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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) 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.

JEL D53; G12; C13

Keywords Herding behavior; market return; trading volume

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1. Introduction

Since the advent of behavioral finance in the 1980s, a considerable amount of research in finance has been devoted to the employment of psychological concepts in order to picture the evolution of stock prices on the grounds of various aspects of investor's behavior. A substantial part of this research has focused upon the specific issue of herd behavior, which used to be confined traditionally within the realm of the popular Finance literature (Kindleberger, 1978; Soros, 1987; Galbraith, 1994). Academic interest on this issue has been notably intense during the last couple of decades and has led to the generation of a voluminous research output, as the reviews of Bikhchandani and Sharma (2000) and Hirshleifer and Teoh (2003) illustrate.

Herding in financial markets has been typically described as a behavioral tendency for an investor to follow the actions of others. Practitioners are interested in whether herding exists, because the reliance on collective information rather than private information may cause prices to deviate from fundamental value and present profitable trading opportunities. Herding has also attracted the attention of academic researchers, because the associated behavioral effects on stock price movements may affect their risk and return characteristics and thus have implications for asset pricing models.

Theoretical models of herding behavior have been developed by Bikhchandani, Hirshleifer and Welch (1992), Scharfstein and Stein (1990), and Devenow and Welch (1996). Empirical studies have mainly focused on detecting the existence of herding behavior among mutual fund managers (Lakonishok, Shleifer, and Vishny, 1992; Wermers, 1999) or financial analysts (Trueman, 1994; Graham, 1999; Welch, 2000; Hong, Kubik, and Solomon, 2000; Gleason and Lee, 2003; Clement and Tse, 2005).

Measuring herding empirically has proved challenging. Besides some special contexts or experimental settings, it is difficult to separate imitating behavior from clustering of trades. The empirical herding literature for the most part, therefore, uses herding as a synonym for systematic or clustered trading. Herding measures are, therefore, at best noisy proxies for imitative behavior. When herding is defined in a more general sense of clustered trading, specific forms of systematic trading patterns deriving from past returns, capital gain and loss position, and attention can also be interpreted as herding. However, when it comes to drawing conclusions on asset pricing, it is the overall clustering that is the primary concern.

The empirical study usually does not test a particular model of herding behavior described in the theoretical literature; instead, they gauge whether clustering of decisions, in purely statistical sense, is taking place in financial markets or within certain investor groups. Two streams of empirical literature have been developed to investigate the existence of herding in financial markets. The first stream analyzes the tendency of individuals or certain groups of investors to follow each other and trade an asset at the same time [Lakonishok *et al.* (1992) and Wermers (1995)]. These studies use the trading volume to detect herding in financial market. The second stream focuses on the market-wide herding, that is, the collective behavior of all participants towards the market views and therefore buying or selling particular asset at the same time [Christie and Huang (1995), Chang et al. (2000) and Huang and Salmon (2001, 2004, 2006)]. These measures are based on the cross-sectional dispersion of beta to detect herding toward the market index.

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

Herd behavior is a term implying alignment to a mode of collective conduct and is expressed as a "similarity in behaviour" following the "interactive observation" of *actions* and *payoffs* (arising from those actions) among individuals (Hirshleifer and Teoh, 2003). In the stock market context, herding involves the intentional sidelining of investors' private information in favor of the observable "consensus" (Bikhchandani and Sharma, 2000) irrespective of fundamentals (Hwang and Salmon, 2004) and the roots of such behavior can be traced to a series of factors be they of psychological or rational nature.

The most widely used herding measure is that invented by Lakonishok, Shleifer and Vishny (1992). This measure seeks to detect whether more investors are trading on either the buy or sell side of the market than would be expected if investors traded independently. Lakonishok, Shleifer and Vishny (1992) use the investment behavior of 769 U.S. tax-exempt equity funds managed by 341 different money mangers to empirically test for herd behavior. Lakonishok, Shleifer and Vishny (1992). conclude that money managers in their sample do not exhibit significant herding. There is some evidence of such behavior being relatively more prevalent in stocks of small companies compared to those of large company stocks. Lakonishok, Shleifer and Vishny (1992) explanation is that there is less public information on small stocks and hence money managers pay relatively greater attention to the actions of other players in making their own investment decisions regarding small stocks.

