A New Measure of Herding Behavior: Derivation and Implications

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Abstract—If price and quantity are the fundamental building blocks of any theory of market interactions, the importance of trading volume in understanding the behavior of financial markets is clear. However, while many economic models of financial markets have been developed to explain the behavior of prices -predictability, variability, and information content- far less attention has been devoted to explaining the behavior of trading volume. In this article, we hope to expand our understanding of trading volume by developing a new measure of herding behavior based on a cross sectional dispersion of volumes betas. We apply our measure to the Toronto stock exchange using monthly data from January 2000 to December 2002. Our findings show that the herd phenomenon consists of three essential components: stationary herding, intentional herding and the feedback herding.

Keywords—Herding behavior, market return, trading volume.

I. INTRODUCTION

HERDING behavior has been examined extensively in the areas of economics ([23] and [41]), physics ([43], [44], [45] and [34]), and sociology [36]. As one would expect with inquiries that span several disciplines, there is no clear consensus on the definition of herding in the literature; however, certain common themes emerge. First, herding is usually defined in terms of crowd behavior – that is, a group is defined as a herd if members of that group tend to move more strongly with each other than with the collective movement of other groups. Second, herding can be based on fundamentals or herding can be faddish. In the former case, imperfectly rational agents deduce information from the behavior of other agents in the herd perhaps because of the additional cost of obtaining or verifying information from outside the herd. Herding can be based on fads if agents behave irrationally and limits to arbitrage prevent prices from rapidly converging to fundamental values. Even rational informed agents may decide to ride the fad when fundamental information and/or arbitrage are costly.

Herding may be either rational or irrational. Most of the theoretical finance literature focuses on rational herding. Reference [4] classifies rational herding further into three subcategories: informational-based herding, reputation-based herding, and compensation-based herding. One of the first informational-based herding models was built by [3]. He analyzes a sequential decision-making model in which each decision-maker takes into account the decisions made by the previous investors before taking her own decision. He finds a unique Nash equilibrium that is characterized by fairly extensive herding. In various circumstances, depending on the decisions of the first few agents, a decision-maker located later in the sequence rejects her private information and decides to mimic others' actions. In this case, the decision maker joins a so-called informational cascade, in which accumulation of information stops altogether.

Theoretical and empirical research on herding has been conducted in an isolated manner. Theoretical study focuses on the causes and implications of herding. Thus far, 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 ([30] and [50]). 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 ([9], [7], [24], [25] and [26]). 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 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 our starting point the model of [25], but we employ a proxy pioneered by [30] 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 four 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 our new measure on Toronto stock exchange. Finally, the fifth section offers concluding remarks and discusses implications of our findings.

II. Literature Review

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.

Various empirical measures have been proposed to detect herding. The most widely used herding measure is that invented by [30]. This measure (hereafter LSV) 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.

Reference [30] uses the investment behavior of 769 U.S. tax-exempt equity funds managed by 341 different money mangers to empirically test for herd behavior. Reference [30] concludes 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. Their 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.

Reference [20] uses the quarterly ownership data on portfolio changes of 274 mutual funds between 1974 and 1984. Using the LSV measure, they find similar levels of herding as found by [30]. Relating it to momentum trading, [20] find more herding by investors in buying past winners than investors selling past losers. To control for significant heterogeneity in the mutual funds, they differentiate funds according to their investment objectives: aggressive growth funds, balanced funds, growth funds, growth-income funds, income funds. They find even less herding after controlling for objectives.

Reference [50] 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. Reference [50] finds a significant level of herding by mutual funds using the PCM measure.

Reference [50] uses the LSV measure and data on quarterly equity holdings of virtually all mutual funds that were in existence between 1975 and 1994 and finds that for the average stock there is some evidence of herding by mutual funds. For [50] sample the average level of herding computed over all stocks and quarters for the two decades covered is 3.4. While statistically significant, this value is only slightly larger than that reported by [30] suggesting that there is somewhat greater herding among mutual funds than among pension funds. An analysis of trading behavior, when a larger number of funds are active in a stock, shows that herding by mutual funds does not increase with trading activity and actually falls off as the number of active funds increases. This is due to the fact that stocks traded by a large number of funds tend to be large capitalization stocks and herding in these is generally lower.

Measuring the herding behavior on the basis of [30] 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.

These studies view herding behaviour as a collective buying and selling actions of the individuals in an attempt to follow the performance of the market or any other economic factors or styles. Here, herding is detected by exploiting the information contained in the cross-sectional stock price movements.

Reference [9] 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

Using daily and monthly returns on U.S. equities, [9] find a higher level of dispersion around the market return during large price movements, evidence against herding.

Reference [7] proposes a modification to the model presented by [9]. Their model uses the cross-sectional absolute standard deviation (hereafter CSAD) of returns as a measure of dispersion to detect the existence of herding in the U.S., Hong Kong, Japanese, South Korean and Taiwanese markets. Reference [7] notes that the [9] approach is a more stringent test, which requires "a far greater magnitude of nonlinearity" in order to find the evidence of herding.

