√	-	-	-	-	-	-	-
Consumer Goods	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Consumer Services	√	-	-	-	√	√	-	-	-	-	√	-	-	-	-	√	-	-	√	-
Financials	-	√	-	-	√	-	-	√	-	-	-	-	√	-	-	-	-	-	-	√
Healthcare	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Industrials	-	√	-	-	√	-	√	√	-	-	-	-	-	-	-	-	-	-	-	√
Oil & Gas	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Technology	√	√	√	√	√	√	√	√	√	√	√	√	√	√	√	√	√	√	√	√
Utilities	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-

	Sector Conditions affecting Institutional Industry Herding																			
	Sector Returns					**Sector Volatility**					**Sector Volume**					**Sector Concentration**				
Sector	**(+)ve**	**(-)ve**	**High**	**Mid**	**Low**	**(+)ve**	**(-)ve**	**High**	**Mid**	**Low**	**(+)ve**	**(-)ve**	**High**	**Mid**	**Low**	**(+)ve**	**(-)ve**	**High**	**Mid**	**Low**
Basic Materials	-	-	-	-	-	-	-	-	-	-	-	-	√	-	-	-	-	-	-	-
Consumer Goods	-	-	-	-	-	-	-	-	-	-	-	-	√	-	-	-	-	√	-	-
Consumer Services	-	√	-	√	-	√	-	√	√	-	√	-	√	-	-	√	-	√	-	-
Financials	-	√	-	-	-	-	-	-	-	-	-	-	-	√	-	-	-	-	√	-
Healthcare	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Industrials	-	√	-	-	√	-	√	√	-	-	-	√	-	-	√	-	√	-	-	√
Oil & Gas	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Technology	√	√	√	√	√	√	√	√	√	√	√	√	√	√	√	√	√	√	√	√
Utilities	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-

However, in that case, the authors examined whether fund managers intentionally herd at the market level and whether their herd behavior was reflected through various market conditions (market returns, market volatility, and regulatory environment); their results indicated the presence of herd intent on behalf of the Portuguese fund managers and the authors attributed this phenomenon to professional reasons. In our case, instead of examining the intent of fund managers to herd at the market level, we examine herding intent at the sector level; what is more, we use several conditions (returns, volatility, volume, concentration) not only at the market level but at the sector level as well. By doing so, we can identify whether herding intent at the industry level is more reflected through market or sector conditions.

Starting with the aggregate market results, these indicated that there is significant herding on behalf of the Spanish fund managers. Moving to the sector level, we found evidence of significant herding in the Consumer Services, Industrials, and Technology sectors. In addition, we examined the interaction between institutional industry herding and a series of conditions, both at the market and sector level; these were returns, volatility, volume and concentration of trading. Our results indicated that there is significant herding in behalf of fund managers in the Spanish market primarily during periods where the overall market or the sector examined is characterized by underperformance, rising/high volatility and high volume.

In the case of underperformance, the sectors where institutional herding is reflected more during quarters of decreasing and/or low market/sectors returns are the Consumer Services, Financials, and Industrials; this phenomenon can be attributed to professional reasons. In periods of declining prices trading is more likely to generate losses, as such less experienced fund managers who are assessed relatively to the performance of the institutional investment sector may choose to copy the trades of their more experienced peers. By doing so, they can "share the blame" by claiming that even though they made good investment decisions (as the more experienced fund managers) the adverse conditions prevailing in the market was the reason of this underperformance.

In the case where institutional herding was more reflected during periods of rising/high volatility in the Consumer Services, Financials, and Industrials sectors, this phenomenon could be attributed to informational considerations. During periods of high/rising volatility there is greater uncertainty and complexity on behalf of inexperienced fund managers as it may be not that easy to interpret correctly the large flow of information during those periods; as such they may resort to herd on the trades of their more experienced peers.

In the where institutional herding was more reflected mostly during periods of high volume in the Basic Materials, Consumer Goods and Consumer Services sectors, this phenomenon could be attributed to informational/professional considerations. High trading volume allows "good" fund managers to trade more easily on their information [Romano (2007)], whereas in the case of low trading volume that would be more difficult since there would be higher liquidity risk. As such, the increased trading activity of the "good" fund managers increases their visibility to the inexperienced fund managers who can copy the trades of the former ones more easily.