Wermers (1995) develops a new measure of herding that captures both the direction and intensity of trading by investors. This new measure, which he calls a portfolio- change measure (PCM) of correlated trading, overcomes the first drawback listed above. Intuitively, herding is measured by the extent to which portfolio weights assigned to the various stocks by different money managers move in the same direction. The intensity of beliefs is captured by the percent change of the fraction accounted for by a stock in a fund portfolio. Wermers (1995) finds a significant level of herding by mutual funds using the PCM measure.

Measuring the herding behavior on the basis of Lakonishok *et al*. (1992) has important limitations. First, this measure captures correlation in trades but does not, by itself, disentangle the determinants of herding. Second, this measure does not take in consideration whether the correlation trades results from imitation or merely reflects that traders use the same information. Finally, this measure is biased when there are limitations to short selling strategies.

Two studies that have proposed methods of detecting herding behavior using stock return data are Christie and Huang (1995) (hereafter referred to as CH) and Chang, Cheng, and Khorana (2000) (hereafter referred to as CCK). CH suggest that the investment decision-making process used by market participants depends on overall market conditions. They contend that during normal periods, rational asset pricing models predict that the dispersion in returns will increase with the absolute value of the market return, since individual investors are trading based on their own private information, which is diverse. However, during periods of extreme market movements, individuals tend to suppress their own beliefs, and their investment decisions are more likely based on the collective actions in the market. Individual stock returns under these conditions should tend to cluster around the overall market return. Thus, they argue that herding will be more prevalent during periods of market stress, which is defined as the occurrence of extreme returns on the market portfolio.

Demirer and Kutan (2006) apply the CH method to examine herding in Chinese equity markets. They use daily stock return data from 1999 to 2002 for 375 Chinese stocks and find no evidence of herding. One of the challenges associated with the approach described above is that it requires the definition of extreme returns. CH note that this definition is arbitrary, and they use values of one percent and five percent as the cutoff points to identify the upper and lower tails of the return distribution. In practice, investors may differ in their opinion as to what constitutes an extreme return, and the characteristics of the return distribution may change over time. In addition, herding behavior may occur to some extent over the entire return distribution, but become more pronounced during periods of market stress, and the CH method captures herding only during periods of extreme returns. Additional challenges arise when applying this method to Chinese stock market data because the relatively short history of these markets makes it difficult for investors to identify when extreme returns occur.

An alternative to the CH test for herding is that of Chang, Cheng, and Khorana (2000) (CCK). They examine several international stock markets, and find no evidence of herding in developed markets, such as the U.S. and Hong Kong. However, they do find evidence of herding in the emerging markets of South Korea and Taiwan. CCK note that the CH approach is a more stringent test, which requires "a far greater magnitude of non-linearity" in order to find evidence of herding.

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 behaviourally 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. HS (2006) note that stock returns and herding are likely to be affected by fundamentals, at the level of the market or the individual firm. They use variables such as the dividend-price ratio, the Treasury bill rate, the term spread, and the default spread in their analysis of herding in the US, UK, and South Korean equity markets.

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:

$$V_i = \alpha_i + \beta_i V_m + \varepsilon_i \tag{1}$$

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:

$$V_{i,t} = \beta_{i,m,t} V_{m,t} \tag{2}$$

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:

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

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:

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

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:

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

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

And

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

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:

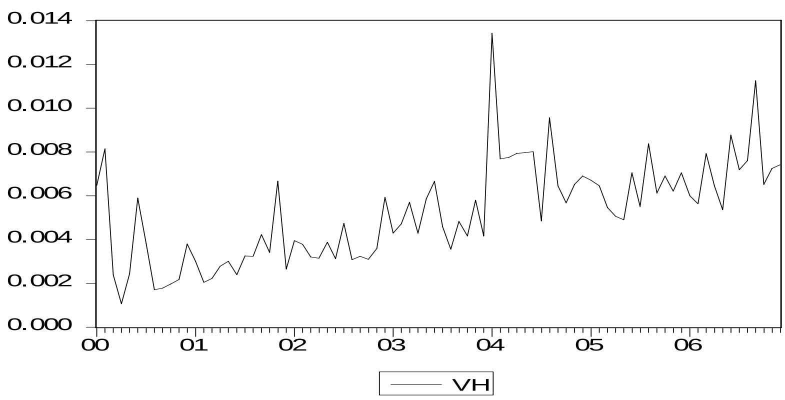

Figure 1: Evolution of VH measure for S&P/TSX60 index

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:

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

Where:

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

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

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

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

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

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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