International Journal of Economics and Financial Issues
Vol. 3, No. 1, 2013, pp.214-228
ISSN: 2146-4138
www.econjournals.com

Herding Behavior under Markets Condition: Empirical Evidence on the European Financial Markets

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ABSTRACT: This study presents four main contributions to the literature of behavior herding. Firstly, it extends the behavioral researches of herding of the investors on a developed market and mainly on a European market as a whole. Secondly, we are interested in examination of herding behavior at the level of sectors by using data at the levels of companies. Thirdly, this document estimates the implications of herding behavior in terms of returns, volatility and volume of transaction. Fourthly, the herding behavior is revealed as well during the period of the recent global financial crisis in 2007-2008 and of Asian crisis. Our results reveal a strong evidence of herding behavior sharply contributed to a bearish situation characterized by a strong volatility and a trading volume. The repercussion of herding during the period of the recent financial crisis is clearly revealed for the sectors of the finance and the technology.

Keywords: Herding behavior; European financial markets; Financial crisis; Cross-sectional returns.
JEL Classifications: G15; G14

1. Introduction

In view of the various questionings of the classic financial theory or the theory of efficiency, the researchers were incited to develop a new current of research excluding certain hypotheses of this theory and to explain perfectly the functioning of financial markets. In this regard, the modern financial theory bent to privilege a new approach of the finance focused principally on the way of apprehending, of including or of modeling the real behavior of the people of the finance and its impact on the functioning of financial markets.

This new theory tries to connect a set of anomalies observed on financial markets in hypotheses relating to the individuals behavior. In particular, this theory takes into account the human dimension and the psychological aspect of the individual and aims to establish links between the human psychology and the fluctuations in stock markets. Although the results obtained by this new approach of research are the object of debate, it appears today rapidly growing.Kahneman andTversky(1979) put the people and their psychology in the center of the debates to reach at a better understanding of financial markets. It seems thus, it is vital to put the people and their rationality limited to the center and to introduce a kind of variable of irrationality into the theory. Such irrationality may be realized on the financial market by the herding behavior of the investors. The herding , which is defined, in a general way, as a set of correlated individual behavior; suppose a decision-making at the same time systematic and erroneous on behalf of a group.

The herding is a very wide-spread strategy in our days in the financial world and begins to have particular interests for the academic researches. So, the question which arises is to arrest the effects which can be aroused, if a herding behavior will take place, on the profitability and the efficiency of financial markets. This phenomenon obtained its relevance in particular after the financial crisis of

1990. A variety of studies focused on the measure of the impact of the distortions resulting from the herding behavior during the periods of the financial crises (Hwang and Salmon, 2004;Gavriilidisa et al., 2007). The previous theoretical studies proposed multiple phenomena and explanations which can be at the origin of an attempt of imitation by an individual of particular behavior and consequently which are of motivations of herding behavior. Lu (1995) expresses, that psychological factors can be at the origin of the release of a blind conformity behavior for some academic researches. In this sense the optimism and the pessimism can explain such a behavior. In its study; Lu (1995) explains that the phenomenon of herding takes place as the contagion of feeling. For Devenow and Welch (1996); the will of confirmer and the feeling of insecurity can be also at the origin of a herding behavior. In their study; these academicians showed how by copying the share of the other participants to the financial market the investors feel more secure. The contributions of Lu (1995) and Devenow and Welch (1996) established the explanations of irrational herding. More recently, the other psychological arguments for this phenomenon were examined. The aversion to the regret, a moderate self-confidence and the other ways motivated the release of a herding behavior by the investors. (Rubinstein, 2001;Shiller, 2002).

Informative justifications (The waterfalls basic model) and the others related to the reputation and to the structures of compensations or remunerations also contributed to the explanation of the rational herding (Banerjee, 1992;Scharfstein and Stein, 1990) In this regard, the investor can have an intrinsic preference for the conformity and be led to ignore his deprived information about the situation and to reproduce or to imitate the behavior of the agents who made a decision upstream to him (Avery and Zemsky, 1998,Bilkchandanietal., 1992). The idea is that the investor tends to privilege a herding behavior as soon as this last one becomes suspicious on its capacity of prediction or still when he dreads the future. The distinction“spurious herding” of the “intentionalherding” turns out so crucial to prevent erroneous analyses (Walter, 2008).Diversified empirical studies emphasized the examination of herding of the investors in various contexts. The empirical literature distinguishes two categories of measure of blind conformity behavior. A first category of herding tends towards the herding allocated to an average of an investors group to buy or to sell simultaneously particular securities.

These studies are based on the composition of the investors’ portfolios and theirtransaction flow (Lakonishoket al., 1992;Grinblatt et al., 1995;Oehler, 1998; Wermmers, 1999; Wylie, 2005; Walter, 2008; Puckett and Ya, 2007;Voronkova and Bohl, 2005). This category takes interest in the detection particularly the detection of herding behavior for institutional investors. In the second category, there is a focus on the herding in general which was indicated, as, «collective behavior of all the participants”. The share returns were at the origin of the empirical evidences of these studies (Christie and Huang, (1995), Chang and al., (2000) Hwang and Salmon (2004)).The main objective of this document is motivated by the contributions of this last category. So we aim; to examine the existence of a herding behavior as well as its dynamics on the financial market. We are interested firstly to reveal the degree of herding on a market developed mainly the European market. Exactly we are going to be interested in this study in the Stoxx 600 index as representative of the country Euro-Zone. Our choice is motivated by the domination of the institutional investors which tend to privilege a herding behavior to maintain a good reputation in every industry. Indeed, several institutional investors attach due importance to the councils of the other professionals related to their decisions on purchases and sales of the most volatile shares. Likewise, the individual investors tend to be less informed than the institutional investors thus; they will need to base their decisions on the acts of the others without taking into account their own evaluations. So, the institutional investors are as individual investors who can provoke the phenomenon of herding on the target market. Secondly; we are going to focus more; at the level of this work, on examination of the degree of herding for all the industries of companies establishing the stock market index Euro Stoxx 600. In this respect, our study is enrichment mattering for the recent literature which examines the herding behavior in a context of the industry and generally for an emerging market (Choi and Sias, 2009). To study the herding behavior from a perspective of industry/sector is interesting; in our opinion; for several reasons among which mainly: the typical affectation of the financial analysts will take place at the level of the industry or the institution specialists of which they are; and they also return the information through their industrial classifications. Also, several business managers formulate their recommendations at the level of a single sector. Also, this study may be a source specifies for the investors and also get more reliability for the examination of a herding behavior. Thirdly, in the term of the studies recently proposed by Connolly and Stivers (2006), Statmanet al. (2006) and Griffin et al., (2007), we recognize the role of the variable volume of transactions with regard to the volatility of the shares. We are interested to examine how the herding behavior implies three main indicators of markets namely: volume; volatility and returns of stocks. Finally, according to the common intuition, the herding behavior seems to be more spread during the crisis. We are going to perceive the role of the financial crisis of "subprime" and Asian in the proofs of herding behavior.

