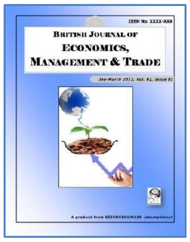

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Testing Herding Effects on Financial Assets Pricing: The Case of the Tunisian Stock Market

Abderrazek Elkhaldi[1*] and Yosra Ben Abelfatteh[2*]

[1]Department of Finance, Faculty of Economic Sciences and Managements of Sousse, University of Sousse, Tunisia.
[2]Master in Finance, Faculty of Economic Sciences and Managements of Sousse, University of Sousse, Tunisia.

Authors' contributions

This work was carried out in collaboration between the two authors. Author AE designed the study, performed the statistical analysis and managed the implications of the study. Author YBA managed the literature review and wrote the first draft of the manuscript. Both two authors read and approved the final manuscript.

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ABSTRACT

This paper highlights the contribution of behavioral finance to explain market anomalies since the eighteens. Particularly, we use herding behavior approach to elucidate financial asset pricing. Our study is based on Hwang and Salmon methodology [1], in which we use a state space approach based on Kaman's filter to detect herding behavior in financial market [2]. We use a data of ten listed firms in the Tunisian Stock Exchange Market during the period June 2002 and May 2013. Our results seem to confirm that Tunisian Stock Exchange Market is affected by herding anomaly and that securities return must not deviate significantly from the overall profitability of the market. This can be explained by the fact that in such situation, investors tend to ignore their own information and pass align their investment decisions according to general market tendency.

Keywords: Herding effects; assets pricing; herding mania; behavioral finance.

**Corresponding author: Email: Abderrazek.Elkhaldi@gnet.tn, yosra.benabdelfatteh@yahoo.fr;*

1. INTRODUCTION

Efficient market hypothesis represents one of the main pillars of modern finance. It takes its origin from the monumental works of Bachelier in his mathematical thesis called the theory of speculation [3]. In this context, Fama has built the theoretical body of efficiency hypothesis based on the assumption of agent rationality. However, this hypothesis has been overly contested and rejected by several studies [4]. This rejection of informational efficiency paradigm was driven by submerged critics against agent rationality assumption. Those observations were qualified as anomalies, since researchers didn't find an explanation to their existence in a context of market efficiency. Hence, Shiller was a pioneer by addressing critics to market efficiency hypothesis and bringing out several market anomalies [5]. In fact, variance bound tests noted that stock prices are largely more volatile than dividend forecasting. Excess volatility has caused a dramatic damage to market efficiency theory. In fact, this problem has been more serious than other anomalies such as January effect, holydays effect or day of the week effect. Excess volatility occurs when prices tend to change independently of fundamentals. It has been often guided by sunspot, fads and investors' spirit. Therefore, stock market anomalies have opened a firing window against classical finance and offered opportunities to alternative explanations of stock market performance. Further, this new paradigm based on behavioral finance does not believe in investors' rationality as a central proposition. However, it assumes that market anomalies find their origins in heuristic simplification, excess of confidence, emotions, self-control and herding. These behavioral biases prevent investors from calculating assets' fundamental values. Thus, persistent gaps between observed prices and fundamental values take place. This excess volatility of stock prices compared to their fundamentals is one of the main proofs of agent irrationality behavior, which represents a direct violation of market efficiency hypothesis. Indeed, financial market anomalies raised researchers' interest to find explanations and to propose alternative models that explains those observations, such as behavioral approaches. This new research field was justified by the fact that all finance, economics and management are human sciences.

Behavioral finance became an alternative to classical theory, based on both human and psychology. It is also based on investors' irrationality and their tendency to build their decisions according to beliefs, emotions and psychology rather than fundamentals. Olsen maintains that behavioral finance doesn't aim to define a rational behavior but to predict its systematic and financial implications [6]. In another word, it is admitted that behavioral finance could provide significant explanations of market efficiency and pricing.

Herding is one of the main fields of behavioral finance. Herding can be defined as a situation called following the crowd which consists on leaving private information (those who determine market efficiency and agent rationality hypothesis) to imitate others strategies [7].

