New sight of herding behavioural through trading volume

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Abstract

In this study, we employ an innovative new methodology inspired from the approach of Hwang and Salmon (2004) , Hachicha et al (2007) and based on the cross sectional dispersion of trading volume to examine the herding behavior on Toronto stock exchange. Our findings show that the herd phenomenon consists of three essential components: stationary herding which signals the existence of the phenomenon whatever the market conditions, intentional herding relative to the anticipations of the investors concerning the totality of assets, and the third component highlights that the current herding depends on the previous one which is the feedback herding.

Keywords: herding behavior; market return; trading volume.
JEL :D53,G12,C13

1. Introduction

Recent research has shown that herding behavior is a relevant phenomenon in stock markets. Yet, various definitions are used by academics regarding their respective research objectives. Herding behavior has been defined as "behavior patterns that are correlated across individuals" (Devenow and Welch (1996))1, "a group of investors trading in the same direction over a period of time" (Nofsinger and Sias (1998))2, and is said to arise when "individuals alter their private beliefs to correspond more closely with the publicly expressed opinions of others" (Cote and Sanders, 1997)3. Obviously, herding involves that individuals behave alike. Nevertheless, this notion of likeness alone is insufficient. Correlated behavior might merely occur either by chance or because traders have access to the same sources of information or because they infer information similarly. Therefore, a further intentional element has to be added that can best be bounded as social pressure, imitation or conformity. The latter has been defined by Aronson (1992) as "a change in a person's behavior or opinions as a result of real or imagined pressure from a person or a group"4. Because of this psychological element, herding in that case guides to systematic sub-optimal decision-making correlated to the best aggregated choice. In addition, herding does not automatically involve irrational behavior. In fact, there are many circumstances in which investors amend their behavior in a rational way as a response to perceived social pressure.

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[1] Devenow, A. and Welch, I., 1996. "Rational herding in financial economics." *European Economic Review*, 40, 603-615.

[2] Nofsinger, J. R., Sias, R.W., 1999. "Herding and Feedback Trading by Institutional Investors." *Journal of Finance*, 54, 2263-2316.

[3] Cote, I. and Sanders, D., 1997. "Herding behavior: explanations and implications." *Behavioral Research in Accounting* 9 (1), 20-45.

The presence of herding behavior has a considerable effect on the aptitude of the price to aggregate private information dispersed among market traders. Herding behavior can cause "informational cascades:" situations in which no more private information is revealed. Such blockages of information can arise once the price is far away from the intrinsic value of the stock. Thus, herding behavior can cause long lasting misalignments between the price and the intrinsic value of an asset. Herd behavior, i.e., the choice to pursue the actions of one's predecessors, can arise as the outcome of a rational choice because there are multiple sources of asymmetric information in the market and overall the economy.
Even though the theoretical research stipulate the presence of relevant imitation phenomenon through the financial markets, the empirical results of surveys applied to diverse markets still oscillate between the existences or not of this bias.

To improve the existent measures and to investigate the herding towards the market in major financial markets is 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 our starting point the model of Huang and Salmon (2004), but we employ a proxy pioneered by Lakonishok, Shleifer, and Vishny (1992) which is the trading volume. Secondly, we shall apply our herd measure to detect herding behaviour in Toronto stock market. We use monthly data from January 2000 to December 2006.

This paper is divided into fore additional sections. In the second section we provide a review of the literature on the herding measurement. The third deals with methodological details and the presentation of our new measure of herding. The forth includes the data description and empirical evidence based on our new measure on Toronto stock exchange. Finally, the fifth section offers concluding remarks and discusses implications of our findings.

2. Literature review : Herding measures

The measures used to detect herding behaviour in the literature are the LSV (Lakonishok, Schleifer and Vishny 1992), CSSD (Cross sectional standard derivation: Christies and Huang 1995), CSAD (Cross sectional absolute deviation: Chang, Cheng and Khorana 2000), the HS Hwang and Salmon and DH (dynamic herding model): Hachicha and al (2007). We present different measures of herding by estimating the following empirical specification.

Lakonishok, Shleifer and Vishny (1992) propose a statistical measure of herding behavior (hereafter LSV). It defines and measures herding as the average tendency of managers group to buy or to sell particular stocks at the same time, compared to the situation where everyone acts independently. As it is called a herding measure, it really assesses the degree of correlated trading among investors. Herding obviously lead to correlated trading, but the reverse need not be true. Since a market is comprised of a supply and a demand side, not all participants in the market can flock together in a herd. Hence, herding is only likely to occur when a homogenous subgroup of investors is investigated. The LSV measure gauges their average tendency to wind up on the same side of the market in a particular stock and in a particular time period. A number of empirical studies have focused on the existence of institutional correlated trading activity and its impact on stock prices. LSV defines the Herding Measure $H_{i,t}$ for stock i and period t as follows:

$$H_{i,t} = \left| P_{i,t} - E\left[P_{i,t}\right] \right| - AF_{i,t}$$

$$P_{i,t} = \frac{Nbr\ institutions\ buying_{i,t}\ (B_{i,t})}{Nbr\ institutions\ buying_{i,t} + Nbr\ institutions\ selling_{i,t}\ (S_{i,t})}$$

This herding measure computes the proportion of managers trading on one side of the market, above the random proportion. Values of $H_{i,t}$ that are significantly different from zero indicate herding behavior. The adjusted factor is defined as follow:

$$AF = E\left[\ \left| P_{i,t} - E\left[P_{i,t}\right] \right|\ \right]$$

Where the expectation is calculated under the null hypothesis $B_{i,t}$ follow a binomial distribution with the parameter $E[P_{i,t}]$.

