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Modeling Informational Cascade Via Behavior Biases

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This study contributes to the debate concerning individual investors' herding behavior with new evidence from the Toronto stock market. We use four different methodologies suggested by Lakonishok, Shleifer and Vishny (1992), Christie and Huang (1995), Chang, Cheng and Khorana (2000) and Hwang and Salmon (2004) to test whether returns don't behave as predicted by the capital asset pricing model. We also develop a new measure of herding behavior based on the cross sectional deviation of volumes. This measure allows us to model the cycle of informational cascade and explain it, from volume approach, by the alternation between two psychological biases: herding behavior and the disposition effect. The analysis is carried out using monthly data from January 2000 to December 2006 for the S&P/TSX60 and its components as the most representative stocks. Our results show that the progressive formation of cascade is due to the presence of herding, while the rapid fall is explained by the rising of the disposition effect.

Field of research: Disposition effect, herding behavior; informational cascade, returns, trading volume.

1. Introduction

The behavioral finance theory uses herding to describe the correlation in trades ensuing from investors' interactions. This concept suggests that it is reasonable for less sophisticated investors to imitate market gurus or to seek advice from victorious investors, since using their own information will incur less benefice and more cost. The consequence of this herding behavior is, as Nofsinger and Sias (1999) noted, “A group of investors trading in the same direction over a period of time.” Empirically, this may lead to observed behavior patterns that are linked across individuals and that fetch about systematic, erroneous decision-making by all populations (Bikhchandani, Hirshleifer, and Welch, 1992). So, in addition to news per se, investors’ trading behavior can cause stock prices to deviate from their fundamentals. As a result, stocks are not appropriately priced. There are varieties of herding models that have been presented. Generally, we separate models that produce rational prices in efficient markets from those that can potentially give rise to price bubbles and crashes that are due to temporary price pressures pushing market prices away from fundamental values.

The main rational models are those of Froot, Scharfstein, and Stein (1992) and Hirshleifer, Subrahmanyam, and Titman (1994). These models attribute herding to investors following the same sources of information. So, investors trade rationally in response to new information and the resulting herding has a contemporaneous price

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impact as price pressures shift prices from some initial level towards their fundamental value. However, in both models, herding finishes when the information is fully reflected in prices.

The irrational models are those from the literature on fads and cascades. Some early work on fads in security markets appears in Dreman (1979), Friedman (1984), and more recently in Barberis and Shleifer (2003). A variation on the work on fads is the informational cascades model presented by Banerjee (1992) and Bikhchandani, Hirshleifer, and Welch (1992). Essentially, these studies hypothesize that certain assets become popular for non-informational reasons and that investors may simultaneously search for acquiring large holdings of these assets. The joint action of many investors creates momentary price pressures that can drive prices up to unrealistically high levels so long as these stocks stay in vogue. When an asset ended to be in vogue, their prices may fall precipitously. The rise and fall of prices may not be associated with any relevant information arriving in the market. An important feature of these models is that individual agent behavior is completely rational, but the framework in which agents operate can produce prices that do not correspond to fundamental value.

Avery and Zemsky (1998) analyse the theoretical relations between herding (an informational cascade) and the informational efficiency of the market. They consider a context where each agent receives an independent, but noisy, signal of the true value of a financial asset. Herding occurs if the agents ignore their signal and decide to buy or sell based on the trend in past trades.

There are in other stream in herding literature review which is based a compensation-reputation scheme. So, an investor’s compensation depends on how his performance compares to other investors’ performance and on whether deviations from the consensus are potentially costly (Scharfstein and Stein (1990), Roll (1992), Brenan (1993), Rajan (1994, Trueman (1994) and Maug and Naik (1996)).

Considered as a non-quantifiable behavior, herding cannot be directly measured but can only be inferred by studying related measurable parameters. The studies conducted so far can be generally classified into two categories. The first category focuses directly on the trading actions of the individual investors. Therefore, a study on the herding behaviour would require detailed and explicit information on the trading activities of the investors and the changes in their investment portfolios. Examples of such herd measures are the LSV measure by Lakonishok, Shleifer and Vishny (1992) and the PCM measure by Wermers (1995).

In the second category, the presence of herding behaviour is indicated by the group effect of collective buying and selling actions of the investors in an attempt to follow the performance of the market or some factor. This group effect is detected by exploiting the information contained in the cross-sectional stock price movements. Christie and Huang (1995), Chang, Cheng and Khorana (2000) and Hwang and Salmon (2001, 2004, 2006) are contributors of such measures.

In this paper, we study herding behavior in the Toronto Stock Exchange (TSX). Some characteristics of TSX suggest that herding could take place there. Despite rapid growth in trading volumes and market capitalization during the past decade, TSX cannot be characterized as being a particularly efficient market. Apart from energetic corporations, the publicly traded companies in TSX are small in terms of market capitalization and number. So, it can be room for informational asymmetries that trigger herd behavior in the stock exchange.

In our empirical evidence we apply on our data the main four measures of herding behavior of Lakonishok, Shleifer and Vishny (1992), Christie and Huang (1995), Chang, Cheng and Khorana (2000) and Hwang and Salmon (2004). We use monthly stock returns from January 2000 to December 2006. Our findings indicate evidence of herding using LSV (1992) and HS (2004) while basing on cross sectional dispersion shows that the Toronto stock exchange doesn't exhibit a herding effect.

To improve the existent measures and to investigate the herding towards the market in major financial markets form the main purpose of our paper. There are two specific objectives to this study. Firstly, we intend to propose a new herd measure to detect the degree of herding in financial market. In constructing this measure, we take as a starting point the model of Christie and Huang (1995), but we employ a proxy pioneered by Lakonishok, Shleifer, and Vishny (1992) which is the trading volume. Secondly, we attempt to use this measure in modelling understanding the cycle of informational cascades. Our results show that return is caused partly by the disposition effect of the past period and the herding behavior of the before past period. We find also that the progressive formation of cascade is due to the presence of herding, while the rapid fall is explained by the rising of the disposition effect.

The remainder of this study is organized as follow: the second section summarizes the main studies in financial literature that investigates for the existence of herding behavior in various stock markets. The third section presents our database and the used methodology. Finally, the last section concludes.

2. Literature review

Several empirical papers have tested for herding behavior. Depending on the types of data being used in developing the models for herd measure, we can broadly identify two main categories of studies.

2.1. *Lakonishok, Shleifer and Vishny (1992)*

Considering the importance of the capital managed by institutional investors, several works are devoted to the study the herding behavior of fund managers. Lakonishok, Shleifer and Vishny (1992) propose a statistical measure of herding behavior (hereafter LSV) as an average tendency of fund managers group to buy or to sell particular stocks at the same time, compared to the situation where every one acts independently.