Reference [7] examines individual returns on a monthly basis and finds a significant non-linear relationship between equity return dispersion and the underlying market price movement of the South Korean and Taiwanese markets, providing evidence of herding within these emerging markets. They do not, however, find evidence to support the presence of herding in the developed markets of the U.S., Hong Kong, and Japan.

Reference [25] develops a new measure (hereafter HS) 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, [25] 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.

Reference [26] notes 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.

III. METHODOLOGY

Some of the best thinking occurs when we approach old topics in fresh ways. Consider the topic of sentiment. Through our normal lenses, we parse the world into bulls and bears. Suppose, however, we look at sentiment differently and measure it as the degree to which traders behave in more vs. less differentiated ways. If traders respond to markets in a non-differentiated way, they move as a herd, and we would expect transacted volume to be lopsided toward advancing or declining stocks. In a differentiated mode, market participants discriminate between better and worse investments and apportion volume to advancing and declining issues accordingly.

Our methodology is based on trading volume and measures herding on the basis of the cross sectional dispersion factor sensitivity of volume. More specifically, when investors are behaviourally biased, their perceptions on the risk-volume relationship of assets may be distorted. To see how herding biases the risk–volume relationship, we first consider what could happen when herding exists in the market model.

Yet the asset pricing literature has centred more on prices and much less on quantities. So, 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, completely ignoring the information contained in quantities. Then, 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 : volume of security i ,

V_m : volume of market.

If investors herd towards the market consensus, then it is possible that as individual asset trading volume follow the direction of the market, their betas will deviate from their equilibrium values. Thus, the beta of a stock does not remain constant, but changes with the fluctuations of investors' sentiment. As a result, 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.

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, this equilibrium relationship no longer holds, both the beta and the trading volume will be biased. More specifically, the relation between the equilibrium beta ($\beta_{i,m,t}$) and its behaviourally biased equivalent ($\beta_{i,m,t}^b$), is the following:

$$V_{i,t}^b / V_{m,t}^b = \beta_{i,m,t}^b = \beta_{i,m,t} - h_{m,t}(\beta_{i,m,t} - 1) \qquad (3)$$

Where:

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

$V_{m,t}^b$: the behaviorally biased volume of market at time t.

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

When $h_{m,t} = 0$, $\beta_{i,m,t}^b = \beta_{i,m,t}$ there is no herding. When $h_{m,t} = 1$, $\beta_{i,m,t}^b = 1$ 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:

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

We have then:

$$\beta_{i,m,t}^b = \frac{\beta_{i,m,t} + s_{i,t}}{1 + s_{m,t}} \qquad (4)$$

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.

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 $\beta_{i,m,t}^b$. 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:

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

Where N_t is the number of stocks at time t.

One major obstacle in calculating the herd measure is that $\beta_{i,m,t}^b$ is unknown and needs to be estimated. It is well documented that betas are not constant but time varying ([22], [11], [12] and [13]). Several methods have been proposed to estimate time varying betas by [18] and [2].

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 $\beta_{i,m,t}^b$ for asset i at time t.

However, $H_{m,t}^{'}$ is also numerically affected by statistically insignificant estimates of $\beta_{i,m,t}^b$. The significance of $b_{i,m,t}$ can change over time, affecting $H_{m,t}^{'}$ even through $\beta_{i,m,t}^b$ is constant. To avoid this, we standardize $b_{i,m,t}$ with its standard deviation. So, we obtain the standardised beta herding:

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

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.

We can address to $H_{m,t}^*$ herding measure two major critics. The first is related to the joint hypothesis which is CAPM. This model is based on hypothesis of the efficiency theory. However, the phenomena that we study here represent a psychological bias that contradicts this hypothesis. Thus the existence of herding reflects the market inefficiency. The second deal with the systematic risk which is assumed in this model to be equal to the unit. But this assumption is unrealistic, because of the existence of several factors that deviates this risk from 1 such as market microstructure and sentiment biases including herding.

For these reasons, we use a dynamic approach to evaluate the systematic risk of the market. So, we assume that the dynamic volume volatility follows GARCH (1,1) process:

$$V_{m,t} = a + b V_{m,t-1} + \varepsilon_t \tag{8}$$

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

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

The same approach is applied for every asset:

$$V_{i,t} = a + b V_{i,t-1} + \varepsilon_t \tag{9}$$

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

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

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

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

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:

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

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

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

With:

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

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

- *Stationary herding* (*CST*): Represented by the constant term, which means that the herding behavior always exists in markets. This is a robust result because there is at least one investor who imitates the actions of others. So, no market will be completely free of herding. Thus we argue that there is either more or less herding in a market at some particular time compared to another, so herding is a matter of degree.

- *Intentional herding* (*IH*): This component emerges when there are abnormal volume changes, which indicate that the market passes through an instable situation. So, no private information can be used to beat the market. In consequent, they imitate voluntary other, and follow the dominant action. This situation occurs when investor anticipations are far from the market tendency. So, the herding increases in function of the number of rational investors ([23] and [12]).