This specification of return, lead by Christie and Huang (1995), develop measures to directly test for the impact of herding behaviour on asset prices. The CSSD as defined by CH is expressed as:

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

Where $R_{i,t}$ is the observed return on firm i at time t and $R_{m,t}$ is the market portfolio return or the cross-sectional average of the N firm in the portfolio at time t. this dispersion measures quantifies the average proximity of individual returns to the realized average. The CH suggest that participants are most likely to suppress their prior information in favour of the market consensus during periods of extreme volatility. CH empirically survey whether equity return dispersions are significantly lower than average during periods of extreme market movements. They estimate the following empirical specification:

$$CSSD_t = \alpha + \beta^L D_t^L + \beta^U D_t^U + \varepsilon_t$$

D_t^L and D_t^U two dummy variables designed to capture differences in investor behaviour in extreme up or down versus relatively normal markets.

Chang, Cheng and Khorana (2000) modify the CH (1995) model. They use the cross-sectional absolute standard deviation (CSAD) of returns as a measure of dispersion to find herding in the U.S., Hong Kong, Japanese, South Korean and Taiwanese markets.

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

Their model suggests that if market participants herd around indicators, a nonlinear relationship will result between the absolute standard deviation of returns and the average market return during periods of large price movements. By including an additional regression parameter, CCK develop a more sensitive means of identifying herding than that of Christie and Huang (1995).
The CSAD as defined by CCK is expressed as:

$$CSAD_t = \alpha + \lambda_1 |R_{p,t}| + \lambda_2 [R_{p,t}]^2 + \varepsilon_t$$

Groyal and Santa-Clara (2003) and Hwang and Satchell (2002) show that cross-sectional volatility and time series volatility are theoretically and empirically significantly positively correlated and the return predictability moves together with cross-sectional standard deviation of individual stock returns.
Among the latest to contribute to the development of herd measures are Hwang and Salmon (2001, 2004). HS's model finds its origin in the capital assets pricing model CAPM. When there is herding towards the market portfolio and the equilibrium CAPM relationship no longer holds, both the beta and the expected asset return will be biased. Thus, in HS's model, the herd measure is simply the cross- sectional dispersion of betas and evidence of herding is indicated by a decrease in this extent.

the equilibrium CAPM relationship: $E_t(r_{it}) = \beta_{imt} E_t(r_{mt})$
the relationship held in the presence of herding towards the market is:

$$\frac{E_t^b(r_{it})}{E_t(r_{mt})} = \beta_{imt}^b = \beta_{im} - h_{mt}[\beta_{im} - 1] \quad ; \quad H_{mt} = \phi_m H_{mt-1} + \eta_{mt}$$

$$H_{m,t} = \frac{1}{N}\sum_{i=1}^{N}(\beta_{i,t} - 1)^2$$

Where $E_t^b(r_{i,t})$ and β_{imt}^b are the market's biased short run conditional expectation on the excess return of asset i and its betas at time t, and $h_{m,t}$ is a latent herding parameter that changes over

time, $h_{m,t}$ is a latent herding parameter that changes over time, $h_{m,t} \leq 1$,and conditional on market fundamentals.

If $h_{m,t}$ =0, $\beta^{b}_{imt} = \beta_{imt}$ so there is no herding and the equilibrium CAPM applies.

If $h_{m,t}$ =1, β^{b}_{imt} =1 so $h_{m,t}$ =1 suggests perfect herding towards the market portfolio in the sense that all the individual assets move in the same direction with the same magnitude as the market portfolio.

If $0 \langle h_{mt} \langle 1$, some degree of herding exists in the market determined by the magnitude of $h_{m,t}$.

Dynamic Herding model DH

Hachicha and al (2007) develop a new approach to measuring herding based on the HS's measure and a dynamic multivariate GARCH model to analyze the systematic risk of the market. They presume that the dynamic volatility of the market as well as of the asset follows GARCH (1.1) process described as below:

$$h_{i,t} = \mu + \alpha h_{i,t-1} + \beta \varepsilon^{2}_{i,t-1}$$

$$h_{m,t} = \mu + \alpha h_{m,t-1} + \beta \varepsilon^{2}_{m,t-1}$$

Where h_t denotes the conditional volatility of the residue for both market and security.

The dynamic herding measure is given by the equation above as the sum of the difference between the volatility of the asset and the volatility of the market:

$$DH_t = \frac{1}{N}\sum_{i=1}^{N} |h_{i,t} - h_{m,t}|$$

The different measures presented are insufficient even incapable to mark the significance of the psychological bias in the price dynamic. A later investor belonging to different sub population looks for making a transaction rather than exchange information. If power herding occurs, returns on individual shares would be more than usually clustered around the market returns as investors deny their private opinion in favor of the market consensus. A model with preferential attachment and deviation: the number of agents is growing within groups in the market and at every time a stock price will be calculated. Hence, a later agent either joins an existing group or acts individually following his private information and no herding is realized. The cluster weight distribution takes place to determinate the equilibrium of each group then the general equilibrium of overall financial market.

3. Methodology

Our methodology is based on trading volume and measures herding on the basis of the cross sectional dispersion factor sensitivity of volume. The first step we use the security market line with trading volume to show that valuable information about price dynamics can be gleaned from trading volume.

So, the market security line can be expressed as:

$$V_i = \alpha_i + \beta_i V_m + \varepsilon_i \qquad (1)$$

Where:

V_i : trading volume of security *i* ,

V_m : market trading volume .

We reckon that the action of investors intently following the market performance inadvertently upsets the equilibrium in the risk-volume relationship that exist in the conventional Capital Assets Pricing Model (CAPM). The following explains the principle behind their proposed herd measure.

So, we argue that when herding occurs, there exists a more pronounced shift of the investors' beliefs in order to follow the market portfolio. This would upset the equilibrium relationship and thus causes betas and the expected stock trading volumes to become biased.

Then, in equilibrium we write:

$$V_{i,t} = \beta_{i,m,t} V_{m,t} \qquad (2)$$

Where:

$V_{i,t}$: volume of security *i* at time *t* ,

$V_{m,t}$: volume of market at time *t*.

When there is herding towards the market portfolio, the relation between the equilibrium beta ($\beta_{i,m,t}$) and its behaviourally biased equivalent ($\beta^{b}_{i,m,t}$), is the following:

$$V^{b}_{i,t} \Big/ V^{b}_{m,t} = \beta^{b}_{i,m,t} = \beta_{i,m,t} - h_{m,t}\left(\beta_{i,m,t} - 1\right) \tag{3}$$

Where:

$V^{b}_{i,t}$: the behaviorally biased volume of security *i* on period *t*.