2. Theoretical and Empirical Studies on Herding Behavior

2.1. The definitions and the motivations of a herding behavior

Within the literature of herding behavior, a large number of definitions proposed to arrest this behavior. These definitions distinguished two great forms of herding: irrational and rational.In an irrational perspective, a herding behavior is likened to a scenario of collective actions taken by individuals in uncertain conditions. The investors privilege such a behavior to reduce the uncertainty and assure their needs to feel in confidentiality (Devenowand Welch, 1996). In a rational perspective, a herding behavior is likened to a situation where the investors are tried to redress their performances and their reputations by ignoring voluntarily their own analyses and to reproduce another manager who possesses a source of more reliable information or the analysis competencies of more eminent decisions. (Bikchandani and Sharma, 2001).At the same time for a better categorizing of these justifications, it’s indispensable to distinguish between rational herding and irrational herding. This last one returns potentially the asset prices beyond the fundamental values having for consequence the yields reversals (Puckett and Yan,2007).While the rational herding can engender efficient prices favoring to the financial markets to seize the information in the asset prices more quickly which would form otherwise. The model indicated to the explanation of irrational herding is essentially to the behavioral approach. Most of the theoretical financial literature is focused on the rational herding behavior. Bikchandani and Sharma (2001) classify the rational herding in three under categories: herding based on the information, the herding based on the reputation and the herding based on the compensation.

The herding based on the information is the first set of theoretical models of herding which is attributed to the works of Banerjee (1992), Bikhchandaniet al. (1992). According to this theory, in a context of uncertainty on the individual signals, the imitation of the other one or the group can improve the personal information. The idea that the agents deduct the useful information’s by observing the shares of the previous agents, to the point that they ignore in an optimal manner their own private information. The second subset that is named the herding based on the reputation describes the idea that the investors and more exactly the institutions who are subjected at the risk of reputation by acting differently from the crowd, so they can ignore their own information deprived to act with herding. This behavior can also be considered as behavior “principal- agent relationship”. The third subset of herding is known under the name of herding based on the remuneration. The idea is that the method of payment can establish a reason for privileging the blind conformity behavior. The explicit clause concerning the relative performance of the administrators, which is written by the principals to limit the ineffectiveness’s caused by the problems of "the moral hazard" and "the opposite selection" can be an additional incentive in the herding behavior (Visser and Swank, 2008).

2.2. The empirical studies

The empirical literature diverted to estimate the scale of herding in financial markets, distinguishes two categories of the measure of herding according to the nature of the defined data. The measures based on the composition of the investors’ portfolios and on the transaction flow of investors (Lakonishok, 1992;Wermers,1999). These measures are particularly interested to estimate the intensions of herding of the assimilated institutional investors or at an average of an investors group to buy (or to sell) simultaneously particular securities (Lakonishok, 1992;Grinblattand al., 1995; Oehler, 1998;Wermers, 1999; Wylie, 2005; Walter, 2008; Puckett and Yan, 2007;Voronkova and Bohl, 2005) in strong changes of the securities fractions held by the institutional (Nofsinger and Sias, 1999;Sias, 2004; Kim and Sias, 2005;Dasguptaand al., 2008;Siaset al., 2007). More recently, the study of Puckett and Yan (2007) based on the measure of herding developed by Lakonishok (1992) reveals levels of herding more important for weekly detentions of 776 American institutional investors than those announced by the previous studies concerning American funds. Also, the estimations of the study of

Walter (2008) focused on 60 mutual funds specialized in shares German announce levels of herding slightly higher than those obtained for the other developed financial markets. The second category of herding is based on the shares returns (Christie and Huang, 1995; Chang et al., 2000, and Hwang and Salmon, 2004). A first methodology based on the dispersal of returns of all the shares by the cross-sectional standard (or absolute) deviations of the returns to estimate the herding behavior; including the study of Christie and Huang (1995)on United States markets, that of the Chang and al., 2000 on international shares; Gleason et al. (2004) on the forward contracts negotiated on the European stock exchanges and the study of Gleason and al. (2004) on "the Exchange Traded Funds " American (ETF), Demirer and Kutan (2006), and Tan et al. (2008) on the Chinese shares. With the exception of the study of Tan and al 2008, the previous studies, this above noted, announce, generally, results in favor of the rational theory of assets valuation and conclude that the herding does not establish a factor mattering in the calculation of the securities returns during the periods of stress markets. More recently, Zhengand al. (2010) examine the herding behavior in the same order of spirit as Tan and al (2008) on a set of emerging markets and presses in particular those United States, Latin America, Australia, France, German and Asian markets. With the exception of Latin America and the United States all the other financial markets are marked by the existence of a herding behavior. For four European countries (Portuguese, Italian,Spanish and Greek) Philippaset al. (2011) reveal the existence of an imitative behavior only for the Greek and Italian markets. The second methodology based on cross- sectional variability of factor sensitivities, instead of returns, is suggested by Hawang and Salmon (2004). Their findings provide supports for herd formation in the South Korean market.