The LSV measure is based on transactions of a sub group of participants during a given period. it is founded on the difference between the observed probability that a given stock can be sold (or bought) by a group fund manager during a given quarter and the probability that the same stock is sold (or bought) if every manager acts independently. Authors include an adjustment factor in order to correct the measure bias of the couple stock-quarter where assets are not traded by a sufficient number of participants. When this measure is significantly different from zero, we can confirm the existence of herding behavior.

LSV define the herding measure, $H_{i,t}$, for stock *i* and period *t* as follows:

$$H_{i,t} = \left| p_{i,t} - E\left[p_{i,t} \right] \right| - AF_{i,t} \quad (1)$$

Where: $p_{i,t}$ is the proportion of managers who had a net purchase in stock *i* during period *t:*

$$p_{i,t} = \frac{Number\ of\ institutions\ buying_{i,t}\ (B_{i,t})}{Number\ of\ institutions\ buying_{i,t} + Number\ of\ institutions\ selling_{i,t}\ (S_{i,t})} \quad (2)$$

$AF_{i,t} = E\left[\left| p_{i,t} - E\left[p_{i,t} \right] \right| \right]$ is the adjustment factor.

The inclusion of $E\left[p_{i,t} \right]$ in equation (1) controls for aggregate shifts into or out of stocks during a particular quarter, while the adjustment factor accounts for the fact that the first term in equation (2), which is an absolute value, is always greater than zero. Under the null hypothesis of no herding, we expect $H_{i,t}$ to be insignificantly different from zero.

LSV find an average herding measure equal to 0.027, i.e., if the expected proportion of buyer managers is 50%, the, 52.7% of fund managers change their portfolio to a given direction and 47.3% in the opposite sense. The median is even weaker, 0.01, which implies that there is no herding in the couple stock-quarter.

2.2. Christie and Huang (1995)

Christie and Huang (1995) examined the investment behavior of market participants in the U.S. equity markets. They argued that, when herding occurs, individual investors usually suppress their own information and valuations, resulting in a more uniform change in security returns. Therefore, they employed a cross-sectional standard deviation of returns (CSSD) as a measure of the average proximity of individual asset returns to the realized market average.

$$CSSD_t = \sqrt{\frac{1}{N-1} \sum_{i=1}^{N} \left(R_{i,t} - R_{m,t} \right)^2} \quad (3)$$

Where: $R_{i,t}$ is the observed stock return on firm *i* at time *t* and $R_{m,t}$ is the cross sectional average of the *N* returns in the aggregate market portfolio at time *t*.

By quantifying the degree to which asset returns tend to rise and fall in concert with the portfolio return, this measure captures the key attribute of herd behavior. This dispersion measure quantifies the average proximity of individual returns to the realized average. Christie and Huang (1995) argue that rational asset pricing models predict that the dispersion will increase with the absolute value of the market return since individual assets differ in their sensitivity to the market return. On the other hand, in the presence of herd behavior security returns will not deviate too far from the overall market return. This behavior will lead to an increase in dispersion at a decreasing rate, and if the herding is severe, it may lead to a decrease in dispersion.

Christie and Huang (1995) suggest that individuals are most likely to suppress their own beliefs in favor of the market consensus during periods of extreme market movements. Hence, Christie and Huang (1995) empirically examine whether equity return dispersions are significantly lower than average during periods of extreme market movements. They estimate the following empirical specification:

$$CSSD_t = \alpha + \beta^L D_t^L + \beta^U D_t^U + \varepsilon_t \quad (4)$$

Where:

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

$D_t^U = 1$, if the market return on day t lies in the extreme upper tail of the distribution; and equal to zero otherwise.

The dummy variables aim to capture differences in investor behavior in extreme up or down versus relatively normal markets. The simple model clarifies that in the existence of herd behavior, at least one of β^L, β^U would be statistically significant. In addition, the correct signs are minus. Negative β^L means that investors herd around the market performance when the return trend is extremely negative, the downside; and, negative β^U, the upside. Positives β 's will mean a contradiction. Using daily and monthly returns on U.S. equities, Christie and Huang (1995) find a higher level of dispersion around the market return during large price movements, evidence against herding.

Christie and Huang (1995) test the presence of herding behavior in the US stock market by using both monthly and daily data for NYSE and AMEX from July 1962 to December 1988. The monthly data for NYSE firms were from December 1925 to December 1988. They study the existence of herd behavior under several market conditions. They pointed out that based on assumption of rational asset pricing models; larger fluctuations in market return will result in enhance in stock return dispersions. The study findings are inconsistent with the forecast of herding behavior during phases of market stress.

2.3. Chang, Cheng and Khorana (2000)

Christie and Huang (1995) study investor's behaviors during market stress by analysing cross- sectional standard Dispersion (CSSD). They argue that if traders make their investment decision on the basis of their exclusively information and price predictions, the individual asset returns will not diverge considerably from the overall market return during stress periods. Chang, Cheng, and Khorana (2000) (hereafter CCK) extend the model of Christie and Huang and introduce a new and more powerful approach, cross-sectional absolute deviation of returns (hereafter CSAD) model:

$$CSAD_t = \frac{1}{N}\sum_{i=1}^{N}\left|R_{i,t} - R_{m,t}\right| \quad (5)$$

The method formulated by Chang and al. (2000) is based on general quadratic relationship between $CSAD_t$ and $R_{m,t}$ of the form:

$$CSAD_t = \alpha + \gamma_1\left|R_{m,t}\right| + \gamma_2 R_{m,t}^2 + \varepsilon_t \quad (6)$$

The estimator γ_2 is designed to capture trader behavior differences during market stress periods. In line with the rational asset pricing model, equity return dispersions are rising and linear functions of the market return. Chang, Cheng and Khorana (2000) state if investors herd during periods of relatively large price swing, the average market return and CSAD will be inverse and non-linear relations. In other words, in equation (6), if coefficient γ_2 is negative and is statistically significant, then the market participants herd when the market is up or down. So, if herding is present, then the non-linear coefficient γ_1 will be negative and statistically significant; otherwise a statistically positive γ_2 indicates no evidence of herding.

Chang, Cheng, and Khorana (2000) examine monthly basis data of several international stock markets, and find no evidence of herding in developed markets, such as the U.S, Japan and Hong Kong. However, they do find a significant non-linear relationship between equity return dispersion and the underlying market price movement of the emerging markets of South Korea and Taiwan providing evidence of herding.