$V^{b}_{m,t}$: the behaviorally biased volume 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 model in (3) is generalized as follows. Let $\delta_{m,t}$ and $\delta_{i,t}$ represent sentiment on the market portfolio and asset *i* respectively. Then the investors biased expectation in the presence of sentiment is:

$$V^{b}_{i,t} = V_{i,t} + \delta_{i,t} \text{ and } V^{b}_{m,t} = V_{m,t} + \delta_{m,t}$$

We have then:

$$\beta^{b}_{i,m,t} = \frac{\beta_{i,m,t} + s_{i,t}}{1 + s_{m,t}} \tag{4}$$

Where $s_{m,t} = \dfrac{\delta_{m,t}}{V_{m,t}}$ and $s_{i,t} = \dfrac{\delta_{i,t}}{V_{m,t}}$ represent sentiment in the market portfolio and asset *i* relative to the market trading volume.

So, the degree of beta herding is given by:

$$H_{m,t} = \frac{1}{N_t}\sum_{i=1}^{N_t}\left(\beta^{b}_{i,m,t} - 1\right)^{2} \tag{5}$$

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

$$H^{'}_{m,t} = \frac{1}{N_t}\sum_{i=1}^{N_t}\left(b_{i,m,t} - 1\right)^{2} \tag{6}$$

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. To avoid this, we standardize $b_{i,m,t}$ with its standard deviation. So, we obtain the standardised beta herding:

$$H^{*}_{m,t} = \frac{1}{N_t}\sum_{i=1}^{N_t}\left(\frac{b_{i,m,t}-1}{\hat{\sigma}_{\varepsilon_i,t}/\hat{\sigma}_{m,t}}\right)^2 \quad (7)$$

Where:

$\hat{\sigma}_{m,t}$ is the sample standard deviation of market volume at time *t*.

$\hat{\sigma}_{\varepsilon_i,t}$ is the sample standard deviation of the OLS residuals.

Two principle criticisms can be addressed to the HS herding measure. The first deals with the joint hypothesis. Thus the authors have based their herding measure on the rationale CAPM whose principle hypothesis is the efficiency of the market, or the existence of herding phenomenon signals the inefficiency of the market. The second criticism is related to the measure of the systematic risk of the market. In that respect, HS's model considers the systematic risk of the market equal to 1. This is far from the empirical reality. In fact, there is so many factors, apart from the herding behaviour, that result in the deviation of the systematic risk from 1 such as the market microstructure and investor's psychology. That is why we adopt, in our new herding measure, a dynamic approach to estimate the systematic risk of the market, precisely, we suppose that the dynamic volatility of the market follows a GARCH (1.1) process described as below:

$$V_{m,t} = a + bV_{m,t-1} + \varepsilon_t \quad (8)$$
$$h_{m,t} = \mu + \alpha h_{m,t-1} + \beta \varepsilon^2_{m,t-1}$$

With: $\varepsilon/I_{t\text{-}1} \rightarrow N(0, h_t)$

The same approach is applied for every asset:

$$V_{i,t} = a + bV_{i,t-1} + \varepsilon_t \quad (9)$$
$$h_{i,t} = \mu + \alpha h_{i,t\text{-}1} + \beta \varepsilon^2_{i,t-1}$$

With: $\varepsilon/I_{t\text{-}1} \sim N(0, h_t)$

By replacing the volatility measures in the specification (7) by their expression as given by the equations (8) and (9), we obtain the following specification:

$$VH_{m,t} = \frac{1}{N_t}\sum_{i=1}^{N_t}\left|(\mu_i - \mu_m) + \left(\beta_i \varepsilon^2_{i,t-1} - \beta_m \varepsilon^2_{m,t-1}\right) + \left(\alpha_i h_{i,t-1} - \alpha_m h_{m,t-1}\right)\right| \quad (10)$$

Where

$h_{i,t}$: measures the dynamic volume volatility of the asset *i* at time *t*,

$h_{m,t}$: measures the dynamic volume volatility of the market at time *t*.

We can write:

$$VH_{m,t} = \sum_{i=1}^{N_t}\left|\frac{(\mu_i - \mu_m)}{N_t} + \frac{\left(\beta_i \varepsilon^2_{i,t-1} - \beta_m \varepsilon^2_{m,t-1}\right)}{N_t} + \frac{\left(\alpha_i h_{i,t-1} - \alpha_m h_{m,t-1}\right)}{N_t}\right| \quad (11)$$

This measure shows that the herding behaviour consists in three components:

$$VH_{m,t} = \sum_{i=1}^{N_t}\left|cst + IH + FH\right| \quad (12)$$

With:

$$cst = \frac{\left(\mu_i - \mu_m\right)}{N_t}$$

$$IH = \frac{\left(\beta_i \varepsilon_{i,t-1}^2 - \beta_m \varepsilon_{m,t-1}^2\right)}{N_t}$$

And

$$FH = \frac{\left(\alpha_i h_{i,t-1} - \alpha_m h_{m,t-1}\right)}{N_t}.$$

This measure show that the herding behaviour consists in three components:

- The first one is related to the constant term which prove that the herding behaviour exist whatever the market conditions. This affirmation is consistent with the reality. In fact it is strongly probable that there is at least one investor who imitates the actions of the others.
- The second component deals with the anticipation error of the investors concerning the totality of assets.
- Finally, the third component highlights that the current herding depends on the previous one. This result finds its theoretical basis in the information cascades theory (Givoly and Palmaon (1985) and Welch (1992; 2000).

4. Empirical evidence of the new measure of herding

4.1 Databases:

We base our empirical design on the premises of the main index of Toronto stock exchange which is the S&P/TSX60 index that includes the largest companies. Our data include monthly prices and volumes during the period spanning between January 2000 and December 2006, so we have 5124 observations. The historical constituent lists for the S&P/TSX60 were obtained from the web site www.investcom.com.