The purpose of this paper is to test herding effects on financial assets pricing in the case of the Tunisian stock market. Particularly, we pay attention to herding behavior phenomenon as a sign of market anomaly commonly known as excess volatility. We apply a non linear model based on Hwang and Salmon stochastic approach called state space model. Hence, we exclude linear specifications such as Christie and Huang as much as it has been proved that it is unable to detect herding in stock market in both normal and extreme market conditions [8]. The originality of this specification lies in the possibility to compute the value of a latent variable using observed one. The originality of our study in comparison to previous works for the case of the Tunisian stock market is the use of daily data for a period of 12 years, which provides 27,170 observations for 10 listed firms. In this condition, our study will be organized as follows:

Second section will provide both a literature and an empirical review of herding behavior studies. Section 3 will be dedicated to Model presentation and methodology justification. Section 4 and 5 will expose respectively data and sample, then present results and interpretation. Finally section 6 concludes.

2. LITERATURE REVIEW

2.1 Theoretical Literature

Herding behavior occurs when investors decide to imitate others decisions, or when they simply observe market tendency rather than following available information or constructed expectations. Susskind defines Herding behavior as a set of individual behaviors presenting correlations [7]. However, many investors may buy or sell the same securities, simply because they have received correlated information. They then act independently. Herding behavior appears when investor is intuitively ready to make a financial investment decision independently of all other investors' decisions, but he changes his position when he finds that they have left their position even when he holds private information.

Herding behavior can be cleaved into two different types. First, we find misleading Herding behavior that takes place when a hole of common objectives is shared by a group and all members of the group have the same information. In such case, every investor makes his own decision independently. However, it is possible to see many similar behaviors that can be assimilated to herding. Moreover, this behavior is based on fundamentals changes such as a sudden rise in interest rates. Second, we find intentional herding that occurs when investors imitate intentionally and voluntarily other investors' behavior. This form of Herding behavior often refers to a strategy known as positive feedback [9]. It consists on buying securities whose earnings have exceeded market benchmark. In this case, herding seems to be an irrational behavior that oppose financial markets efficiency hypothesis.

2.2 Empirical Literature

It is important to consider that theoretical backgrounds concerning herding behavior have been initiated by Banerjee and Bikchandani and Hirshleifer and Welch [10], [11]. These studies have considered herding behavior in an abstract environment in which more informed agents (those detaining private information) have the opportunity to make consecutive decisions. They conclude that such agents tend to adopt the same behavior even if this decision is in contradiction with the information they hold. All they do is copying the others' actions. Lakonishok, Shleifer and Vishny have proposed a statistical measurement of herding behavior [12]. In fact, they have calculated a mean tendency of a group to buy (or to sell) shares at the same time compared to the situation where every investor have to negotiate individually his position. Indeed, this statistical measurement evaluates negotiation profiles correlations for a group of investors having similar portfolios. This technique has been often criticized because it is based on investors' number and ignores transaction volume effects. This leads Wermers to propose another indicator of herding behavior that integrates not only group's common market position but also transaction volume significance [13]. He called this indicator as portfolio change measurement. It is often used to study correlated negotiations in order to evaluate how assigned similar portfolios tend to go at the same direction.

Based on those different indicators, many studies have been performed in order to detect herding behavior in financial markets. Avery and Zemsky, Lee, Cipriani and Guarino have studied the situation where both informed and uninformed traders have to deal with unknown securities managed by market makers according to daily transaction volumes and orders. This situation makes difficult the emergence of herding behavior [14-16].

Avery and Zemsky maintain that herding behavior occurs not only due to uncertainty about asset's pricing but also when uncertainty characterizes model parameters or the occurrence of an informational event [14].

In the case of funds managers, many studies have focused on managers' conformism when dealing with securities. Results have shown that fund managers are largely hostage of herding behavior. In this context, Friends et al. have found that institutional investors often imitate their successful competitors' decisions [17]. This behavior is called: *« follow the leader ».* Lakonishok, Shleifer and Vishny have made a survey based on 341 mutual funds during the period 1985-1990 [12]. Their results concluded the existence of a Herding behavior caused by securities with low transaction volume. Werners et al. maintain that herding behavior among funds managers is clearly perceivable relatively to past assets price increase rather than short terms decreases [13].

Chang et al. have analyzed different operators in several international stock markets (Unites States, Hong Kong, South Korea, Taiwan, China and Japan) during the period 1963 to 1997 [18]. Authors tried to exhibit Herding behavior. Their results have shown that both American and Chinese markets are not affected by herding behavior, partial evidence was found in the Japanese market and a significant result in emerging markets especially for South Korea and Taiwan.