When we controlled for market/sector trading concentration we did not identify any pattern on the significance of herding, though there has been some scant evidence of herding in some sectors. What we should emphasize at this point is that the most extreme cases of insignificant herding were met in the smallest sectors of our samples. The Healthcare, Oil & Gas and the Utilities sectors showed no evidence of herding irrespectively of any market condition controlled for. On the other hand, there was overwhelming evidence of herding in the Technology sector in all the conditions examined. This could be due to the fact that the specific sector consists of relatively small stocks, which fund managers perceive as riskier; thus, they resort to herding in order to minimize the perceived risk. In addition, since the majority of the assets held by firms in the Technology sector are intangible, this could increase the difficulty for investors to analyze the perspectives of these stocks, thus leading them to herd on their peers' actions.

Concluding, our results indicate that fund managers in the Spanish market industry herd, with their herd behavior interacting with several market and sector conditions. The sectors where the presence of herding is more evident are the Consumer Services and the Industrials and to lesser extent the Financials, the Basic Materials and the Consumer Goods sectors. The fact that institutional investors are found to herd more on the Consumer Services and the Industrials sectors is quite interesting as these two sectors comprise almost three quarters of the Spanish Economy's GDP[35]. As such, bad decisions made by fund managers in these sectors would indicate bad understanding of the economy's fundamental sectors; hence, lower skills. This finding is in line with the study by Zhou and Lai (2009), which found that herding is more pronounced on the Financials and the Property & Construction sectors, the two dominants sectors of Hong Kong. These results support our hypothesis that fund managers' industry herding is driven by

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

intent and this can be attributed to the informational and professional concerns of the fund managers.

5.7 Conclusion

The question on what alters institutional investors' intent to herd has not been examined in depth. The only research so far, to our knowledge, that examines this issue is that of Holmes *et al.* (2011), which examined this issue under the premises of the Portuguese market. More specifically, the authors found that the intent of fund managers to herd at the aggregate market level is reflected through differences in various market conditions examined in their paper. The gap that we found in the relevant literature and we examined in this chapter is whether the intent of institutional investors to industry herd is more reflected through market or sector conditions; an issue that has not been examined before. As market and sector conditions reflect different informational sets, it is important to know which of the two alters the intent of fund managers to herd. In order to do so, we used data from the Spanish mutual fund industry. More specifically, we used quarterly portfolio holdings for a period of fourteen years, namely from June 1995 till September 2008. To test whether the herd behavior found in the sectors examined is intentional or not, we controlled for a series of conditions (returns, volatility, volume, and concentration of trading) at both the market and sector level. Our results indicate that the fund managers in the Spanish market herd significantly not only at the aggregate market level but at the industry level as well since we documented interactions of their herd behavior in each sector with the market/industry states controlled for. This was primarily the case for the Consumer Services, Financials, and the Industrials sectors and to a lesser extent for the Basic Materials and the Consumer Goods sectors. In the above mentioned sectors, fund managers were found to significantly herd during periods of market/sector underperformance, rising/high volatility, and high volume. Our results suggest that fund managers do industry herd and that this behavior is driven by intent motivated by informational and professional reasons.

Concluding, our results contribute to the literature by providing supporting evidence to the research of Holmes *et al.* (2011) who found that institutional investors herd intentionally at the market level, this reflected through differences in various market conditions, and that this herd behavior is driven by professional and informational reasons; however, our study takes a further step finding that fund managers intentionally herd at the industry level and that this herd behavior is not only influenced by market conditions but by industry-specific conditions as well. The findings of our study can have important implications for both the investment community and regulatory authorities. In the first case, it is important for the investors to know the impact of the market/sector conditions on the levels of industry herding, as it could potentially affect their investment strategies, especially those that engage in sector investing styles. In the latter case, it is important for the regulatory authorities to focus on the reasons that drive institutional investors to industry herd intentionally and try to minimize its impact, as herding is found to have a destabilizing effect on the stock prices.