2.4. Hwang and Salmon (2004)

Hwang and Salmon (2004) (hereafter HS) develop a new measure in their study of the US and South Korean markets. This model is price-based and measures herding on the basis of the cross-sectional dispersion of the factor sensitivity of assets. More specifically, HS (2004) argued that when investors are behaviorally biased, their perceptions of the risk-return relationship of assets may be distorted. If they do indeed herd towards the market consensus, then it is possible that as individual asset returns follow the direction of the market, so CAPM-betas will deviate from their equilibrium values.

In the event of herding prevailing in the market, the cross-sectional dispersion of the stocks' betas would be expected to be smaller, i.e. asset betas would tend towards the value of the market beta, namely unity. It is on these very premises that their herding measure is based. More specifically, they assume the equilibrium beta (let $\beta_{i,m,t}$) and its behaviourally biased equivalent ($\beta^b_{i,m,t}$), whose relationship is assumed to be the following:

$$E^b(R_{i,t}) \Big/ E(R^b_{m,t}) = \beta^b_{i,m,t} = \beta_{i,m,t} - h_{m,t}\left(\beta_{i,m,t} - 1\right) \qquad (7)$$

Where:

$E^b(R_{i,t})$: the behaviorally biased conditional expectation of excess returns of security *i* on period *t*.

$E(R^b_{m,t})$: the behaviorally conditional expectation of excess returns of market at time *t*.

$h_{m,t}$: is a time variant herding parameter ($h_{m,t} \leq 1$).

When $h_{m,t} = 0$, $\beta^b_{i,m,t} = \beta_{i,m,t}$ there is no herding. When $h_{m,t} = 1$, $\beta^b_{i,m,t} = 1$ suggests perfect herding towards the market portfolio in the sense that all the individual assets move in the same direction with the same as the same magnitude as the sense as the market portfolio. In general, when, $0 < h_{m,t} < 1$, some degree of herding exists in the market determined by the magnitude of $h_{m,t}$.

The form of herding under discussion represents market-wide behavior. So it is preferable to use all assets in the market than a single asset to eliminate the effects of idiosyncratic movements in any individual $\beta^b_{i,m,t}$. Then, the definition of beta herding represents changes in the cross sectional variance of the betas that originate from herding.
So, the degree of beta herding is given by:

$$H_{m,t} = \frac{1}{N_t}\sum_{i=1}^{N_t}\left(\beta^b_{i,m,t} - 1\right)^2 \qquad (8)$$

Where N_t is the number of stocks at time *t*.

One major obstacle in calculating the herd measure is that $\beta^b_{i,m,t}$ is unknown and needs to be estimated. It is well documented that betas are not constant but time varying (Harvey (1989), Ferson and Harvey (1991, 1993), and Ferson and Korajczyk (1995)). Several methods have been proposed to estimate time varying betas by Gomes, Kogan and Zhang (2003) and Ang and Chen (2005).

Using the OLS betas, we could then estimate the measure of herding as:

$$H'_{m,t} = \frac{1}{N_t}\sum_{i=1}^{N_t}\left(b_{i,m,t} - 1\right)^2 \qquad (9)$$

Where $b_{i,m,t}$ is the OLS estimator of $\beta^b_{i,m,t}$ for asset *i* at time *t*.

However, $H'_{m,t}$ is also numerically affected by statistically insignificant estimates of $\beta^b_{i,m,t}$. The significance of $b_{i,m,t}$ can change over time, affecting $H'_{m,t}$ even through $\beta^b_{i,m,t}$ is constant. Hwang and Salmon (2004) assume that the herding parameter follows an AR(1) process and their model becomes:

$$\log[Std_c(\beta^b_{i,m,t})] = \mu_m + H_{m,t} + \upsilon_{m,t} \qquad (10)$$

$$H_{m,t} = \phi_m H_{m,t-1} + \eta_{m,t} \qquad (11)$$

Where $\eta_{m,t} \sim iid(0, \sigma^2_{m,\eta})$

The above system of equations (10) and (11) accommodates herding as an unobserved component. To extract the latter, Hwang and Salmon (2004) employ the Kalman filter. Thus, in the above setting, the $\log[Std_c(\beta^b_{i,m,t})]$ is expected to vary with herding levels, the change of which is reflected through $H_{m,t}$. Special attention is drawn here to the pattern of $H_{m,t}$. If $\sigma^2_{m,\eta} = 0$, then $H_{m,t} = 0$ and there is no herding. Conversely, a significant value of $\sigma^2_{m,\eta}$, would imply the existence of herding and (as the authors state) this would further be reinforced by a significant ϕ_m . The absolute value of the latter is taken to be smaller than or equal to one, as herding is not expected to be an explosive process.

3. Data and Methodology

3.1. Database

In our study we use data of the Toronto stock market on the premises of its main index, the S&P/TSX60. This later was officially launched on December 31st 1998, maintained by the Canadian S&P Index Committee. It is designed to represent leading companies in leading industries; the S&P/TSX 60 covers approximately 73% of Canada's equity market capitalization. This index is a large-cap index for Canada. It is a market cap weighted, with weights adjusted for available share float, and is balanced across 10 economic sectors. Offering exposure to 60 large, liquid Canadian companies, the S&P/TSX60 is the basis for the largest companies on the Toronto Stock Exchange selected on the premises of their participation in the market capitalisation. We chose the top-capitalization index of the market in order to mitigate against thin trading which lead to errors in empirical estimations in Finance.

Our data includes monthly trading volume and returns both for the S&P/TSX60 as well as its constituent stocks and covers the period from January 2000 until December 2006 so we obtain 5124 observations. The historical constituent lists for the S&P/TSX60 were obtained from the web site www.investcom.com.

3.2. Methodology

3.2.1. Application of previous measures of herding

The major objective of this research is to assess if firms in Toronto stock exchange exhibit herding and to what extent. For this reason we fed the four measures of herding to our historical data.

A. Empirical evidence of LSV (1992)

We have mentioned above that LSV (1992) is one of the most widely used measures in the empirical herding literature. To establish that the change from quarterly to monthly snapshots provide very similar estimates of herding, we now replicate these studies using our dataset. We adopt a herding measure to detect herd behaviors in Toronto stock exchange based on Lakonishok and al.(1992).

In order to calculate the LSV measure, we assume that:

$B_{i,t}$ is the number of stock which return is positive;

$S_{i,t}$ is the number of stock which return is negative.

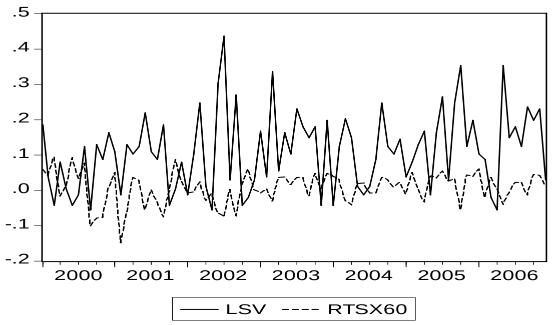
$E\left[p_{i,t}\right]$ is calculated as the average of $p_{i,t}$ over all stocks *i* in month *t*.