Demirer, Gubo and Kutan have used Christie and Huang (1995) and Chang et al. (2000) methodologies in order to detect Herding behavior in international stock markets of six different regions (Africa, Asia, Western Europe, Central Europe, Latin America, and Middle East) [19]. They tested whether earnings follow CAPM's statements. They concluded that Herding behavior exists in both Asia and Middle East markets.

Hachicha et al. have tested herding at a monthly horizon using both Tunindex and BVMT indexes during the period from 02/01/1999 to 31/12/2005 [20]. They found that herding exists whatever the market condition. They divided herding effect into three components: Constant term showing herding for all market conditions, error term reflecting investors anticipations and a third component reflecting dependency between current and previous herding.

Khan and Park have studied herding contagion between Southeaster Asian countries (Thailand, Malaysia, Indonesia, Korea, and the Philippines) during and after 1997 Asian financial crisis [21]. Using macro models in order to capture contagion effect, they found a strong evidence of herding contagion between the studied countries.

More recently, Cipriani and Guarino have developed a theoretical model of Herding behavior and then they have tested it for data carried from the NYSE [22]. They have focused on traders' Herding behavior during a transaction day by focusing on an only asset during many days.

Al-Shboul has studied herding for the case of the Australian stock market during the period 2003 and 2010 using daily and monthly data of 251 Australian listed firms [23]. Using Christie and Huang methodology, he didn't find any herd behavior for both daily and monthly data. However, when using Chang, Cheng and Khorana, he found evidence of herding in the up and the down market, which indicates that Australian investors tend to show an asymmetric herding with respect to financial crisis.

Al-Shboul has studied herd behavior in the Jordanian equity market before and after the financial crisis of 2008 [24]. He applied both Christie and Huang and Chang, Cheng and Khorana methodologies. For the first specification, herding was not found in normal and extreme market conditions.

The second model using Chang, Cheng and Khorana confirms the absence of linear herding in the Jordanian market before and after the crisis. However, a non linear herding was found for the case of nonfinancial firms.

In a colossal study, considering 35,328 different stocks, Chen has tested herding for the case of 69 countries over 10 years [25]. He used three different approaches; Christie and Huang, Cheng and Khorana and the methodology of Hwang and Salmon. He found that the first approach is unable to detect herding in all markets (developed, emerging and frontier). Then he concluded that only nonlinear models of Cheng, and Khorana and Hwang and Salmon are able to detect herding globally.

3. MODEL PRESENTATION

In this paper, we adopt the methodology of Hwang and Salmon (2004). They use cross-sectional dispersion of the systematic risk coefficient called beta that the authors call "beta herding" measurement. This technique allows us to separate changes caused by fundamentals from those due to Herding behavior. It also offers the possibility to detect herding comparatively to other factors. The main idea of this test is to prove that investors are used to ignore their own convictions in order to follow market's tendency even though they have to go in contradiction with their own predictions.

Hwang and Salmon (2004) focused on Herding behavior in logic of market performance according to many factors such as size, growth, value for a sample of securities belonging to S and P 500 index and a sample of securities belonging to KOSPI for Korean stock market.

The classical definition of Herding behavior maintains that investors imitate one another by buying and selling the same securities at the same time. However, in our study, we consider that herding behavior occurs when investors try to follow global market performance. Henceforth, investors tend to build their strategies on the basis of global market performance, macroeconomic factors and competitors' management.

Indeed, Herding behavior is synonymous of a bad asset valuation since we have to make irrational decisions basing on biased opinions and beliefs. As a consequence, herding behavior makes more difficult assets pricing and earning anticipation.

In order to detect Herding behavior impact in the earning-risk relationship, Hwang and Salmon (2004) examine the CAPM in a context of Herding behavior. In fact, when investors follow global market tendency to make their decision on buying or selling assets, market Betas (β_{imt}) tend to deviate from their equilibrium values. In another word, cross-sectional dispersions of the β_{imt} become lower compared to equilibrium situation. Hence, Herding behavior in comparison to market portfolio can be defined as a decrease of the estimated market beta ($\hat{\beta}_{imt}$). Consequently, a fast and significant decrease of the estimated market beta variance indicates a systematic risk gathering and aggregation around the value of one, which means a more and more alignment in assets pricing around market performance. In this situation, we can say that herding behavior takes place.