3. Methodology

In the following, we present the different steps of methodology that will allow us to measure changes in degree of herding behavior in European financial markets. We are interested as well in the concept of herding behavior assimilated to independent behaviors which provide a dispersion of returns from the average return depending on the variety of individual signals. The measure of herding behavior that we use is inline with the studies of Tan et al. (2008) and Zhenget al., (2010) based on two measures proposed by Christie and Huang (1995) and Chang and al. (2000) to detect the herding behavior through cross-sectional stock returns. However, the measure of dispersion of returns ($\mathbf{CSAD_t}$) used differs from that proposed by Chang et al., (2000). Their measure which was derived from the conditional version of CAPM may be questionable, while the measure used in this study is based on the method used by Christie and Huang (1995), Gleason et al. (2004) and Tan et al. (2008), which does not require estimating beta. In examining the degree of herding behavior, differently from the above cited studies, we focus more on companies of all industries constituting the European stock index Stoxx 600. In this context, our study is, we believe, an important addition to recent literature which tests the behavior herding in industrials context (Choi and Sias, 2009).

3-1 Foundation of estimated model

So cross-sectional absolute standard deviation among individual firm returns within a particular group of securities $\mathbf{CSAD_t}$ is used as a measure of dispersion returns, and formulated as follows:

$$CSAD_t = \frac{1}{N}\sum_{i=1}^{N}\left|R_{i,t} - R_{m,t}\right| \tag{1}$$

This return dispersion methodology is suggested by Chang and al. (2000) although our test for herding is similar to that of Chang et al. (2000), our measure of $\mathbf{CSAD_T}$ differs from theirs. These authors show that a (CAPM) model of rational evaluation assets does not only predict that the dispersion of returns in absolute value is an increasing functions of market returns, but also that this relation is linear. During periods of extreme market movements, these academics suggest that one might expect the relation between return dispersion and market return to be non-linearly increasing or even decreasing. To detect herding behavior, we modify the specification of Chang and al., (2000) and then we note:

$$CSAD_t = \gamma_0 + \gamma_1 R_{m,t} + \gamma_2\left|R_{m,t}\right| + \gamma_3 R_{m,t}^2 + \varepsilon \tag{2}$$

The equation noted above differs from the original equation proposed by Chang et al., (2000) at term $R_{m,t}$ which is included on the right side. This specification allows taking care of the asymmetric of the investor behavior during different market conditions. (Zhenget al., 2010; Chiang et al., 2000).While $CSAD_t$ is a measure of return, $R_{m,t}$ is the value of an equally weighted realized return of shares component each industry treated. According to this methodology, herding would be recorded by a lower or less than proportional increase in the cross sectional absolute deviation $CSAD_t$ during periods of strong market movements.

3-2-Herding behavior under different market conditions

Starting with the fundamental assumption of Christie and Huang (1995) that the behavior herding is more pronounced during periods of extreme market stress, in this section we will discuss advantage of European stock returns by examining under what market conditions herding behavior is revealed. More specifically we are interested in the following to estimate the possible asymmetric effects of behavior herding based on returns, return volatility, trading volumes as variables that can define such periods.

3-2-1 Herding behavior under up and down markets:

The asymmetric characteristics of asset returns were illustrated by a majority of empirical evidence1. In the following we will be interested to examine first the reaction of investors in the months when the market is rising compared to the months when the market is down. To do so, instead of dividing the sample in each case and estimating the model separately as in Tan et al., (2008), we follow a more robust approach recently proposed by Chiang et al., (2010) which instead uses a dummy variable in a single model. However, this approach is adopted separately for each industry covered in our study as follows:

$$CSAD_{i,t} = \gamma_0 + \gamma_1(1-D)R_{m,t} + \gamma_2 DR_{m,t} + \gamma_3(1-D)R^2_{m,t} + \gamma_4 DR^2_{m,t} + \varepsilon_t \qquad (3)$$

We divide the data into two groups using a dummy variable D which takes the value 1 when the portfolio return is negative and zero when the market portfolio return is positive.

Hypothesis 3.2.1.If herding effects are established while we expect γ_3 and γ_4 coefficients are statistically significant and negative, with $\gamma_3 < \gamma_4$ if effects are more pronounced in the months when the markets are bearish.

3-2-2 Herding behavior and excessive volatility of returns

Gleason et al. (2004) suggest that the tendency to mimic is more pronounced during periods characterized by information flows and / or abnormal volatility. This intuition was supported by Tan et al., (2008) in the Chinese stock market. We then examine the potential effects of asymmetric herding behavior in relation to price volatility in the European market by pressing the following approach:

$$CSAD_{i,t} = \alpha + \gamma_1 D^{Hvolatility}\left|R_{m,t}\right| + \gamma_2(1-D^{Hvolatility})\left|R_{m,t}\right| + \gamma_3 D^{Hvolatility}R^2_{m,t}$$
$$+\gamma_4(1-D^{Hvolatility})R^2_{m,t} + \varepsilon_t \qquad (4)$$

Where $D^{Hvolatility}$ is a dummy variable that takes the value 1 during the month characterized by excessive volatility and 0 otherwise. Market volatility is assumed to be high (or excessive) if it exceeds the weighted average of the volatilities of six months preceding our study period and vice versa.

Hypothesis 3.2.2 If the effects of this behavior are established then we expose $\gamma_3 < 0$ and $\gamma_4 < 0$, with $\gamma_3 < \gamma_4$ whether these effects are more common during the months characterized by high volatility market.