4.2 Results and discussion

We first apply the new herding measure on our database. The results of the new herding measure are illustrated by the figure below:

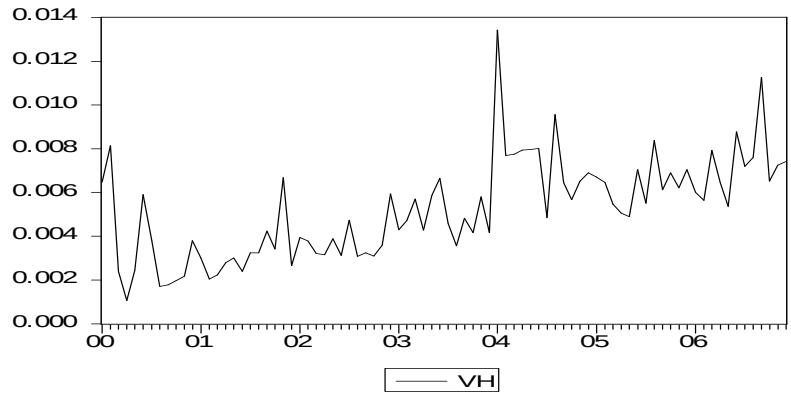

Figure 1: Evolution of VH measure for S&P/TSX60 index

This figure shows the evolution of our herding measure in Toronto stock market during period from 2000 to 2006. We remark several upwards cycles of herding behavior but do not seem to be large enough to search plausible interpretations of the relative movements in herding from economic events.

Robustness tests

In order to highlight the robustness, we tend to examine the relationship between the herding phenomenon and the three principle elements of the market: the return, volatility and trading volume.

We test the following regressions:

$$R_{m,t} = \alpha + \beta VH_t + \varepsilon_t \quad (12)$$

$$V_{m,t} = \alpha + \beta VH_t + \varepsilon_t \quad (13)$$

$$Vol_{m,t} = \alpha + \beta VH_t + \varepsilon_t \quad (14)$$

Where:

$R_{m,t}$ the market return at time *t*,

VH_t the herding measure at time *t*,

$V_{m,t}$ the trading volume of the market at time *t*,

$Vol_{m,t}$ the volatility of the market index at time *t*.

Table (1) show that the herding behavior is always strongly significant for the main components of the stock prices dynamic: return, trading volume and volatility.

Table 1: Contemporary Relation between herding, return, volatility and trading volume

	Coefficients estimates		*Student-test*		*Stability of the relationship*	*Normality of residuals*		
	Alpha	*Beta*	*t* alpha*	*t* beta*	*Test Chow*	*Skewness*	*Kurtosis*	*Jarque-Bera*
$R_{m,t}$	-0.021141	5.268435	-1.773245	2.522140	0.908671	-0.400506	3.387540	2.771327
Vm_t	0.002285	0.089781	23.14568	5.190377	5.070019	0.066811	2.818523	0.177761
$Vol_{m,t}$	0.002377	-0.182732	15.41026	-6.750660	17.00437	1.754785	6.260549	79.36274

***, **, * denote statistical significance at the 1%, 5% and 10% levels respectively

Concerning equation (12), we record that the market returns and the trading volume factors increase when herding is more relevant. Results of equation (13) conclude that a large trading volume is a necessary condition for the existence of herding behavior among investors. This finding is consistent with the literature:, Chen, Lee and Rui (2000) and Hachicha, Bouri and Chakroun (2008).

Because of herding leads to a greater concentration of agents on one side of the market (Schwert and Seguin (1993)), we find negative beta implying that when herding phenomenon exists, the volatility is excessively low

In order to test the authenticity of these relations, we carry the Chow and the normality test. The Chow test reveals that the relation between herding behavior and market return lacks of stability. The normality test of residuals records positive skewness for volatility and trading volume, and negative one for return. So, for volatility and trading volume, the residuals series is characterized by slop towards the left, whereas returns show slop towards the right. A higher kurtosis indicates strong probability of extreme points. The returns residuals series are characterized by proportionally low flatness while those of volatility reveal strong flatness which gives higher JB (79,36).

From these tests we conclude at first that the relation between herding behavior and return shows non stability at the aggregated level. Second, the results of normality test reveal a phenomenon of asymmetry that can be a sign of the presence of non linearity. So, we advance three propositions in order to study the causes of non stability:

- *First assumption:* The relationship between herding behavior and market return differs according to microstructural data. So the non stability can disappear if we study this relation in the level of individual stocks in one hand. And in the other hand, we can check the impact of several criteria on this relation like: activity sector, size effect, book to market value and liquidity criteria.

The loss of stability of the relationship between herding behavior and market return leads us to separate individual stocks into four groups according to activity sector, size, book to market and liquidity criteria and to see if there are different relation between herding and returns on these classes. Hence, we obtain sub samples of energetic and non energetic firms, small and big size companies, high and low value book to market companies or liquid and illiquid companies.

To test this relation we estimate the following regression:

$$R_{i,t} = \alpha + \beta VH_{i,t} + \varepsilon_t \qquad (15)$$

Where:

$R_{i,t}$: Return on stock *i* at time *t*;

$VH_{i,t}$: Herding measure for the stock *i* at time *t*;

The estimated coefficients of this regression are summarised in the table 2.