In an equilibrium situation the CAPM is presented as follows:

$$E_t(r_{it}) = \beta_{imt} E_t(R_{mt}) \tag{1}$$

Where,

r_{it} and r_{mt} represent respectively excess return of asset « i » and the market *at time t*;
β_{imt} is a measure of systematic risk;

$E_t(r_{mt})$, is a conditional probability *at time t*

In the case of the CAPM specification, we have to estimate β_{imt} in order to calculate the value of an asset *i*. However, when investors' beliefs follow global market performance beyond equilibrium situation, investors tend to confound individual assets earning to the market one. As a consequence, we find a new biased market beta.

In such case, a Herding behavior can be highlighted in the corresponding market. Since this kind of behavior takes place especially in the context of crisis, it is expected that beta dispersion have to decrease significantly during these periods.

However, although conventional CAPM supposes that β_{imt} are constant, several empirical studies have shown that betas are not constant as maintained by Harvey and Ferson and Harvey and Ferson and korajczyk [26-29]. Changes in betas are mainly explained by industry mutations or debt level increase. Those changes are infrequent and could not occur in short time horizon. This leads Hwang and Salmon (2004) to conclude that betas changes are caused by behavioral anomalies rather than fundamentals variations. They maintain that a significant change in betas among the time reflects a change in the level of investors' mood. Therefore, Herding behavior among market portfolio does not preserve CAPM equilibrium. Consequently, β and $E_t(r_{it})$ will become biased.

For the equilibrium situation, Hwang and Salmon (2004) assume that the following relationship can be accepted in the context of Herding behavior among market performance:

$$\frac{E_t^b(r_{it})}{E_t(r_{mt})} = \beta_{imt}^b = \beta_{imt} - h_{mt}(\beta_{imt} - 1) \tag{2}$$

Where,

h_{mt} is a parameter detecting Herding behavior occurrence in the market. It changes over time. When $h_{mt} \leq 1$, Herding behavior will be conditioned by market fundamentals. $h_{mt}=0$, in this case, $\beta^b_{imt}=\beta_{imt}$, herding behavior does not exist and CAPM's equilibrium will be maintained. Finally, $h_{mt}=1$, we have $\beta^b_{imt}=1$, this means that asset's expected excess return will equal that of market portfolio. In another word, $h_{mt}=1$ means an absolute case of Herding behavior around the global market performance. Hence, all assets are following the same tendency with the same magnitude than market portfolio. In general, when $0<h_{mt}<1$, Herding behavior exists, but his magnitude depends on h_{mt} value.

4. DATA AND SAMPLE

In this study, we use stock returns of ten companies included in the Tunisian stock market index (BVMT-index). The list of companies is presented as follows: ATL (leasing), ATTIJARI BANK (banking), BH (banking), ELECTRO STAR (electronic industry), SOTUTEL (Cabling and networking), BIAT (banking), TUNISAIR (airline service), STB (banking), UIB (banking) and la BT (banking). Tunisian stock market includes 59 companies, while BVMT index is composed by 34 firms. In order to get a continuous and significant data, we have retained companies with most available data and quotations. All data were extracted from Tunisian stock exchange market.

Individual returns are calculated as follows:

$$R_{it} = \frac{\left(P_t - P_{t-1}\right)}{P_{t-1}} \tag{3}$$

Where, P_t is the closing price of the asset *i* at time *t*.
Market return is calculated as the average of individual returns:

$$R_{mt} = \sum_{i=1}^{N} \frac{R_{it}}{N} \tag{4}$$

N is the number of companies composing the sample.

Data cover the period lying between the 3rd of June 2002 and the 31st of Mai 2013, which represents a period of 11 years daily frequency (5 days week). Then we get 27170 observations for the 10 companies of the sample.

After market earnings calculation, our attention will focus on herding behavior towards market benchmark. In this condition, our approach based on Hwang and Salmon (2004) one, will be subdivided into two steps. In a first step, we estimate market beta for all assets composing our sample. Then, beta values will be used to calculate cross-sectional standard deviations of estimated betas.