3-2-3 herding behavior and excessive trading volume

Based on the intuition, suggests that the herding behavior may intensify the trading volume in a subset of securities; (Tan et al., 2008); we examine hereafter the possibility of the presence of any asymmetric effects during periods characterized by high or low transaction volumes. These potential effects will be examined by estimating for each industry selected the following specification:

$$CSAD_{i,t} = \alpha + \gamma_1 D^{Hvolum}\left|R_{m,t}\right| + \gamma_2(1-D^{Hvolum})\left|R_{m,t}\right| + \gamma_3 D^{Hvolum}R^2_{m,t}$$
$$+\gamma_4\left(1-D^{Hvolum}\right)R^2_{m,t} + \varepsilon_t \qquad (5)$$

[1]Ball and Kothari (1989) ;Bekaert and al (2009)

We divide the data into two groups using a dummy variable $\mathbf{D}^{\mathbf{Hvolum}}$ that takes the value 1 during the month characterized by an excessive trading volume and 0 otherwise. Identically to the approach used to market volatility, trading volume is assumed to be high (or excessive) if it exceeds the weighted average of trading volume of six months preceding our study period and vice versa. In this context, the assumption to estimate will be reformulated as follows:

Hypothesis3.2.3 If the effects of this behavior are established, then we expect $\gamma_3 < 0$ and $\gamma_4 < 0$, with $\gamma_3 < \gamma_4$ if these effects are more common during the months characterized by a high trading volume.

3-2-4 herding behavior and financial crises

Based on the intuition affirms that the effects of herding may be more intensive during periods of market stress, which is defined as the occurrence of extreme returns in the market portfolios. (Christie and Huang, 1995; Chang et al., 2000) Recent experience suggests that the movements of extreme returns occur continuously in times of crisis. Therefore, it is relevant to consider whether the extreme market movements, such as financial crises, could alter the course of the degree of herding. The recent global crisis called "subprime" and that Asian crises provide an appropriate context to test this hypothesis. The frame work in this period of extreme movements is assumed to be captured by testing the significance of a dummy variable, $\mathbf{D}^{\mathbf{crisis}}$, which takes the value 1 during the period of the crisis and 0 otherwise. To do this, we estimate the following specification for each industry covered in our study and the two crises studied.

$$CSAD_{i,t} = \gamma_0 + \gamma_1 R_{m,t} + \gamma_2 \left|R_{m,t}\right| + \gamma_3 R_{m,t}^2 + \gamma_4 R_{m,t}^2 . D^{crisis} + \varepsilon_t \quad (6)$$

4. Data

To examine the profile of herding toward the market, our study is conducted on a portfolio of 174 shares constituting the stock index; EuroStoxx600, with a monthly frequency from January 1998 until December 2010.The criterion for choosing from these 174 shares is based on the fact that they were consistently listed in the Euro Stoxx 600 since 1998.The Euro Stoxx 600 offers an exposure to securities of large, medium and small capitalization of the European developed countries measured and weighted by market capitalization based on the floating.The choice of this index is motivated by the number of shares fairly representative of the European market and for reasons of sample homogeneity. The 174 shares chosen above have more than 50% of the total market capitalization. The decomposition of our sample was based on the suggestion revealed by the empirical literature of herding behavior: one group is more likely to herd if it is sufficiently homogeneous, since each member faces a similar decision problem, and each member can see the transactions of other group members (Bikhchandani and Sharma, 2001). We apply the methodology described above on groups of stocks classified on the basis of industry classification[2]. Then we assign each of the 174 firms to one of ten-sector groups including: Oil & Gas, Basic Materials, Industrials', Consumer Goods, Health & Care, Consumer Services, Telecommunication, Utilities, Financials and Technology. Monthly stock returns are respectively determined by applying the following formula $R_{i,t} = \left[\ln\left(\frac{P_{i,t}}{P_{i,t-1}}\right)\right]$; which $P_{i,t}$ represents the monthly closing prices of month t for stock (i). We then calculate the returns of market portfolio based on equally weighted portfolio of all firms in each sector classification.

Table (1) summarizes the descriptive statistics respectively for average monthly returns and dispersion returns of market portfolio. Examining Table 1, we reveal that all the sectors studied are characterized by average monthly returns, standard deviations and medians consistently low. The average monthly returns of market portfolio range from a minimum of - 0.003479 for the technology sector to a maximum of 0.001055 for the financial sector.The average monthly return volatility, measured by the standard deviation varies between a maximum of respectively 0 .06533, 0.065470 and 0.067008 for the sectors of technology, basic materials and finance and a minimum of 0.036684

[2]The classification of stocks can be affected in terms of industry (Christie and Huang 1995) exchange or currency countries (Gleason et al., 2004)

for the utilities sector.These observations also tell us that the technology, basic materials and financesectors were the most extreme variations per month with a monthly maximum return, respectively, 0.163088, 0.161466 and a minimum respectively of -0.242140 ; -0.249156 and -0.197008.A statistical perspective of these variables also gives us an idea of the quality estimation that is good for these variables since the variances are generally quite low. About the panel A.2 summarizes the descriptive statistics of $CSAD_{i,t}$ for each sector. Following the conclusions of a panel, we observe higher volatility for the technology sector.