The adjustment factor $AF_{i,t}$ is calculated using a binomial distribution under the hypothesis of no herding:

$$AF_{i,t} = \sum_{B_{i,t}=0}^{N} \left\{ \left| \frac{B_{i,t}}{N} - E[p_{i,t}] \right| \times \left(C_{B_{i,t}}^{N} \right) \times E[p_{i,t}]^{B_{i,t}} \times (1 - E[p_{i,t}])^{N-B_{i,t}} \right\} \tag{12}$$

For each month, we calculate the $H_{i,t}$ measure according with equation (1). Our first assessment will be to analyze the evolution of this measure during the 84 months of our sample. This evolution is depicted in graph (1).

Graph 1: Evolution of LSV measure for overall sample



As shown in Figure (1), our sample seems to follow a cyclical herding pattern and the herding measure does not vary much across the six years in sample. Graph (1) shows a significant magnitude of herding around a bearish periods, when market returns is in extreme lower tails. This result is consistent with our image of investors being frantic to herd in an ‘abnormal’ circumstance.
In the next step, the herding measures are computed in each stock-month. Results are reported in the table (1).

Table 1: Results of LSV (1992) herding measure

$H_{i,t}$	
Mean	***t-student***
0,1109	9,310*

This table reports the average herding measure with the corresponding t-student for the entire sample.
* denotes significance at 5% level.

In table 1, we present the overall levels of herding exhibited by our sample, for the all period from 2000 to 2006. The herding measure of 11.09% shown in table (1) is the Lakonishok and al. (1992) measure of herding computed over all stock-month during the 6-year period. This positive and significant measure can be interpreted as meaning that, if 100 investors trade a given stock, then approximately eleven more investors' trade on one side of the market than would be expected if there was no positive feedback trading between traders. In other words, if the number of changes in holdings was, a priori, equally balanced between positive and negative changes, 61.09% (50%+11.09%) of investors trade in one direction and the remaining 38.91% (50%-11.09%) trade in the opposite direction.

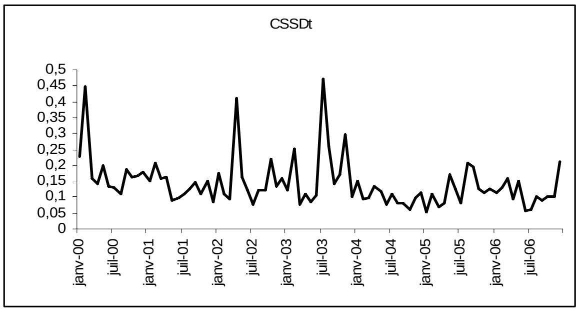
The overall level of herding behavior we find is much superior to that reported in previous studies using UK and US mutual and pension fund data. The overall level of herding in our study is close to what has been reported by Choe, Kho and Stulz (1999) for their study on the herding behavior of foreign individual investors in the Korean stock market (they find no herding measure below 20%), the study of Laboa and Serra (2007) who find an average of 11.38% of herding measure in Portugal stock exchange and the work of Bowe and Domuta (2004) on Jakarta stock exchange.

B. Empirical evidence of CSSD (1995)

In this part, we further consider if herd behavior is so prevalent on Toronto stock exchange. To measure herd behavior, we use the cross-section dispersion (CSSD) of individual stock returns proposed by Christie and Huang (1995).

We compute the cross sectional standard deviation as defined in equation (3). The evolution of this measure is shown in graph (2).

Graph 2: Evolution of Cross-sectional standard deviation

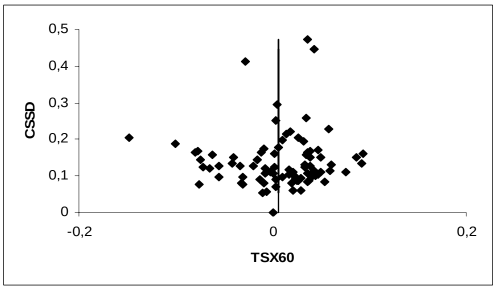


This graph unveils the CSSD for the market index over the sample, which varies substantially in some periods. We record three major jumps during our sample period corresponding to February 2000, April 2002 and July 2003. Dispersions appear to be medium which reflect the absence of herding behavior. But this can't by them be a guarantee of the absence of herding. So, we test an additional model to obtain a more comprehensive analysis:

$$CSSD_t = \alpha + \gamma_1 \left| R_{m,t} \right| + \gamma_2 R_{m,t}^2 + \varepsilon_t \qquad (13)$$

Under normal conditions, the conditional CAPM specifies a linear relationship between CSSD and market returns. However, if herding occurs during periods of market stress, then a nonlinear relationship defined by equation (13) will also exist (Gleason and al. (2004)). If herding is present, then γ_2 will be significantly negative, implying that the deviation of stock returns from market returns declines during periods of stress.

Graph 3: Relationship between the cross-sectional standard deviation and the corresponding market return



In figure (3) we plot the CSSD measure for each month and the corresponding market return for Toronto using stock return data over the period from January 2000 to December 2006. The CSSD-market return relation does indeed appear to be non-linearly positive. Focusing on the two hand side area where realized average monthly returns were negative and positive, the estimated coefficients and the corresponding t-statistics for our model (equation 13) are reported in table (2).

Table 2: Regression of herding measure

	TSX60
α	0.136884 (13.23162*)
γ_1	0.078965 (0.403390)
γ_2	2.659808 (0,949972)

This table reports the regression results with the independent variables equal to the absolute return on the market index and the squared market return.
* denotes statistical significance at 5% level.

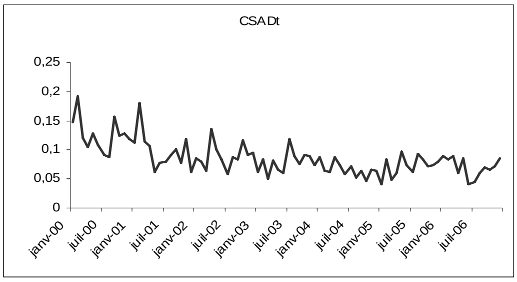
Looking at the results of equation (11) presented in table (2), with CSSD as the dependent variable, we see that the linear term is positive and not significant while γ_2 is significant and positive. This result points to the absence of herding during periods of high market stress. This finding indicates that herding is not a phenomenon that characterizes the Toronto stock exchange. To the contrary, the results indicate that during periods of market stress, investors trade away from the market consensus as proxied by the TSX60. Hence, the prediction of rational asset pricing model has not been violated.The results in Table 2 are similar to results reported by Christie and Huang (1995), and Chang and al. (2000), who also don't find evidence of herding in US equity markets.