In a second step, we run Herding behavior measurement toward market benchmark. In fact, herding behavior toward market performance will be captured by h_{mt}. However, we must indicate that both h_{mt} and β_{imt} are two unobservable values that we try to estimate.

As for the first step, we use market model to estimate $\hat{\beta}^{b}_{imt}$ using Ordinary Least Square specification (OLS). We consider daily data to estimate monthly values of $\hat{\beta}^{b}_{imt}$.
Market model is presented as follows:

$$R_{itd} = \alpha^{b}_{it} + \beta^{b}_{imt} R_{mtd} + \varepsilon_{itd} \quad (5)$$

td indexation means that data are daily during month *t.*

Market excess return is the average return of the 10 considered assets of the sample. It also means the built market benchmark according to the considered sample of our study.

For each month and during all the period, we estimate market model for the 10 studied assets in order to get market beta. So, we run market model 1310 times (131 regressions for each asset) in order to get 131 monthly values of market beta. Once estimated, we have to calculate the cross-sectional standard deviation for each value of beta. This statistic is calculated as follows:

$$Std\left(\beta^{b}_{imt}\right) = \sqrt{\frac{\sum_{i=1}^{N}\left(\beta^{b}_{imt} - \overline{\beta^{b}_{imt}}\right)^{2}}{N}} \quad (6)$$

Where, $\left(\overline{\beta^{b}_{imt}}\right) = \frac{1}{N}\sum_{i=1}^{N}(\beta^{b}_{imt})$ and N_t is the number of considered assets for month *t*.

Since β^{b}_{imt} cross-sectional mean β^{b}_{imt} (or β_{imt}) is always equal to 1, we get :

$$\begin{aligned} Std\left(\beta^{b}_{imt}\right) &= \sqrt{E\left(\left(\beta_{imt} - h_{mt}\left(\beta_{imt} - 1\right) - 1\right)^{2}\right)} \\ &= \mathrm{E}\left(\left(\beta_{imt} - 1\right)^{2}\right)\left(1 - h_{mt}\right) \\ &= \mathrm{Std}\left(\beta_{imt}\right)\left(1 - h_{mt}\right) \end{aligned} \quad (7)$$

Where *E (.)* and *Std (.)* respectively represent the cross-sectional expected value and standard deviation. The first part of the equation represents betas' standard deviation, while the second one is relative to the direct function of Herding parameters. As Hwang and Salmon (2004), we suppose that *Std* (β_{imt}) does not exhibit any systematic movement and that *Std* (β^{b}_{imt}) changes can be attributed, at a short run time, to changes in h_{mt}.

In order to extract h_{mt} de *Std* (β^{b}_{imt}), we have to run a logarithm transformation to the previous equation (7):

$$\log [Std(\beta^{b}_{imt})] = \log [Std (\beta_{imt})] + \log (1-h_{mt}) \quad (8)$$

With:

$$\log [Std (\beta_{imt})] = \mu_m + v_{mt} \quad (9)$$

Where,

$$\mu_m = E [\log [Std (\beta_{imt})]$$
$$v_{mt} \sim iid\ (0, \sigma^{2}_{mv})$$

And,

$$H_{mt} = \log(1-h_{mt})$$

In this condition, H_{mt} varies overtime and has a dynamic process. Hwang and Salmon (2004) suppose that H_{mt} AR(1), then they get the following model :

$$\log[Std(\beta^{b}_{imt})] = \mu_m + H_{mt} + v_{mt} \quad (10)$$

$$H_{mt} = \varphi_m H_{mt-1} + \eta_{mt}$$

Where η_{mt} is *iid* (0, $\sigma^2_{m\eta}$).

The authors get a state-place model that can be estimated with Kalman filter methodology. The authors emphasize that the whole interest of this specification is to study the latent variable movements (H_{mt}) despite the important significance of both μ_m and v_{mt}. Indeed, when $\sigma^2_{m\eta} = 0$, equation (10) becomes:

$$\log[Std(\beta^{b}_{imt})] = \mu_m + v_{mt} \quad (11)$$

This means that there is no herding in this case (H_{mt}=0). However, a significant value of $\sigma^2_{m\eta}$ means that herding exists. Furthermore, a significant value of φ supports this observation. Hwang and Salmon (2004) assume that the herding process H_{mt} should be stationary in order to avoid an explosive process of herding towards market portfolio. Authors require that $|\varphi| \leq 1$.