Table 1. Descriptive statistics of the average monthly returns of sectors and cross -sectional return dispersion ($\mathbf{CSAD_t}$)										
Panel A.1 monthly returns of portfolio										
Sectors / Descriptive statistics	Oïl& gaz	BASIC Materials	Financial	Industrials	consumer Goods	Health& care	consumer services	Telecom-munication	Utilities	Technology
Mean	-0.001818	-0.000144	0.001055	-0.000857	0.000393	0.000127	0.000987	-0.000481	0.000274	-0.003479
Median	0.006244	0.007755	0.009366	0.002153	0.005640	0.007191	0.009738	0.006900	0.002220	0.005084
Maximum	0.120450	0.161466	0.102626	0.136491	0.187717	0.149424	0.179484	0.135556	0.101617	0.163088
Minimum	-0.260283	-0.249156	-0.197008	-0.217294	-0.176909	-0.282267	-0.218455	-0.257409	-0.135802	-0.242140
Standard deviation	0.058464	0.065470	0.067008	0.054892	0.056352	0.062397	0.058686	0.067408	0.036684	0.065333
Skewness	-1.342238	-0.777202	-1.100581	-1.005916	-0.441540	-0.920447	-0.914032	-1.022719	-0.354072	-0.709162
Kurtosis	6.789753	5.188145	4.812402	5.437583	4.750571	5.541871	5.390461	5.269548	4.207256	4.530796
Jarque-Bera	140.1962	46.82697	52.84441	64.93032	24.98815	63.61457	58.86480	60.67531	12.73309	28.30735
Probability	0.000000	0.000000	0.000000	0.000000	0.000004	0.000000	0.000000	0.000000	0.001718	0.000001
Observations	156	156	156	156	156	155	156	156	156	156
N	174	174	174	174	174	174	174	174	174	174
Panel A.2: $CSAD_t$										
Sectors / Descriptive statistics	Oil& gaz	BASIC Materiels	Financials	Industrials	consumer Goods	Health& care	consumer services	Telecom-munication	Utilities	Technology
Mean	0.058503	0.060055	0.058188	0.062735	0.057159	0.060035	0.057743	0.049516	0.057941	0.057125
Median	0.053566	0.053828	0.052642	0.058443	0.051650	0.054083	0.052108	0.042230	0.054043	0.051481
Maximum	0.240293	0.156258	0.145689	0.156000	0.195663	0.181776	0.139042	0.195755	0.130443	0.172921
Minimum	0.015951	0.019375	0.027501	0.031597	0.021591	0.017995	0.024843	0.005766	0.024208	0.015091
Standard-deviation	0.028703	0.027063	0.021436	0.023323	0.026710	0.027028	0.022261	0.028829	0.023146	0.029644
Skewness	2.412754	1.312181	1.232168	1.288799	1.981295	1.446648	1.411637	1.330637	0.817145	1.177660
Kurtosis	13.38388	4.574985	4.859581	4.933964	9.231557	5.951411	4.917298	6.321382	3.339712	4.955787
Jarque-Bera	852.2188	60.89102	61.95143	67.49752	354.4737	110.3211	75.70489	117.7407	18.11099	60.92213
Probability	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000117	0.000000
Observations	156	156	156	156	156	156	156	156	156	156
N	174	174	174	174	174	174	174	174	174	174

5. Empirical Results

Given the importance of the anticipation of the opinions in the decision-making on to financial markets; we are inclined in this section to estimate and to explain the existence and the evolution of herding behavior in term of the market conditions. We discuss the results obtained in a similar vein that the methodology presented in this paper.

5.1. Herding behavior of the European investors

After having calculated the $CSAD_{i,t}$ for every sector by the formula (1), we examine the existence of herding behavior by estimating the relation which describes the cross-sectional of returns (the equation 2) by the ordinary least squares (OLS).The table 2 represents the results of the estimation of the equation 1 for every sector being reviewed. A value of the coefficient γ_3 significant and negative (in the equation 1) is an index of the existence of the herding phenomenon. The results of the $CSAD_{i,t}$ represented in the table 2 show that all the values of coefficient γ_3 are statistically significant and negative for all the sectors being reviewed, exceptionally of the consumer goods, for a monthly frequency. Indeed, for this last sector the coefficient γ_3 is negative but not significant, so indicating a proof against herding behavior for this sector. Nevertheless the proof of herding noticed for the rest of sectors underlines that the potential of this behavior differs from one sector to another in terms of the scale of this coefficient. These ideas are drawn from results obtained by Gleasonand al., (2004) who have concluded, in their study; that the choices of the participants' investment are rational for the sectors of the identified European markets.

Table 2. Estimates ($CSAD_{i,t}$) for the shares of each sector:

$$CSAD_t = \gamma_0 + \gamma_1 R_{m,t} + \gamma_2 |R_{m,t}| + \gamma_3 R^2_{m,t} + \varepsilon$$

Absolute deviation\ Industry	constant	$R_{m,t}$	$\|R_{m,t}\|$	$R^2_{m,t}$
Oil&gaz	0.052045***	0.018593*	-0.058206*	-2.127985***
	(0.0000)	(0.06238)	(0.06028)	(0.0012)
BASIC Materiels	0.14378*	-0.233450	0.127834*	-0.375081***
	(0.08673)	(0.0000)	(0.08725)	(0.0000)
Financials	0.048579***	-0.038593*	0.154027**	-1.85173**
	(0.0000)	(0.02540)	(0.01582)	(0.0471)
Industrials	0.050845	-0.15873	0.223801	-0.376921***
	0.0000	0.0000	0.0300	(0.0000)
consumer Goods	0.048179***	-0.010312*	0.000359	-1.34573
	(0.0000)	(0.7296)	(0.9977)	(0.1645)
Health & care	0.045947***	-0.769342***	0.241725**	-0.35671***
	(0.0000)	(0.0000)	(0.0109)	(0.0000)
consumer services	0.047004***	-0.068953***	0.197140**	-1.731485***
	(0.0000)	(0.0078)	(0.0370)	(0.0008)
telecommunication	0.039242***	-0.079603	0.293012**	-0.919458***
	(0.0000)	(0.0493)	(0.0291)	(0.0000)
Utilities	0.049009***	0.186754***	0.081671**	-1.56321**
	(0.0000)	(0.0000)	(0.05111)	(0.0423)
Technology	0.049009***	0.024804**	0.081671**	-0.894356***
	(0.0000)	(0.04651)	(0.05111)	(0.0000)
***, **,* : level of significance respectively at the 1%, 5% and 10%				
The numbers in the parentheses () are p-value				

5.2 Herding behavior under up and down markets

After this analysis, we present the results of the estimation of the specification (1) by using the Ordinary Least Squares technique. The table 3 represents the results from the regression of herding which aims at examining the possibility of asymmetric effects of the herding behavior, for every sector identified and for a monthly frequency during period from 1/01/1998 to 31/12/2010, as well as in bullish and bearish markets. By focusing on the coefficient of market returns once squared, we observe a coherent proof of herding with our previous results. Indeed, with the exception of the coefficient of herding of the consumer goods sector, the rest of sectors expose negative and statistically significant values. More explicitly, most parts of the studied sectors show a negative and significant sign for the coefficient of herding, independently of the fact that the equation is estimated during the bullish and bearish months. Nevertheless for the two sectors health &care and consumer service the negativity and the significance of coefficient of herding is only recorded during the bearish months.