C. Empirical evidence of CSAD (2000)

In this subsection, we elaborate the empirical test of herding along the lines of Chang, Cheng and Khorana. This test allows detecting herd behavior in Toronto stock market. Our testing methodology is based on cross-sectional absolute standard deviations (CSAD) among country returns.

At first, we calculate the cross sectional absolute deviation as defined in equation (5). The evolution of this measure is shown in graph (4).

Graph 4: Evolution of Cross-sectional absolute deviation



This graph unveils the CSAD for the market index over the sample, which varies substantially in some periods. We record three major jumps during our sample period corresponding to February 2000 and 2001. Dispersions appear to be medium which reflect the absence of herding behavior. But this can't by them be a guarantee of the absence of herding.

Table 3: Regression of herding measure

	TSX60
α	0.075521 (13.05958*)
γ_1	0.013214 (0.053109)
γ_2	4.890322 (2.242475*)

This table reports the regression results with the independent variables equal to the absolute return on the market index and the squared market return.
* denotes statistical significance at 5% level.

According to results shown in table (3), with CSAD as the dependent variable, we see that the linear term is positive and non significant, while the other is significant and positive. This result points the absence of herding during periods of high market stress. This finding indicates that herding is not a phenomenon that characterizes the Toronto stock exchange. To the contrary, the results indicate that during periods of market stress, investors trade away from the market consensus as proxied by TSX60. Hence, the prediction of rational asset pricing model has not been violated. The results in table 3 are similar to results reported by Christie and huang (1995) and Chang et al. (2000), who also find no evidence of herding in US equity markets.

D. Empirical evidence of HS (2004)

In this subsection, we elaborate the empirical test of herding along the lines of Hwang and Salmon (2004). This test allows detecting herd behavior in Toronto stock market.

Graph 5: Evolution of the HS (2004) measure

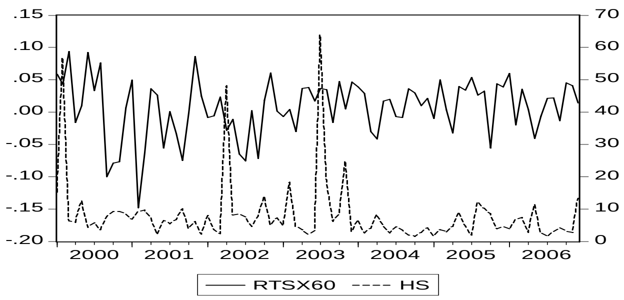


Figure 4 presents the evolution of herding diagrammatically (according to equation (22)). We observe that herding appears to present us with a multiplicity of short-lived fluctuations; it also assumes more distinctive (smoother) directional movements. As the Figure also illustrates, herding assumes values well above unity (between 1.0383221 and 45.6360723), which indicates that extreme degrees of herding towards the Toronto Index were observed during our sample period.

Table 4: Regression of herding measure

	TSX60	
μ_m	-0.0039159	(2.0070163*)
ϕ_m	0.796223989	(5.7626789*)
$\sigma_{m,\upsilon}$	0,089301848	(2.250574*)
$\sigma_{m,\eta}$	0,03148151	(3.16108*)
$\sigma_{m,\eta} / \log[Std_c(\beta^b_{i,m,t})]$	0,431773951	

* denotes statistical significance at 5% level.

As Table 4 illustrates, both the persistence parameter (ϕ_m) as well as the standard deviation ($\sigma_{m,\eta}$) of the state-equation error ($\eta_{m,t}$) are statistically significant. These results thus indicate the presence of significant herding towards the Toronto Index during our sample period.

The bottom row of Table 4 provides us with the signal-proportion value (calculated by dividing $\sigma_{m,\eta}$) by the time series standard deviation of the logarithmic cross-sectional standard deviation of the betas, ($\log[Std_c(\beta^b_{i,m,t})]$), which according to Hwang and Salmon (2004) indicates what proportion of the variability of the $\log[Std_c(\beta^b_{i,m,t})]$ is explained by herding. As Hwang and Salmon (2004) showed empirically in their paper, the bigger the value of the signal-to-noise ratio, the less smoothly over time herding evolves. Our results show us that the signal-proportion value is about 43 percent.

The findings of Table 4 appear robust to the inclusion of market direction and market volatility in the original Hwang and Salmon (2004) model.

After applying the four measure of herding behavior on Toronto stock exchange, we find contradicting results. The LSV and HS measures give evidence of herding behavior, while the CSSD and CSAD confirm the absence of this bias.

3.2.2. Informational cascades modeling

A. Deviation of volume: herding behavior and the disposition effect

Any asset pricing model that attempts to establish a structural link between asset prices and underlying economic factors also establishes links between prices and quantities such as trading volume. In fact, asset pricing models link the joint behavior of prices and quantities with economic fundamentals such as the preferences of investors and the future payoffs of the assets. Therefore, the construction and empirical implementation of any asset pricing model should improve both price and quantities as its keys elements. Even from a purely empirical perspective, the joint behavior of price and quantities reveals more information about the relation between asset prices and economic factors than prices alone. Yet the asset pricing literature has centered more on prices and much less on quantities. For example, empirical investigations of well known asset pricing models such as the

Capital Asset Pricing Model (CAPM) and Security Market Line (SML) have focused exclusively on prices and returns, and have completely ignore the information contained in quantities. Then, we hope to show that even if our main interest is in the behavior of prices, valuable information about price dynamics can be gleaned from trading volume.

Since herding is a coordinated action, there need to be some observable signals that investors can follow. Trading volume could have served as one such common signal. In order for market participants to herd and ignore their own priors, the volume signal has to be large enough to persuade investors that other things might be happening. Consequently, investors may come to believe that it is in their best interest to follow the crowd. In other words, herd behavior is more likely to occur following high trading volumes in the previous period. At the same time, it is important to control for informational trading. By definition, information arrives randomly, which suggests that changes in trading volume can serve as a proxy for a herding measure. Then, we focus on the volume implications of herding by investigating whether trading volume reveal the presence of herd behavior.