In order to measure herding extent, we use Kalman filter to estimate parameters of equation 10. In a first step, this filter enables us to separate observed variables (called signal) from latent ones (called internal state). Kalman filter can be presented as an iterative algorithm that aims to estimate unobservable (latent) variables. The program code can be written as follows:

```
@signal logracine=c(1) +HTT+[var=exp(c(2))]        (12)

@state HTT=c(3)*HTT(-1)+[var=exp(c(4))]            (13)
```

The first equation is called the predictive step. It produces estimates of the current state variables, along with their uncertainties. In E-views program, we note this first step as HTT or SV1, while the second is called state equation. In E-views algorithm, the first command indicates that dependent variable is observed while second one clarifies that independent variables are not.

5. RESULTS AND INTERPRETATIONS

For the case of the Tunisian stock market, results of herding space-state model are recapitulated in Table 1. We note that the model filters out 131 observations (131 months). Estimated results were reached after 11 iterations with a maximum likelihood of -86.72.

Coefficient c (1) corresponds to μ of equation (10). This coefficient is significant at a significance level of 5%.

Coefficient c (2), refers to the logarithm of the variance of log [Std (β_{imt})] relative to equation (9). At a same time, it represents the error term of equation (10). In fact, the estimated variance of the error term v_{mt} is written in an exponential form during space-state modeling, in order to avoid negative values. Hence, estimated value of σ^2_{mv}=e(-1.858459)=0.156. As a consequence, σ_{mv}=0.39497.

Coefficient c(4) represents the logarithm of the error term variance in the « state equation » (log ($\sigma^2_{m\eta}$). So we can write: $\sigma^2_{m\eta}$=exp(-3.177272)=0.0417. Then $\sigma_{m\eta}$=0.2042. This estimated value of the standard deviation of η_{mt} is statistically and significantly different from zero at 5% significance level. It indicates that herding exists towards market's benchmark for the case of the Tunisian stock market for all considered assets of our sample. In fact, H_{mt} of equation (10) is statistically and significantly different from zero.

This result is approved by the significant value of c (3) that corresponds to the term φ_m of equation (10). φ_m is equal to 0.7068. It is lower than one. This means that H_{mt} is stationary and then that herding towards market performance is strongly significant in the Tunisian stock market during the considered period for all studied assets. The result joins those of Hachicha et al. (2008) confirming the existence of herding behavior and maintaining that there is at least one investor who imitates the actions of the others.

Table 1. Herding space-state model for Tunisian stock market benchmark

	Coefficient	Std.Error	Z.Statistic	Prob
C(1)	-0.136867**	0.069695	-1.963797	0.0496
C(2)	-1.858459***	0.288502	-6.441760	0.0000
C(3)	0.706896***	0.226042	3.127275	0.0018
C(4)	-3.177272***	1.119482	-2.838162	0.0045

*, **, *** *significant at 10,5 and 1% level respectively*

Moreover, Fig. 1 shows herding statistic measure evolution ($h_{mt}=1-exp(H_{mt})$) in the Tunisian stock market during the period lying between June 2002 and May 2013. This value of h_{mt} is calculated on the base of market model beta. Herding statistic shows that herding varies overtime and that many changes have occurred during the considered period. At many times, h_{mt} was positive, while for many others, it was very low and even negative. We can also note that for all the period, h_{mt} did never reach the value of 1 which means that we did never meet an extreme case of herding towards market benchmark during the period of our study.

The most important value of h_{mt} was 0.30. It was reached during the month of June 2012. The least value was -0.39 during the month of September 2002. Moreover, Fig.1 emphasizes on different cycles of herding and reversed herding towards market benchmark.

In fact, herding and reverse herding are two mechanisms that act synergistically. In a one hand, reverse herding is synonymous of mean reversion of β_{imt} into long run equilibrium values. While herding occurrence is confirmed, reverse herding must take place gradually in order to make a systematic adjustment based on under and over valuation towards CAPM's equilibrium because at long term, prices tend to reach equilibrium values.