Table 2: Contemporary Relation individual stock returns and herding behavior

	Alpha	**Beta**		**Alpha**	**Beta**
AXP	-0.023934*	7.944775**	LUN	0.290341**	-26.34658**
BWR	-0.034191	10.20517***	MDS	-0.010258	2.564533**
AEM	0.005773**	3.840824**	MFC	0.029134**	-2.963825*
AGU	0.031549*	-2.563415	MBT	0.003088*	1.471710
BLD	-0.072278	14.42493**	NA	0.019894**	-0.654800
BBDB	-0.043610**	6.147591**	OCX	-0.066657*	12.28835**
BCE	-0.045699*	7.581060**	NCX	0.031698**	-4.977744**
BMO	0.005461**	0.376417	NT	-0.348678	90.42754***
BNS	0.035854	-4.974487	NXY	0.009613**	*1.017142**
BVF	-0.027250*	4.126872**	PCA	0.072074	*-11.00651***
CCO	0.076834**	-10.44190***	POT	0.043501**	*-5.440221***
CM	0.010862*	0.608905	PWTUN	0.033840*	*-4.458646***
CNQ	0.032856**	-3.423949*	RCIB	-0.066155**	*14.01927**
CNR	0.046397*	-7.225976**	RIM	-0.124248*	*31.04774***
COSUN	7.569261*	-1170.540**	RY	0.008548**	*-0.921394**
CAR	6.510103*	-1006.035*	SAP	0.039282	*-6.576924***
CMH	-0.050487	10.72947***	SCC	-0.037456**	*7.618134***
CLS	-0.037607	5.108363**	SGF	-0.050376*	*24.97430***
ELD	0.046219*	-1.759768	SU	-0.004657**	*3.273652***
ENB	0.032518*	-4.808217**	T	-0.025617*	*6.978544***
EMA	0.009824	-0.698876	TA	0.029785**	*-3.966694**
FTS	0.030850*	-4.172169*	TCKB	0.028617*	*-0.176648**
FTT	0.034199**	-3.262198**	TEO	0.025538**	*-1.423641*
GEA	-0.018755**	21.56112***	TIH	0.036920*	*-5.175830***
GIL	-0.033217*	9.681616**	TCW	0.044414**	*-3.651392**
HSE	0.031459*	-1.605692	TOG	-0.002077**	*1.275044*
IMN	-0.076467**	19.38323**	TP	0.052437*	*-7.068996***
IMO	0.025029*	-2.573511**	WN	0.046111*	*-7.787362***
K	0.069171	-5.249956*	VETUN	0.053952	*-4.925807**
L	*0.039652**	*-6.562261***	*YRI*	*1.144704*	*7.944775***

***, **, * denote statistical significance at the 1%, 5% and 10% levels respectively

The reading of table n°2 enables us to note that, on 60 estimated betas, 49 are significant. So a total degree of significance is 82% against 100% at the aggregate level. Therefore, the level of significance of the relation herding/returns remains strong, but it decreases at the individual level. Thus, we conclude that the non stability of the relation between herding behavior and stock returns is not due to individual level.
Then, we study the influence of activity sector, size, Book to market and the level of liquidity on this relation. To do that we estimate the following regressions:

- Relation between herding behavior and activity sector returns:

$$R_{si,t} = \alpha + \beta VH_{si,t} + \varepsilon_t \quad (16)$$

Where:

$R_{si,t}$: Return on activity sector at time *t*; *i* = 1 for the banking sector (BS) and *i*= 2 for the non banking (NBS) one;

$VH_{si,t}$: Herding measure for the sector *i* at time *t*;

- Relation between herding behavior and stock returns according to book to market effect:

$$R_{\text{hig } Book,t} = \alpha + \beta VH_{hig\ Book,t} + \varepsilon_t \quad (17)$$

$$R_{low\ Book,t} = \alpha + \beta VH_{low\ Book,t} + \varepsilon_t \quad (18)$$

Where:

$R_{hig\ Book,t}$ ($R_{low\ Book,t}$): Return on high (low) book to market firms at time *t*;

$VH_{hig\ Book,t}$ ($VH_{low\ Book,t}$): Herding measure for return on high (low) book to market firms at time *t*;

- Relation between herding behavior and stock returns according to book to market effect:

$$R_{liquid,t} = \alpha + \beta VH_{liquid,t} + \varepsilon_t \quad (19)$$

$$R_{illiquid,t} = \alpha + \beta VH_{illiquid,t} + \varepsilon_t \quad (20)$$

Where:

$R_{liquid,t}$ ($R_{illiquid,t}$): Return on liquid (illiquid) firms at time *t*;

$VH_{liquid,t}$ ($VH_{illiquid,t}$): Herding measure for return on liquid (illiquid) firms at time *t*.

Table n°3 gathers the results of these regressions.

Table 3: Contemporary relation between return and herding behavior according to the Asset Sorts

	Alpha	**Beta**
	Activity sector	
Energetic sector	-0.014982	4.012967**
Non energetic sector	-0.0102*	4.012158**
	Size	
Big capitalization	0.011211*	6.11211***
Small capitalization	0.015195**	6.15195**
	Book to market	
High book to market	-0.001635	3.10848**
Low book to market	-0.019178	3.13842*
	Liquidity	
Liquid firms	-0.0120**	5.01058**
Illiquid firms	-0.01552	5.01432**

***, **, * denote statistical significance at the 1%, 5% and 10% levels respectively

From this table we record that all beta are positive and significant which enables us to conclude that, generally, the relation herding/returns remains significant in spite of the various criteria of classification. So the non stability is not accorded to assets sort. For the activity sector we remark that the relation remains the same for energetic and non energetic sectors. So the relation between herding and returns is insensitive to the type of activity. Concerning the size effect we record that herding exists across different sizes of stocks in the market. The size criterion does not destabilize the relation herding/returns.

We have also examined herding towards value factors and find that book to market value has no impact on the relation between herding behavior and returns. We find the same evidence for the liquidity effect. The two types of firms reveal a close value of beta, which means that the non stability of the relation herding/return is not due to liquidity criterion.

As a conclusion, we reject our first proposition which stipulate that the non stability of the relation between herding behavior and returns is due to microstructural data.

- *Second assumption:* We suppose that the non stability of the relation herding/return is explained by the existence of non linearity. We assume that the variance of historical returns is not constant in, and as a consequence the risk of stock is modified over the time. So, the study of non linearity can bring light to the causes of non stability between herding and returns. In order to study the non linear relation between herding behavior and stock returns we suggest a GARCH model which has a double interest: from one hand, it takes into account the non linear relation if existing, and in the other hand, it considers the volatility such an explanatory variable in the relation.