Table 3. Estimates of herding behavior in rising and declining stock markets
Panel-A.2

Absolute deviation \ Industry	*Constant*	$(1-D)R_{m,t}$	$DR_{m,t}$	$(1-D)R^2_{m,t}$	$DR^2_{m,t}$
Oil&gaz	*0.053489****	*-0.200823*	*0.097569***	*-2.839253***	*'-1.670114****
	(0.0000)	*(0.06836)*	*(0.0176)*	*(0.04272)*	*(0.0000)*
BASIC Materiels	*0.047567****	*-0.158690****	*-0.399692****	*-4.881043****	*-0.450188****
	(0.0000)	*(0.0000)*	*(0.0005)*	*(0.0000)*	*(0.0000)*
Financials	*0.051622****	*-0.261907****	*-0.167140****	*-5.409935****	*-1.449985****
	(0.0000)	*(0.0012)*	*(0.0000)*	*(0.0128)*	*(0.0142)*
Industrials	*0.053106****	*-0.136817****	*-0.289491****	*-3.642072****	*-1.582344****
	(0.0000)	*(0.0011)*	*(0.0112)*	*(0.0110)*	*(0.0013)*
consumer Goods	*0.048447****	*0.044222**	*0.095384*	*-1.428672*	*-1.42567*
	(0.0000)	*(0.07435)*	*(0.5495)*	*(0.5410)*	*(0.6130)*
Health & care	*0.046347****	*0.199590*	*-0.258698***	*0.354256****	*-0.564037****
	(0.0000)	*(0.1921)*	*(0.0137)*	*(0.000)*	*(0.0008)*
consumer services	*0.047975****	*-0.015756****	*-0.328996****	*1.938671***	*-0.56723****
	(0.0000)	*(0.0000)*	*(0.0020)*	*(0.0299)*	*(0.0000)*
Telecommunication	*0.040477****	*0.093168*	*-0.363237***	*-1.158828***	*-0.928321****
	(0.0000)	*(0.6836)*	*(0.0176)*	*(0.03272)*	*(0.0000)*
Utilities	*0.046520****	*0.108485****	*-0.471279***	*-4.978252***	*-1.34621***
	(0.0000)	*(0.0000)*	*(0.0116)*	*(0.0619)*	*(0.03505)*
Technology	*0.049839****	*1.18606****	*-0.060835*	*-0.886061***	*-0.917033****
	(0.0000)	*(0.0000)*	*(0.6528)*	*(0.03181)*	*(0.0000)*
Panel B.2					
Industries	*up*	*down*	*difference in coefficients*	*F(2.151)*	*P-value*
Oil&gaz	*-2,839253*	*-1,670114*	*-1,169139****	*33.245*	*(0.0000)*
BASIC Materiels	*-4,881043*	*-0,450188*	*-4,430855****	*10.3423*	*(0.0003)*
Financials	*-5,409935*	*-1,449985*	*-3,95995****	*29.165*	*(0.0000)*
Industrials	*-3,642072*	*-1,582344*	*-2,059728****	*19.21*	*(0.0000)*
consumer Goods	*-1,428672*	*-1,42567*	*-0,003002*	*0.234*	*(0.9671)*
Health & care	*0,354256*	*-0,564037*	*0,918293****	*12.78*	*(0.0012)*
consumer services	*1,938671*	*-0,56723*	*2,505901****	*35.129*	*(0.0000)*
Telecommunication	*-1,158828*	*-0,928321*	*-0,230507****	*17.71287*	*(0.0008)*
Utilities	*-4,978252*	*-1,34621*	*-3,632042****	*23.456*	*(0.0000)*
Technology	*-0,886061*	*-0,917033*	*0,030972*	*11.23*	*(0.09978)*

***, **,*: level of significance respectively at the 1%, 5% and 10%
The numbers in the parentheses () are p-value.

Our results also suggest a stronger evidence of herding in particular during months characterized by reductions for the following sectors: Oil & Gas, Basic Materials, Financials, Industrialists, Telecommunication, and Utilities. In this vein, a test of Fisher is led; for the null hypothesis that the coefficients of herding are equal for the bullish and the bearish months; point towards the rejection of this hypothesis so confirming the asymmetry described above. So, this observation offers a circumstantial evidence to the contributions of the behavioral finance that the mimicry behavior can occur when the uncertainty is eminent on the market.

5.3. Herding behavior in period of high and low volatility

The table (4) represents the results concerning the estimation of the possibility of asymmetric effects related to the herding behavior, for every identified sector and for a monthly frequency during the period from 1/01/1998 to 31/12/2010, during the months characterized by low or high volatilities.

Table 4.Estimates of herding behavior in period of high and low volatility

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

Absolute deviation \ Industry	$D^{Hvolatility}\left\|R_{m,t}\right\|$	$_2(1-D^{Hvolatility})\left\|R_{m,t}\right\|$	$D^{Hvolatility}R^2_{m,t}$	$(1-D^{Hvolatility})R^2_{m,t}$	Constant
Oil&gaz	-0.008362	0.345494*	-2.347988***	2.707790	0.043881***
	(0.8547)	(0.0919)	(0.0000)	(0.2838)	(0.0000)
BASIC Materiels	0.286971*	0.238604	0.353590	3.080916	0.042824***
	(0.0170)	(0.3547)	(0.5340)	(0.2201)	(0.0000)
Financials	-0.027955	-0.282635	-2.748573***	-10.66773***	0.051289***
	(0.8023)	(0.2551)	(0.0002)	(0.0020)	(0.0000)
Industrials	-0.030862	0.228924**	-2.270729***	2.771171	0.051192***
	(0.4272)	(0.01681)	(0.0000)	(0.1432)	(0.0000)
consumer Goods	-0.165776	0.518552**	-4.136192***	-1.425931	0.043128***
	(0.2281)	(0.0433)	(0.0000)	(0.6273)	(0.0000)
Health & care	0.173191*	0.445544*	-1.237762***	-0.228011*	0.042975***
	(0.0574)	(0.0105)	(0.0072)	(0.08739)	(0.0000)
consumer services	0.081851	0.433385**	-1.710090***	-0.414952	0.043861
	(0.4275)	(0.0392)	(0.0030)	(0.8509)	(0.0000)
Telecommunication	0.136872	0.396126	0.134118	-1.079567	0.037584***
	(0.3352)	(0.1524)	(0.8407)	(0.6517)	(0.0000)
Utilities	0.241228**	0.389919	-2.957358*	5.995909	0.044457***
	(0.01775)	(0.2778)	(0.0941)	(0.3224)	(0.0000)
Technology	0.102425	0.856886***	-1.183821*	-5.425242*	.037998***
	(0.4295)	(0.0083)	(0.0789)	(0.1003)	(0.0000)