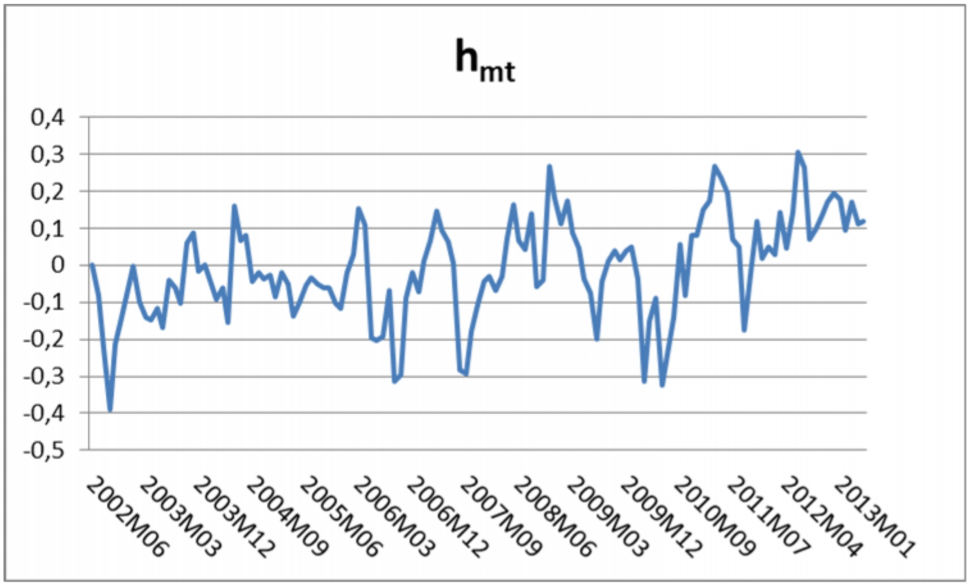

Fig. 1. Herding towards Tunisian market benchmark

Furthermore, Fig. 1 shows that herding behavior is often concomitant with a decrease of individual return dispersion around market benchmark. Hence, herding requires that individual returns must not significantly differ from global market return. In such context, investors are used to ignore their own information and to align their decisions with general market consensus. Consequently, we could consider herding occurrence as a decreasing factor of individual assets pricing dispersion around the market's mean value representing market benchmark.

6. CONCLUSION

In the present paper, we tried to explain market exposure to herding especially when investors tend to imitate others' decisions relying on a golden rule that it is better to be wrong together than to be right all alone. In fact, herding has been considered by several researchers as the main explanation of observed excess volatility. Our results confirm that Tunisian stock market is affected by a herding behavior. The gap we've found between observed values and fundamental ones gives an explanation of excess volatility existence. This result confirms the study of Abaoub and Taamalli based on all listed companies in the Tunisian stock market during the period 2000-2005 [30]. However, it doesn't match the result of Naoui and Khaled that studied the case of 20 listed companies in the Tunisian stock market and didn't find a herding behavior during the period 2006-2008 [31]. Moreover, we join results of Hachicha et al during the period 1999-2005 [20].

In addition, our study based on a state space model and using Calman's filter has the originality of using daily data for about 12 years with a sample of 10 listed firms. It remains one of the most consistent studies on the Tunisian stock market. The study confirms also that nonlinear models are more powerful to detect herding behavior.

The observation of the figure above confirms that herding is persistent for all the considered period and especially after 2008, which means that investors tend to imitate each others in both normal and extreme conditions.

It should be noted that our research interests all investors, market authorities and researchers in financial and management fields. In fact, investors are continuously concerned to know market efficiency degree and to identify all kinds of anomalies that could affect the outcome of their investments. They must know when they would have better to follow other investors or to make their own decision independently.

Similarly, market authorities need to identify herding in order to make the suitable measures to avoid slips and malfunctions.

Researchers in management and financial market fields need also to identify the best and powerful models to detect herding behavior in financial market and to propose alternative ones in order to extend researches in this domain.

Finally we have to maintain that Tunisian Stock market remains one of the smallest financial centers in the word with a daily transaction volume of about 5 millions of Tunisian Dinars (about 2.7 millions of Euros) and a weak liquidity ratio. However, this market is dominated by institutional and collateral investors who guide opinion and influence price making. Indeed, smaller investors tend continuously to build their transactions according to available information about collateral investors.

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COMPETING INTERESTS

Authors have declared that no competing interests exist.

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