The method generally used to test the relation between the couple mean-variance is based on asymmetric GARCH-in-mean models (Glosten, Jagannatan, and Runkle, 1993; Koopman and Uspensky, 2002; Cappiello, and al. 2006). In what follows, we employ a standard asymmetrical GJR-AGARCH (1,1)-in-mean model:

$$R_{m,t} = \varphi_0 + \varphi_1 \sigma_t + \varphi_2 VH_{m,t} + \varepsilon_t \quad (21)$$

$$\sigma_t^2 = \omega + \alpha \varepsilon_{t-1}^2 + \beta \sigma_{t-1}^2 + \lambda I[\varepsilon_{t-1} < 0] \varepsilon_{t-1}^2 \quad (22)$$

With $I = \begin{cases} 1 & \text{if } \varepsilon_{t-1} < 0 \\ 0 & \text{otherwise} \end{cases}$

Equation (21) represents the mean, where equation (22) is a variance equation.

σ_t is a conditional standard deviation;

$R_{m,t}$ is a market return ;

$\varphi_0, \varphi_1, \varphi_2, \omega, \alpha, \beta$ *and* λ are constant parameters;

ε_t is a random error term.

ε_{t-1} is related to the signal quality, in such way that this term is positive when news are good and negative otherwise.

To take into consideration the incremental efficiency of $VH_{m,t}$, we put the augmented mean equation:

$VH_{m,t}$ is an incremental variable which examine the relative power of herding vs. the usual conditional standard deviation in estimating returns. If $\varphi_2 \neq 0$, return and herding are dependent.

Table 4: Return and herding behavior under non linear relation

	Constant	σ_t	$VH_{m,t}$	ω	ε^2_{t-1}	σ^2_{t-1}	$\varepsilon^2_{t-1}\left[\varepsilon_{t-1} < 0\right]$
Aggregated level							
Equation 1							
Market return	-0.0039 (-0.29)	0.05647 (1.02)		0.013*** (4.01)	0.012** (2.03)	0.923*** (32.77)	0.094*** (8.75)
Equation 2							
Market return	0.004** (-0.22)	0.067 (0.98)	5.084** (2.33)	0.013*** (4.2)	0.011* (1.77)	0.923*** (31.90)	0.093*** (9.92)
Liquidity							
Equation 1							
Liquid firms	0.027** (2.44)	-0.025* (-0.50)		0.021*** (5.13)	0.014** (2.68)	0.751*** (27.42)	0.023*** (8.14)
Illiquid firms	0.015 (1.4)	-0.025* (-0.50)		0.031*** (4.52)	0.022*** (3.86)	0.722*** (23.54)	0.062*** (5.75)
Equation 2							
Liquid firms	0.026** (2.62)	-0.130* (-1.68)	3.62*** (6.12)	0.021*** (6.18)	0.009** (2.06)	0.701*** (23.64)	0.024** (2.92)
Illiquid firms	0.018 (1.45)	-0.130* (-1.68)	5.89*** (4.43)	0.033*** (5.11)	0.029** (2.99)	0.748*** (27.01)	0.065** (3.71)
Size							
Equation 1							
Small cap	0.041* (1.72)	-0.021 (-0.84)		0.016** (2.14)	0.050* (1.85)	0.801*** (34.53)	0.091*** (8.18)
Big cap	0.042** (2.12)	-0.016** (-0.93)		0.028*** (4.87)	0.040*** (3.85)	0.614 *** (18.74)	0.072*** (6.43)
Equation 2							
Small cap	0.027** (1.97)	-0.019** (-2.64)	6.91*** (5.90)	0.017** (2.20)	0.043** (1.97)	0.794*** (32.01)	0.088*** (7.31)
Big cap	0.027** (1.97)	-0.015** (-2.71)	6.54*** (4.70)	0.027*** (5.01)	0.042*** (2.77)	0.620*** (18.71)	0.069*** (5.99)
Book to market							
Equation 1							
High BM	-0.0017 (0.51)	-0.017 (-0.41)		0.023*** (4.66)	0.201*** (4.51)	0.564*** (12.74)	0.224*** (7.22)
Low BM	-0.02 (0.11)	-0.009 (-1.28)		0.019*** (3.44)	0.09*** (2.75)	0.745*** (10.96)	0.18*** (4.07)
Equation 2							
High BM	-0.026 (0.64)	-0.017 (-0.40)	3.81** (3.51)	0.022*** (4.57)	0.193*** (4.18)	0.612*** (10.45)	0.227*** (7.25)
Low BM	-0.00186 (0.24)	-0.009 (-1.32)	3.27** (2.14)	0.019*** (3.44.)	0.087*** (24.17)	0.766*** (11.87)	0.17*** (4.05)

***, **, * denotes that coefficient is significant at the 1%, 5%, and 10% levels,

The coefficient of asymmetric shock term indicates that the trading volume react more deeply to bad informations. Concerning the coefficient of conditional standard deviation in equation (22), it is statistically insignificant and provides different signs. So, we cannot confirm the volume-risk trade-off which is consistent with existing researches (Breen and al. (1989), Nelson (1991), Koopman and Uspensky (2002) and Lettau and Ludvigson (2001)). On the other hand, by including $VH_{m,t}$ to the test equation, we report that the coefficient between this term and market return is positive and greatly significant which support the hypothesis return-risk trade-off. The risk is linked with the herding measure rather that the conditional standard deviation derived from the GARCH process.

The second assumption is also rejected.

- *Third assumption:* We assume that the non stability is due to the asymmetric effect. This effect indicates that a negative shock has not the same impact as a positive shock. So the relation between herding behavior and returns differs when speaking about extreme market returns or average market returns. For this purpose, we study this relation at two levels: extreme and average returns.

We have ordered our sample returns into three sub samples, according to median criteria, in order to empirically test if instability is caused by an asymmetric effect. The first sub sample represents average returns that are observations closest to the average of the total sample. The two other sub sample represents extreme up and down returns made up from observations that are further from the average of the total sample in positive and negative tails respectively.