***, **,* : level of significance respectively at the 1%, 5% and 10
The numbers in the parentheses () are p-value

By focusing on the negativity and the significance of the dummy variable, $D^{Hvolatility}$, attached to the variable $R^2_{m,t}$ we notice strong proofs that the volatility of returns affects the absolute cross-section standard deviation $CSAD_{i,t}$ for the majority of identified sectors, exceptionally the basic materials and telecommunications sectors. The results also show that the herding behavior is more likely to be spread during months characterized by strong volatilities. Indeed only the coefficient of herding attached to the financial sector, shows a negative and statistically significant sign during the months of low volatility.

5.4. Herding behavior in period of high and low of trading volume

In this paragraph, we focus on the analysis of the results concerning the regression of the asymmetric effects related to the herding behavior towards level of trading volume (table 5). The strongest result is that the trading volume affects in an asymmetric way the cross-sectional dispersion of returns that in certain sectors including: the Oil & Gas and the finance sectors during months characterized as well by low and strong trading volume. The significance and the negativity of the variable D^{Hvolum} confirm the proof of the existence of the herding behavior during this period for the industrial products sector. Our study reveals that the herding behavior is well contributed to a bearish situation characterized by a strong volatility and transaction volume.

Table 5. Estimates of herding behavior in period of high and low volume

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

Absolute deviation \ Industry	$D^{Hvolum}\left\|R_{m,t}\right\|$	$(1-D^{Hvolum})\left\|R_{m,t}\right\|$	$D^{Hvolum}R_{m,t}^2$	$\left(1-D^{Hvolum}\right)R_{m,t}^2$	Constant
Oil&gaz	0.092186**	-0.289717**	-2.619519***	-5.339197***	0.054043***
	(0.04506)	(0.01528)	(0.0000)	(0.0075)	(0.0000)
BASIC Materiels	0.498875***	0.320196***	-0.817888	0.475017	0.040918***
	(0.0003)	(0.0074)	(0.2641)	(0.4554)	(0.0000)
Financials	0.260783**	-0.109697**	-1.262772*	-2.315672***	0.048953***
	(0.0573)	(0.0441)	(0.07322)	(0.0078)	(0.0000)
Industrials	-0.132312	1.008448**	-0.932119	-11.34472***	-0.001493*
	(0.7268)	(0.0517)	(0.6973)	(0.0170)	(0.08672)
consumer Goods	0.273141**	-0.003884	0.627737	2.672404*	0.048401***
	(0.0104)	(0.9785)	(0.2159)	(0.0172)	(0.0000)
Health & care	0.119827	0.146858	1.366162**	1.269038*	0.047425***
	(0.2743)	(0.2082)	(0.0339)	(0.0975)	(0.0000)
consumer services	0.175380**	0.150493	1.082857**	1.662140	0.046467***
	(0.0873)	(0.2962)	(0.0277)	(0.1258)	(0.0000)
telecommunication	0.479082**	0.069603	0.607060	6.149091	0.046112***
	(0.0139)	(0.8027)	(0.7482)	(0.1620)	(0.0000)
Utilities	0.115863	0.042062	1.943930**	3.214172**	0.048609***
	(0.3292)	(0.7859)	(0.0136)	(0.0449)	(0.0000)
Technology	0.289602***	-0.004863	0.877439	2.567007	0.051493***
	(0.0090)	(0.9776)	(0.1490)	(0.1418)	(0.0000)
***, **,* : level of significance respectively at the 1%, 5% and 10%					
The numbers in the parentheses () are p-value					

5.5. Herding behavior and financial crisis

Given that the effects of herding behavior can be more intensive during stock market bubbles and crashes, so we are interested to discuss the results of the regression of the extreme market movements to know the sub-prime crisis and Asian crisis and the evolution of degree of herding by the significance analysis of the dummy variable during these periods. The panel A of table (6) represents the results of the degrees of herding during the sub-prime crisis for a monthly frequency for every identified sector between 1998 and 2010. On all the identified sectors, by basing itself on the significance of the variable D^{crisis} sub, we notice that the herding behavior is more intensive for the following sectors: finance, technology and Health & care. This last result confirms us that the herding behavior is influenced by the financial crisis of "sub-primes" in particular for sectors very sensitive to this crisis in terms of interdependence and effect of propagation. On the other hand ,the significance of the dummy variable, D^{crisis}, for almost the majority of the identified sectors (basic materials, consumer goods, health and care, consumers services, telecommunications, Utilities, finance and technology). During the period of the Asian crisis, we confirm on one hand, that the herding behavior is influenced by the Asian crisis and implies the effect of contagion and on the other hand, (Zheng etal., (2010)). We also observe that the sector to consumer Goods shows a proof of herding during the studied crises.