First, we define the cross sectional absolute deviation of volumes. This dispersion quantifies the average proximity of individual volumes to the mean. They are bounded from below at zero when all volumes move in perfect unison with the market. As individual volume begin to vary from the market volume, the level of dispersion increase.
The absolute dispersion of trading volumes, DV_t, is measured by the following expression:

$$DV_t = \frac{\sum_{i=1}^{N} \left| v_{i,t} - E\left(v_{i,t}\right) \right|}{N} \tag{14}$$

Where $V_{i,t}$ is the volume of security on firm *i* at time *t* and $E(V_{i,t})$ is the conditional expectation of trading volume of the firm *i* at time *t*. this dispersion measure quantifies the average proximity of individual volume to its expected value.

This formula is used to measure herding when being based on prices. But when it is adapted to the trading volume it will be another implication and significance. The absolute value has only effect to skew the results. The sign of the difference between observed and estimated trading volume has a great importance in the interpretation of stock's market phenomena.

According to the sign of the difference $[v_{i,t} - E(v_{i,t})]$, we can devise the equation (14) into two systems. Such one reflects a psychological aspect of investors in the stock market:

First, when $v_{i,t} \geq E(v_{i,t})$, then the abnormal volumes are positive, which mean that the observed trading volume is higher than the expected one. So the market is characterized by the large trading volume. Since this latter is a voluntary coordinated action, it will be a sign of existence of herding behavior among investors. This approach suggests that trading initiated by those in possession of private information can represent a signal for uninformed traders. In such a framework, uninformed traders, who cannot observe the identity of the person who initiated the trade but only the large trading activity, can herd causing an even higher trading volume and a longer length of abnormal market conditions (Bajo (2006)). So DVh_t is considered as a measure of herding behavior.

$$DVh_t = \begin{cases} \dfrac{\sum_{i=1}^{N}\left[v_{i,t} - E\left(v_{i,t}\right)\right]}{N} & if \quad v_{i,t} \geq E\left(v_{i,t}\right) \\ 0 & if \;\; not \end{cases} \tag{15}$$

Second, when $v_{i,t} < E(v_{i,t})$, the abnormal trading volumes are negative, i.e. the expected trading volume is greater than the observed one. The existence of few high volume traders means that a small proportion of traders are responsible for a substantial amount of trading over a period of time. Then, investors trade less actively and hold loser stocks because they believe that shares which are going to appreciate in price must be retained.

This behavior is consistent with the disposition effect as defined by Kahneman and Tversky (1979). According to this theory, investors are reluctant to unload assets at a loss relative to the price at which they were purchased. Investors tend to keep losers and sell winners, because they guess correctly that losers will rebound and winners will slip back in price. So, we use DVd_t as a measure of the disposition effect.

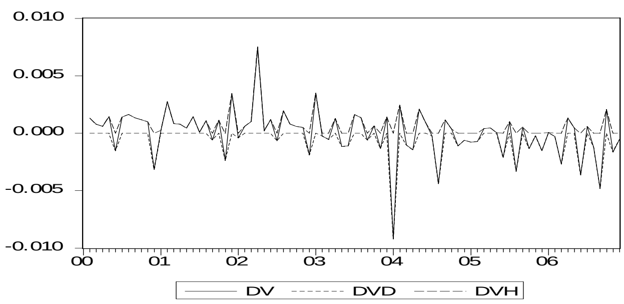
$$DVd_t = \begin{cases} \dfrac{\sum_{i=1}^{N}\left[E\left(v_{i,t}\right) - v_{i,t}\right]}{N} & if \quad v_{i,t} < E\left(v_{i,t}\right) \\ 0 & if \;\; not \end{cases} \tag{16}$$

The volume deviation is then the sum of two behavioral effects. We write DV_t as follow:

$$DV_t = DVd_t + DVh_t \tag{17}$$

Since these two phenomena are contradictory, they can't propagate simultaneously. So, when herding occurs, the market can't be characterized by the disposition effect, and vice versa. Graphic (6) shows the evolution of these measures.

Graph 6: Evolution of (DV, DVD, DVH)



The graphic shows more clearly that the two measures of herding and dispositions effect evaluate in an opposite direction. So the existence of herding behavior cancels the presence of the disposition effect and vice versa.

In order to highlight the robustness of our measures, we tend to examine the relationship between the DVh and DVd and the two principle elements of the market: return and volatility. For this objective, we resort to the Ganger causality test for these relations.

Table 5: causality test between (DVh, DVd) and return

	Lag 1		Lag 2	
	Test 1	Test 2	Test 1	Test 2
DVh	0.82300	0.23745	0.94244	**0.04315**
DVd	0.30100	**0.03704**	0.59040	0.05450

Test 1: return causes (DVh, DVd)
Test 2 : (DVh, DVd) cause return
p-value < 0.05 : causality sense is significant

The results show no evidence of causality between return and the two measures. The p value superior of 0.05 indicates that both herding and disposition effect are not explained by the fluctuation of market returns. This finding is the same for lag one and two. For the second sense of causality, we find different results. First the herding measure causes returns only in lag two. So the delayed herding of two periods explains the actual return. Moreover, the disposition effect causes the return just for lag one. Then, the present return is partly interpreted by the delayed disposition effect of one period.

In short, these results affirm strongly that herding behavior of lag 2 explains the return. This latter is also caused by the disposition effect delayed of one period. We can write that return of time (t) is explained by both disposition effect of (t-1) and herding behavior of (t-2).
We pass, now, to the causality test between this two phenomena and the market volatility.

Table 6: causality test between (DVh, DVd) and volatility

	Lag 1		Lag 2	
	Test 1	Test 2	Test 1	Test 2
DVh	**0.03408**	0.47722	0.08986	0.77543
DVd	**0.02242**	0.82140	0.09044	0.70463

Test 1: volatility causes (DVh,DVd)
Test 2 : (DVh, DVd) cause volatility
p-value < 0.05 : causality sense is significant

The table above provides strong evidence that the volatility causes the disposition effect and the herding behavior. Such result proves the evidence that the herding and disposition phenomenon result in an increase of the market volatility. This result is not verified for the second lag where the p value is superior to the critical value.

For the second sense of causality, we find that the herding behavior does not cause the volatility for the two lags which inconsistent with the literature review (Verma and Verma (2007)). We record the same result for the disposition effect.
The findings of the causality test lead us to think about the existence of a certain alternation between the herding behavior and the disposition effect. This idea is brought from the fact that returns are partly explained by the disposition effect of the past period and herding of before last period. So it appears a sort of cycle between these phenomena.

In order to detect the existence of such a cycle, we transform the DVt series into a sequence of runs. Our goal is to study an existing cycle of life and the correlation between herding and the disposition effect.