The mathematical formulations are as follows:

- At the aggregated level:

$$R_{m,t}^{average} = \alpha + \beta VH_{m,t} + \varepsilon_t \quad (24)$$

$$R_{m,t}^{average\ up} = \alpha + \beta VH_{m,t} + \varepsilon_t \quad (25)$$

$$R_{m,t}^{average\ down} = \alpha + \beta VH_{m,t} + \varepsilon_t \quad (26)$$

- At the individual level:

$$R_{i,t}^{average} = \alpha + \beta VH_{i,t} + \varepsilon_t \quad (27)$$

$$R_{i,t}^{average\ up} = \alpha + \beta VH_{i,t} + \varepsilon_t \quad (28)$$

$$R_{i,t}^{average\ down} = \alpha + \beta VH_{i,t} + \varepsilon_t \quad (39)$$

Where:

$R_{m,t}^{average}$ represents the more close observations to the average of the series,

$R_{m,t}^{average\ up}$ ($R_{m,t}^{average\ down}$) represent the more far positives (negative) observations from the average of the series.

Table 5: Relationship between herding behavior and average Return

	Alpha	**Beta**		**Alpha**	**Beta**
AXP	0,214	11,6833003	LUN	0,31057452	-16,0676835
BWR	-0,03719492	13,40022	MDS	-0,01366917	3,69609854
AEM	0,00475856	4,43606001	MFC	0,03750577	-4,40665228
AGU	0,04165667**	-3,45620683*	MBT	0,00393817**	0,94243621
BLD	-0,06650571	13,7933211	NA	0,02198382*	-0,82275416*
BBDB	-0,04895776	7,57542483	OCX	-0,04909897	15,9978107
BCE	-0,05805653	8,17389237	NCX	0,02970511	-4,59061465
BMO	0,0053963	0,38732945	NT	-0,27375492	131,908669
BNS	0,05175634	-4,31561218*	NXY	0,00685805	*1,09076226*
BVF	-0,03010381	4,26365734	PCA	0,06564686	*-11,861594*
CCO	0,10495391	-8,13999931	POT	0,04636081	*-3,41278944*
CM	0,01433141**	0,57300389**	PWTUN	0,04461158	*-2,82626283*
CNQ	0,01691386	-4,13288357	RCIB	-0,06441741	*19,4958925*
CNR	0,04313374	-5,84849921	RIM	-0,15529848	*25,1241811*
COSUN	3,92398673	-1068,04977	RY	0,01134078	*-0,7916021*
CAR	9,67669869	-924,098038	SAP	0,05604321	*-9,67954565*
CMH	-0,02992953	10,2984552	SCC	-0,04421188	*5,13274554*
CLS	-0,02704355	4,64415238	SGF	-0,03097282*	*32,6466511***
ELD	0,04965926**	-2,01951628*	SU	-0,00551229	*3,51014533*
ENB	0,03862301	-5,40699723	T	-0,02827038	*5,22268983*
EMA	0,01211388	-0,55122491	TA	0,03936721	*-2,49041923*
FTS	0,0268162	-6,04438452**	TCKB	0,01545751	*-0,13654375*
FTT	0,02771868	-4,53466575	TEO	0,0379936	*-1,48387941*
GEA	-0,016296	17,6510798	TIH	0,02397395	*-3,55995343*
GIL	-0,04479618	14,0336934	TCW	0,03080079	*-3,3989305*
HSE	0,02741459*	-1,0328942**	TOG	-0,00242822*	*0,71600639***
IMN	-0,07824709	15,6748441	TP	0,06488941	*-5,10806246*
IMO	0,01547383	-3,19264312	WN	0,05207852	*-6,86202883*
K	0,039155	-3,01608611	VETUN	0,04681308	*-4,3420162*
L	*0,0230849*	*-3,89328621*	*YRI*	*1,54983042*	*9,00831293*

***, **, * denotes that coefficient is significant at the 1%, 5%, and 10% levels,

Table 6: Relationship between herding behavior and extreme up return

	Alpha	Beta		Alpha	Beta
AXP	0,001	7,03832579**	LUN	0,336315**	-26,854061**
BWR	-0,04489346	11,9218603***	MDS	-0,01283443	1,78276312**
AEM	0,00541283**	4,53091639	MFC	0,01926292**	-3,92609912*
AGU	0,03735331*	-1,30938066	MBT	0,00204883*	0,77366734
BLD	-0,10779525	18,45746	NA	0,0107883**	-0,76884172
BBDB	-0,02584702**	3,10348801**	OCX	-0,09140268	18,3779006**
BCE	-0,06170038	8,91998287**	NCX	0,02508583	-2,9399153
BMO	0,00290359**	0,41726455	NT	-0,21744275	119,136519***
BNS	0,04766322	-3,00943333	NXY	0,00974903**	*0,59477638**
BVF	-0,02573768*	3,13955668**	PCA	0,08107636	*-7,61996894***
CCO	0,08024027**	-14,141796***	POT	0,04958195	*-7,17479867*
CM	0,01159053	0,83678149	PWTUN	0,02377958*	*-4,16827834***
CNQ	0,03515435**	-2,59144158*	RCIB	-0,05564773**	*10,2846379*
CNR	0,02591975*	-7,44354879	RIM	-0,08736113*	*42,5100996***
COSUN	11,0950771*	-1174,66644**	RY	0,0077597**	*-1,03631903**
CAR	9,55336325*	-955,25151*	SAP	0,02878951	*-5,28758393***
CMH	-0,05320539	11,807232***	SCC	-0,05437956**	*9,48198283***
CLS	-0,02497896	3,7323162	SGF	-0,04461636	*32,5395453***
ELD	0,06354981*	-0,92069357	SU	-0,00411009**	*4,5463223***
ENB	0,03462798*	-3,34009956**	T	-0,02023821*	*8,7288726*
EMA	0,01173887	-0,68614808	TA	0,02008618**	*-2,02409888**
FTS	0,03732101*	-2,80335491*	TCKB	0,01744647*	*-0,1668353**
FTT	0,04874565**	-2,49401436**	TEO	0,03446213**	*-1,95653974*
GEA	-0,02346724**	13,054672***	TIH	0,0387358*	*-6,48232568***
GIL	-0,04690873*	6,3583351**	TCW	0,02919037**	*-4,69451786*
HSE	0,02261599*	-1,0978602	TOG	-0,00209432**	*0,79915099**
IMN	-0,06852854**	21,3975518**	TP	0,03771772*	*-3,68592395***
IMO	0,03067441*	-1,39613909	WN	0,03044885*	*-9,36207837***
K	0,068651	-6,26921359*	VETUN	0,07374928	*-6,66019663**
L	*0,04897348**	*-6,83583227***	*YRI*	*0,85576355*	*4,89220919***