Table 6. Estimates herding behavior during periods of crisis

Panel A.1 Subprime crisis					
Absolute deviation\Industry	$R_{m,t}$	$R^2_{m,t}$	$\|R_{m,t}\|$	$D^{Subprime}$	C
Oil&Gaz	0.021940**	2.619151***	-0.061621**	0.005223	0.051759***
	(0.05653)	(0.0000)	(0.05823)	(0.4041)	(0.0000)
BASIC Materiels	-0.019424	-0.097611	0.378316***	-0.000577	0.042180***
	(0.5266)	(0.8682)	(0.0009)	(0.9265)	(0.0000)
Financials	-0.039859**	1.564800**	0.149198	-0.002388**	0.048907***
	(0.02413)	(0.0539)	(0.1743)	(0.04208)	(0.0000)
Industrials	-0.074321**	0.893114**	0.222649**	-0.005655	0.051443***
	(0.0174)	(0.01589)	(0.0307)	(0.2552)	(0.0000)
consumer Goods	-0.135657	-2.960496	0.230711	-0.028147	0.010823**
	(0.5413)	(0.2003)	(0.4967)	(0.742)	(0.04395)
Health & care	-0.013743	0.809423	0.241607	0.000657	0.045882
	0.6632	0.1138	0.0112	0.9144	0.0000
consumer services	-0.065631**	0.706992	0.202287**	0.003837	0.046524***
	(0.0124)	(0.2071)	(0.0330)	(0.4195)	(0.0000)
Telecommunication	-0.082827**	-0.914202	0.289215**	-0.004576	0.039814***
	(0.0432)	(0.1960)	(0.0318)	(0.5634)	(0.0000)
Utilities	-0.025436	1.668004	0.368459**	-0.003621	0.045959***
	(0.5651)	(0.3388)	(0.0315)	(0.5122)	(0.0000)
Technology	0.214409	-7.346474***	0.736475**	-0.040982**	-0.016429**
	(0.02672)	(0.0000)	(0.0115)	(0.0134)	(0.02151)
Panel A.2 Asiatic crisis					
Absolute deviation\ Industry	$R_{m,t}$	$R^2_{m,t}$	$\|R_{m,t}\|$	$D^{Asiatic}$	C
Oil&Gaz	0.016373*	2.635545***	-0.062474	0.004417	0.051858***
	(0.06675)	(0.0000)	(0.5778)	(0.5017)	(0.0000)
BASIC Materiels	-0.026826**	-0.218167	0.384754***	0.013758**	0.041270***
	(0.03737)	(0.7080)	(0.0007)	(0.0406)	(0.0000)
Financials	-0.045013	1.501889*	0.142056*	0.011822**	0.048215***
	(0.1791)	(0.0593)	(0.01871)	(0.0216)	(0.0000)
Industrials	-0.070903**	0.916849	0.217101**	0.004101	0.050778***
	(0.0223)	(0.1491)	(0.0361)	(0.4435)	(0.0000)
consumer Goods	-0.115216	-3.195977	0.200312	0.034551**	0.006425
	(0.6000)	(0.1629)	(0.5551)	(0.0424)	(0.6358)
Health & care	-0.026859	0.894450*	0.195095**	0.025383***	0.045923***
	(0.3661)	(0.0670)	(0.0325)	(0.0001)	(0.0000)
consumer services	-0.069901***	0.735208	0.192793**	0.002671	0.046970***
	(0.0073)	(0.1896)	(0.0426)	(0.6012)	(0.0000)
Telecommunication	-0.098288**	-1.344733**	0.327438**	0.027480***	0.037349***
	(0.0136)	(0.0545)	(0.0124)	(0.0015)	(0.0000)
Utilities	-0.032758	1.994186**	0.316010**	0.016992***	0.045328***
	(0.4434)	(0.02415)	(0.0592)	0.0037	(0.0000)
Technology	0.134332**	-6.946513***	0.675547**	0.05919*	-0.014742**
	(0.04929)	(0.0000)	(0.0223)	0.07396	(0.02746)
***, **,* : level of significance respectively at the 1%, 5% and 10%					
The numbers in the parentheses () are p-value					

The studies support the contributions of the behavioral finance that a presence filled with uncertainties maybe led to adopt a careful attitude. At the same time the repercussion of herding behavior for the majority of identified sectors during the period of the Asian crisis that during the sub-prime crisis can be attributed to the mortgage and monetary origin of this last one.

6. Conclusion

Our purpose in this paper was to examine empirically the existence of herding behavior and its dynamics on the developed market such as the European market. According to the suggestion of (Bikhchandani and Sharma, 2001) that a group may more privilege a herding behavior if it is homogeneous enough, given that every member is confronted with a problem of similar decision, and every member can observe the transactions of the other members of the group. We were interested in the examination of herding behavior at the level of 10 sectors composing the Stoxx 600 index and by using data at the level of companies during the period from January, 1998 to 2010.

For the majority of the identified sectors, this study asserts a proof of the existence of herding behavior for a monthly frequency with the exception of the sector of the consumer goods. This observation is against that obtained by Gleason and al., (2004) who conclude from it, in their study; that the choices of investment of the participants are rational for the sectors of the European markets retained Subsequently, we focused on the herding behavioral research in terms of the market conditions, more explicitly we considered the asymmetric effects possible of herding behavior based on the returns, the volatility of the returns and the transaction volumes.

The regression of the herding index in bullish and bearish markets proves unquestionably the existence of herding regardless of the fact that the equation is estimated during the bullish and bearish months. Also, a stronger evidence of herding in particular during months characterized by reductions for certain sectors is registered. So, a Fisher test for the null hypothesis proves that the coefficients of herding are equal, confirming the asymmetry of gregarious behavior relative to the direction of the returns.At the same time the regression of the herding index in a period of strong and low volatility proves unquestionably the existence of a significant herding during months characterized by a strong volatility for all the sectors treated even for the sector of the consumer goods. Nevertheless, the regression of the asymmetric effects of herding behavior towards the level of trading volume asserts that the effects of herding are more contributed to the excess of volatility than with the excess of trading volume.Finally, the regression of the effects of herding during the periods of the recent financial crisis 2007-2008 proves that the herding behavior is influenced by the sub-primes crisis especially in the sectors of the finance and of the technology which is very sensitive to this crisis in terms of interdependence and of contagion effect.Future research should attempt to distinguish between institutional and individual investors because different types of herding behavior may be exhibited.

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