The runs test (also called Wald-Wolfowitz test) is a non-parametric test that checks the randomness hypothesis of a data sequence. Cromwell, Labys and Terraza (1994) formulate the test as follow:

$$DV_{i,t}^{*} = \begin{cases} 1 & \text{si} \quad DV_{i,t} > 0 \\ 0 & \text{si} \quad DV_{i,t} = 0 \qquad t = 1, \ldots\ldots\ldots T \\ -1 & \text{si} \quad DV_{i,t} < 0 \end{cases} \tag{18}$$

Where $DV_{i,t}$ design the turnover of the share *i* at the date *t*.

We put, n_1 the number of times where $DV_t^* < DV_{t+1}^*$, n_2 the number of times where $DV_t^* = DV_{t+1}^*$ and n_3 the number of times where $DV_t^* > DV_{t+1}^*$.

The test's statistic is:

$$stat = \frac{K + \frac{1}{2} - m}{S} \tag{19}$$

Where:

$$K = 1 + n_1 + n_2$$

$$m = \frac{\left(\sum_{i=1}^{3} n_i\right)\left(\sum_{i=1}^{3} n_i + 1\right) - \sum_{i=1}^{3} n_i^2}{\left(\sum_{i=1}^{3} n_i\right)}$$

$$S = \frac{\sum_{i=1}^{3} n_i^2 \left(\sum_{i=1}^{3} n_i^2 + \sum_{i=1}^{3} n_i \left(\sum_{i=1}^{3} n_i + 1\right)\right) - 2\sum_{i=1}^{3} n_i \sum_{i=1}^{3} n_i^3 - \left(\sum_{i=1}^{3} n_i\right)^3}{\left(\sum_{i=1}^{3} n_i\right)^2 \left(\sum_{i=1}^{3} n_i - 1\right)}$$

The statistic follows the normal distribution centered and reduced $N(0,1)$ under the null hypothesis of independence of DV_t.

The application of the run test releases a statistic value equal to 2.18. This result confirms an existence of cycle in the DV_t series. So there is an alternation between the disposition effect and the herding behavior. If this period is characterized by a herding behavior, the next one is branded by the deposition effect.

Since these two behaviors have a great effect on the abnormal volumes, we expect that the succession of herding behavior and disposition effect may affect an alternation in the sign of abnormal volumes. In other words, the period of herding is characterized by an increasing of volume which means a positive sign of abnormal returns. Then, a period of disposition effect causes a diminution of trading volume because of the holding of assets. So, the sign of abnormal volumes will be negative. This cycle is branded by a rotation between increasing and decreasing of trading volume. Such cycle is regarded as an informational cascade.

In general, an informational cascade is a situation in which every subsequent actor, based on the observations of others, makes the same choice independent of his private signal (Bikhchandani and al., 1992; Welch, 1992; Banarjee, 1992). In other words, an information cascade arises when a sequence of imperfectly informed decision makers, each of whom observes all previous decisions, has reached a point after which all future decision makers will rationally ignore their private information. Hence, learning ceases as subsequent decision makers infer nothing new from observing any of the actions. Information cascades are predicted to occur, possibly after very few decisions, despite the wealth of information available and despite the common interest of all decision makers. In such cascade, an individual considers it optimal to follow the behavior of her predecessors without regarding her private signal since her belief is so strongly held that no signal can outweigh it. This herding behavior participates in the formation of cascades, but the new arrival of little information can destroy this cascades. Once investors know their mistake, they will change their investment strategy to reduce the loss. The behavior of investor is then reflected in trading volume which fluctuates in the way of creating a cascade cycle.

B. Modeling an informational cascade through herding and disposition effect

According to formula (17), we suppose that the abnormal volumes are due to a combination between the herding behavior and the disposition effect. Moreover, the run test has shown a certain interaction and alternation between these two behaviors. Basing on these results, we attempt in the following paragraph to model the informational cascade provided by this interaction on the Canadian stock market.
We remember that a positive abnormal volume reflects a herding behavior $(DV_t = DVh_t \text{ and } DVd_t = 0)$ and a negative sign is due to a disposition effect $(DV_t = DVd_t \text{ and } DVh_t = 0)$. Moreover, we know that informational cascades pass into two phases. A phase of 'increasing' is explained by rising of the herding behavior in a stock market. The second phase of 'decreasing' or of 'an abrupt fall' is due to the arrival of little bit of public information which over turn the cascade. The investors discover their mistake and decide to hold the stocks to avoid a susceptible loss. Investors may resist the realization of a losing investment, evidence of an error in judgment. This disposition effect implies a negative abnormal volume.

In order to model this cascade, we suppose that each observation of herding constitute a bullish tendency that we attribute a score of 1 (tend=1). In the same way, each observation of disposition effect is considered as a bearish tendency that we attribute a score of -1 (tend=-1). The modeling of informational cascade can be presented as follow:

$$CASCAD_t = \sum_{j=0}^{n} Tend_{t-j} \qquad (20)$$

With:

$$Tend_t = \begin{cases} 1 & if\ DV_t = DVh_t \quad (DV_t > 0) \\ -1 & if\ DV_t = DVd_t \quad (DV_t < 0) \end{cases} \qquad (21)$$

Where:

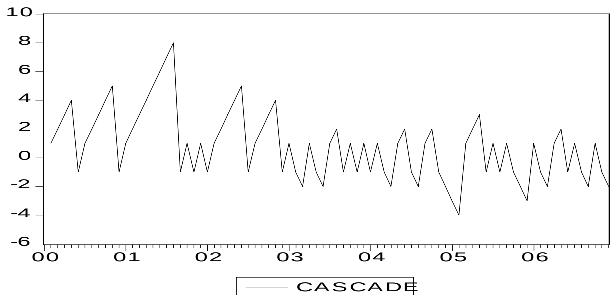
$CASCAD_t$: Measure of the cascade width at time t;

$Tend_t$: Measure of the cascade tendency at time t;

N: is a number of times where $Tend_t$ takes successively the same value.

The application of this model let us draw the graph (7).

Graph 7: Evolution of informational cascades



The graphic above represents the evolution of the measure of informational cascades applied on the Toronto stock exchange from January 2000 to December 2006. First, we observe several cascades during this period of different width. Only the year 2000 until the second half of 2001 is characterized by important cascades. The graphic also shows that the cascades are formed gradually but distorted suddenly. The main explication to this situation is as follow:

When a sequence of agents takes identical actions as they try to exploit the information available from the history of previous action choices, this will be reflected on trading volume. So the herding behavior leads agents to sell or to buy commonly which is interpreted by a progressive increase in volume or positive abnormal volumes. The poor aggregation of information in informational cascades means that decisions will also be poor, even if the signals possessed by numerous individuals could in principle be aggregated to determine the right decision with virtual certainty. Since the model is fully rational, individuals understand perfectly well that the precision of the public pool of information implicit in predecessors' actions is quite modest. As a result, the arrival of an individual with deviant information or preferences can dislodge a cascade. When the majority of investors discover their mistake, they prefer minimizing the risk by holding stocks. So, they act together at the same time as it is shown by the rapid increasing in the graph. This investor's reaction reflects well the disposition effect. So, we can say that the herding behavior explains the progressive formation of the cascade, while the disposition effect interprets the sudden fallen of this one. The informational cascade is as a result, explained by the moving of trading volume caused by the investor behavior biases.