***, **, * denotes that coefficient is significant at the 1%, 5%, and 10% levels, extreme up stock returns.

Table 7: Relationship between herding behavior and extreme down return

	Alpha	Beta		Alpha	Beta
AXP	0,00107875**	7,84046789**	LUN	0,36792956**	-40,1692831**
BWR	-0,04677751	14,8641179***	MDS	-0,01235579	2,53165729**
AEM	0,00423488**	3,52750287**	MFC	0,01589441**	-4,77235653*
AGU	0,03835065*	-1,22149675	MBT	0,00186866*	0,87891563*
BLD	-0,07497463	13,8549961**	NA	0,01214688**	-0,68944792**
BBDB	-0,01919898**	2,32331392**	OCX	-0,11343391	25,063081**
BCE	-0,07073312*	12,1209995**	NCX	0,03364807**	-3,87089738***
BMO	0,00312895**	0,29191591*	NT	-0,19325116	96,5825093*
BNS	0,04212344	-3,12614621**	NXY	0,00626182**	*0,55586943***
BVF	-0,01379315*	1,66943407**	PCA	0,11651679	*-8,72351671***
CCO	0,04186639**	-19,0929785***	POT	0,03250336**	*-7,82859307***
CM	0,00774594*	0,62773213	PWTUN	0,03071954*	*-4,25772316**
CNQ	0,0251477**	-2,84748294*	RCIB	-0,05953086**	*8,83808662***
CNR	0,03549821*	-9,39986152**	RIM	-0,08118278*	*43,8585493**
COSUN	10,2962714*	-1755,36791**	RY	0,00943732**	*-1,22229273***
CAR	5,74535576*	-1002,2676*	SAP	0,0384685	*-6,4147972***
CMH	-0,03558224	8,31470105***	SCC	-0,02966993**	*11,2584438***
CLS	-0,01640177	5,28754236**	SGF	-0,05893479*	*42,2518681***
ELD	0,03752895*	-1,19199243	SU	-0,00466332**	*5,12235122***
ENB	0,03431065*	-3,94860142**	T	-0,01663251*	*7,61688279**
EMA	0,00663153	-0,36044399*	TA	0,01380868**	*-1,19717328**
FTS	0,02185246*	-3,52922845*	TCKB	0,02441813*	*-0,16597518*
FTT	0,04505964**	-2,97586673**	TEO	0,03612394**	*-1,76865469***
GEA	-0,02347119**	13,7848218***	TIH	0,05395152*	*-5,66239624**
GIL	-0,0283547*	5,8178673**	TCW	0,0369755**	*-4,11662085*
HSE	0,03048261	-1,4346506**	TOG	-0,00216551**	*0,82725212***
IMN	-0,05120323**	17,2795216**	TP	0,05520768*	*-3,1047689***
IMO	0,04478632*	-1,12720969**	WN	0,03899371*	*-13,7754661**
K	0,07388708	-5,18001044*	VETUN	0,0975117	*-9,35053075***
L	*0,02749152**	*-9,12818607***	*YRI*	*0,45217013*	*5,40334986***

***, **, * denotes that coefficient is significant at the 1%, 5%, and 10% levels,

The decomposition results show that the relation between herding and returns is significant only when returns take extreme values.
Table 5 shows only 9 significant betas which represent 15% of our sample. This result means that herding behavior has no impact on prices dynamics for average returns; i.e., when asset price moves close to the fundamental value, which consequently implies the market efficiency.

In the other hand, betas are highly significant in tables 6 and 7 compared to those of table 5. For the extreme up returns we record that 70% of betas are significant which low than the degree of significance recorded for the extreme down returns that is equal to 92%. This result reflects the asymmetry effect that provides strongly significant explanations to the instability of the relation between herding behavior and returns

The existence of herding behavior during extreme up market is confirmed by the work of Christie and Huang (1995) using both daily and monthly data for NYSE and AMEX from July 1962 to December 1988. In our study, there exists asymmetry that herding during the extreme down markets has great significance related to the extreme up markets. So when the market becomes riskier and is falling, herd increases, while it decreases when the market becomes less risky and rises. These results suggest that herd behaviour is significant and exists dependently of the particular state of the market. However, it is now easy to see how these results are consistent with and explain many previous empirical studies

which argue that ‘‘herding’’ occurs during market crises (Chang, Cheng and Khorana (2000), Hwang et Salmon (2004)).

From these results we can confirm our third proposition which assume that the non stability of the relation between herding behavior and returns is due to asymmetric effect.

5. Conclusion

Herding is widely believed to be an important element of behaviour in financial markets and particularly when the market is in stress. Our study contributes to the literature in several respects. First, we have proposed a new approach to measuring and testing herding in financial market inspired from the model of Hwang and Salmon (2004) and based on trading volume rather then asset returns. Second, when applying our measure to the S&P/TSX60 index using monthly data from January 2000 to December 2002, we found that herding towards the market consists of three components.

A robustness test shows that the relation between herding behavior and return shows non-stability at the aggregated level. For this reason we advance three propositions: the first one stipulates that the non stability of the relation is due to microstructural data. The second explains this non stability by the non linear aspect on the relation, and the third one assumes that the asymmetric effect is the cause of this non stability. We find that the non stability of the relation herding/returns is due to the asymmetric effect in the extreme down returns.

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