Chapter 6

6.1 Conclusion

This thesis aims to contribute to the existing literature of Behavioral Finance by examining two concepts of collective behavior, namely herding and feedback trading. Both of these topics are very important as if such phenomena are widespread, this could lead to the destabilization of asset prices and the increase of the systemic risk of the markets. The first issue addressed is whether market concentration has an impact over the relationship between style investing and herding. As style investing has been found to promote institutional herding in a series of large and developed markets, we examine what is the case under the context of a highly concentrated market. What is next is the examination whether the introduction of the Exchange Traded Funds has a beneficial role towards the market efficiency and whether they depress or not noise trading in the markets these have been introduced to. Finally, the last issue examined in this thesis is whether institutional investors herd intentionally at the industry level and which are the conditions they interact the most with herding, the market or sector conditions?

After providing an extended literature review in Chapter 2 about herding and feedback trading, chapter 3 focuses in the first research question of this thesis, which is identifying the impact of market concentration over the relationship between style investing and herding. As there is an established relationship between style investing and herding in large markets, we explore the possibility that the trading dynamics produced in a concentrated market may have a different impact over the relationship between style investing and herding than those observed in large markets. By testing our hypothesis in a highly concentrated market such as that of Portugal we find that institutional demand over time appears highly significant in the Portuguese fund industry and it is due to funds following the trades of other funds (herding). Furthermore, we find that in the context of a highly concentrated market, style investing does not affect the persistence of institutional demand; the latter remaining significant throughout all tests carried out. More specifically, the herding levels found are quite high and remain robust when we account for various investment styles (consensus analysts' recommendations, momentum, size, value/growth, volatility, and volume). As such, our results indicate that style investing does not constitute a common practice in highly concentrated markets and that it does not have any impact over the significance of herding among fund managers in such kind of market environments.

Our results may have important implications for the professional fund managers and their clients as they are applicable to concentrated markets. A possible idea for further research could be to test for the profitability of the investing styles used in this research and test whether these are of any use for institutional investors when they invest in concentrated markets. In addition, a re-examination of the relationship between style investing and institutional herding after the end of the ongoing credit crisis would be useful as to examine whether there should be any significant difference on the findings of our research.

In chapter 4 we examine the impact of the introduction of the ETFs on the markets these have been introduced to. More specifically, using a sample of eight European markets, we test whether the introduction of the ETFs in these markets depress the level of noise trading or not. Our findings indicate that the launch of the ETFs do have a beneficial role in the markets these have been introduced to, as we find evidence that the level of noise trading declined during the period following the ETF introduction. Or results bear important implications for both the market regulators and the investing community. More specifically, since our sample consisted of developed markets, our findings can be of great importance to the regulatory authorities of emerging or relatively new established markets as the introduction of ETFs in these markets could contribute in a great extent to the completion of these markets. Regarding, the investment community, our results indicate that the ETFs are efficiently priced and they have no destabilizing effect on the spot prices; as such these products can be successfully used as hedging tools on behalf of the investors.

Finally, in chapter 5 we focus on the behavior of institutional investors when investing at the industry level. More specifically, we examine whether fund managers industry herd intentionally and also shed light on the conditions that underlie their intent to herd at the industry level; we test our hypothesis under the context of the Spanish fund industry. Our findings support our hypothesis as we find that fund managers do herd at the industry level in the Spanish market and that this herd behavior is intentional driven by professional and informational reasons. In addition, we find that it is both the market and sector conditions that affect fund managers' intent to industry herd. Our findings have important implication for both the investment community and the regulatory authorities. On the investors' side, it is important for them to know the impact of the market/sector conditions on the levels of industry herding, as it could potentially affect their investment strategies, especially those engaging in sector investing styles. In the case of market regulators, our results suggest that the later should devise ways to encourage institutional investors to effectively diversify their sector investments; one possible solution would be to compare the correlations of the funds' equity investments (both at the market and sector level) and release this information to the public. In this way, investors will have a better insight of the extent of institutional herding and they could factor this information when they select funds to invest in. A possible idea for further research would be to examine which are the leading and following fund managers in the market, as this would provide the investors with an insight on the quality and skills of the managers that manage their investments.

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