Since the herding phenomena always exists in the market, but with different degree; several 'small' cascades appear in the chart. This type of cascades can occur gradually, but never reach a point of complete blockage of information. For example, it can occur that there is always a probability that individuals use their own signals, but where that probability asymptotes toward zero; this leads to 'limit cascades'. Or, if there is some sort of observation noise, the public pool of information can grow steadily but more and more slowly (Vives, 1993). Also, after a choc or when investors have a choice of delaying investment, there can be long periods with no investment, followed by sudden spasms in which the adoption of the project by one firm triggers the exercise of the investment option by many other firms (Chamley and Gale, 1994). So the market is characterized by channels of cascades which occur quickly or gradually and clog up suddenly. These cascades do not destabilize the market but persist for long periods without being detected by the old models.
To validate the robustness of our modeling, we will hereafter demonstrate three major points:

First, we prove that the informational cascade is a combination of the past observation of herding behavior and the disposition effect. So, we estimate the model M1:

$$cascade_t = \alpha + \beta_1 DVh_{t-n} + \beta_2 DVd_{t-m} \qquad (22)$$

Where:

$CASCAD_t$: Measure of the cascade width at time t;

DVh_t : Measure of herding behavior at time t;

DVd_t : Measure of the disposition effect at time t;

n and *m* : The level of n and m is fixed respectively 1 and 2 by minimizing the Akaik criteria of information.

Second, we test the impact of the informational cascade on the price dynamic. So, we estimate the following model M2:

$$r_t = \alpha + \beta cascade_t \qquad (23)$$

Finally, we attempt to deduce the impact of interaction between herding behavior and the disposition effect on price dynamic. This will be by replacing the measure *CASCAD$_t$* in the second model by its value in the first model. So, we obtain M3:

$$r_t = \alpha + \beta_1 DVh_{t-1} + \beta_2 DVd_{t-2} \qquad (24)$$

Table 7: Estimation of the models M1, M2, M3

Model M1				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.668516*	0.320128	2.088278	0.0400
DVh(-2)	528.3188*	240.8352	2.193695	0.0312
DVd(-1)	404.4113*	187.9738	2.151423	0.0345
Model M2				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.009008	0.005097	1.767382	0.0809
CASCAD	-0.004006	0.002052	-1.952094	0.0544
Model M3				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.005167	0.006102	0.846684	0.3998
DVh(-2)	-8.807084*	4.196973	-2.098437	0.0391
DVd(-1)	-8.051092*	3.267929	-2.463668	0.0160

* denotes statistical significance at the 5% level.

The first model (M1) attempts to establish a relation between the informational cascade and the both phenomena. We find significant coefficients which mean that the cascade is due to a combination of herding behavior and the disposition effect. This result is so evident because we have already shown that the formation of a cascade is due to the herding behavior that provokes the phase of increasing, and the fall of cascade is the result of the disposition effect which leads investors to hold assets so it reduces the trading volume.

The second model (M2) estimates a relation between the informational cascade and the price dynamic. We find no significance of this relation. This finding is explained by the low width of the detected cascade (see graph 7). These cascades are not able to destabilize the market or change the price dynamic because they are not strong, and do not persist in time.

For the last model (M3), we attempt to deduce a relation between the two phenomena and the return. We find a strong proof of this relation. The return is then explained partly by the disposition effect of the last period and partly by the herding behavior of the before last period. Since, these two phenomena have a great impact on trading volume; this impact will be reflected on the price dynamic.

4. Conclusion

Contributing to the herding literature which is centred on individual investors, this study not only documents substantial herding among individual investors, but can also establishes a strong findings by applying the most important measures of herding behavior. On a technical note, the findings illustrate the importance of distinguishing between the different measures that can provide contradicted results.

So, this paper addresses the issue of herding behavior in developed market. We use a sample of 60 stocks from the Toronto stock market that constitute the TSX60 index. Our data is constituted from monthly stock returns from January 2000 to December 2006. In order to investigate the presence of herding, we apply four measures: Lakonishok, Shleifer and Vishny (1992), Christie and Huang (1995), Chang, Cheng and Khorana and Hwang and Salmon (2004).

Our finding suggests that the use of CH (1995) and CCK (2000) give no evidence of herding behavior, which means that the prediction of rational asset pricing has not been violated. In the other hand, the employ of both LSV (1992) and HS (2004) gives strong proof of the herding pattern among the Toronto stock market.

Our paper contributes also to the financial literature by modeling the informational cascade. The cycle of this latter is explained by two psychological biases which are the herding behavior and the disposition effect. We have first settled a new measure based on the deviation of volume (DV). According to the sign of abnormal returns, we have split this measure into two formulas. The first called DVh which measure herding behavior and the second called DVd that measure the disposition effect. Using these two psychological measures we have explained the cycle of informational cascade. So the herding behavior leads agents to sell or to buy commonly which is interpreted by a progressive increase in volume or positive abnormal volumes. The poor aggregation of information in informational cascades means that decisions will also be poor, even if the signals possessed by numerous individuals could in principle be aggregated to determine the right decision with virtual certainty. Since the model is fully rational, individuals understand perfectly well that the precision of the public pool of information implicit in predecessors' actions is quite modest. As a result, the arrival of an individual with deviant information or preferences can dislodge a cascade. When the majority of investors discover their mistake, they prefer minimizing the risk by holding stocks. So, we can say that the herding behavior explains the progressive formation of the cascade, while the disposition effect interprets the sudden fall of this one. The informational cascade is as a result, explained by the moving of trading volume caused by the investor behavior biases.

In our empirical study, the granger test shows that return is caused partly by the disposition effect of the past period and the herding behavior of the previous past period. These two phenomena interact as a cycle; their alternation is regarded as an informational cascade. This finding pushes us to set a measure of cascade width based on the sign of abnormal volumes (positive in presence of herding behavior and negative if there is a disposition effect). From this measure we draw a chart of informational cascade evolution that prove the permanent existence of several and small cascades. These cascades are the result of the alternation between the two phenomena and cannot be detected by the old measures. So the market is characterized by channels of cascades which occur quickly or gradually and clog up suddenly.

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