- *Feedback herding* (*FH*): Because of the correlation between the past volume and the herding, it results that the current herding is function of the previous one. This situation is related with the irrational investors. These ones extrapolate past trading volumes and as consequence they follow irrational strategies. This situation is note caused by information but deals just with psychological biases and may cause speculative bubbles [14]. Contrary to the intentional herding, the feedback herding enhances following the size of the crowd. This result finds its theoretical basis in the information cascades theory, which shows that later agents, inferring information from the

actions of prior agents, optimally decide to ignore their own information and act alike ([16] and [49]).

IV. EMPIRICAL EVIDENCE OF THE NEW MEASURE OF HERDING

A. Database

In this study we are testing for herding in the Toronto market on the premises of its main index, the S&P/TSX60. The latter is a value-weighted index including the sixty most liquid stocks selected on the premises of their participation in the market's turnover (number of transactions and trading value) and was officially launched on December 31st 1997. 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 both for the S&P/TSX60 as well as its constituent stocks and covers the period from January 2000 until December 2006 so we have 84 observations for each stock. The historical constituent lists for the S&P/TSX60 were obtained from the web site www.investcom.com.

B. Results and Discussion

We begin our investigation of the presence of herding behavior in the Toronto stock exchange by employing our new measure. The results of the new herding measure are illustrated by the graphic below:
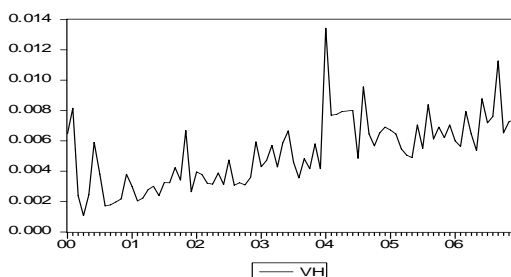

Fig. 1 Evolution of VH measure for S&P/TSX60 index

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.

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.

C. Relationship between Herding Behavior, Return, Volatility and Trading Volume

➢ Relationship between herding behavior, Return, volatility and trading volume at the aggregate level

To further investigate the existence of a link between herding behavior, market return, volatility and trading volume, we propose a simple specification without identifying the nature or the sense of this relationship. However, it is important to signal the contemporaneous characteristic of such relation.

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

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

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

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 I
CONTEMPORARY RELATION BETWEEN HERDING, RETURN, VOLATILITY AND TRADING VOLUME

	Coefficients estimates		Student-test		Stability	Normality of residuals		
	Alpha	Beta	alpha	beta	Test Chow	Skewness	Kurtosis	Jarque-Bera
$R_{m,t}$	-0.021	5.268	-1.773	2.522	0.908	-0.400	3.387	2.771
$V_{m,t}$	0.0022	0.089	23.145	5.190	5.070	0.066	2.818	0.177
$Vol_{m,t}$	0.0023	-0.182	15.41	-6.750	17.004	1.754	6.260	79.362

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

The regression results of (12), (13) and (14) presented in Table I show that the herding behavior is always strongly significant for the main components of the stock prices dynamic: return, trading volume and volatility.

Concerning (12), we record that the beta takes positive values for the market return and trading volume. Which means that the both factors increase when herding is more relevant. The estimations results indicate that when investors herd around the market, this later goes up.

For (13), the results conclude that when herding exists, trading volume is high. So, a large trading volume is a necessary condition for the existence of herding behavior among investors since it is a voluntarily coordinated action.

We find that herding behavior demonstrates a very similar pattern between market return and trading volume. This finding is consistent with the literature: [15], [13] and [8].

Concerning volatility (14), we find negative beta implying that when herding phenomenon exists, the volatility is excessively low. The volatility exhibited is likely to be higher than if agents did not herd because herding leads to a greater concentration of agents on one side of the market [38].

In order to test the authenticity of these relations, we carry out two tests: the first aims to check the stability of the relation, and the second verify the normality of residuals:

- The Chow test reveals significant results for volatility and trading volume and non significant ones for market returns. This finding means that the relation between herding behavior and market return lacks of stability.

- The normality test of residuals is done through three coefficients: skewness, kurtosis and Jarque-Berra. This test

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. Concerning kurtosis, this coefficient is inferior to 3 for trading volume, but superior for return and volatility. A higher kurtosis testifies to the strong probability of extreme points, the tails of distribution are thicker than those of normal distribution. The returns residuals series are characterized by proportionally low flatness while those of volatility reveal strong flatness which gives higher JB (79.36). In contrast, trading volume residual series reveals a proportional peakedness.

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.

In order to study the causes of non stability, we advance three propositions:

- *Proposition 1:* The relationship between herding behavior and market return differ 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.

Generally, when considering herding towards the market, we take the underlying movement in the market itself as given and hence capture adjustments in the structure of the market due to herding rather than adjustments in the market. This may be termed market wide herding and allows us to measure movements in herding within the market which may follow a different path from the market itself ([36] and [19]). Market herding is for instance often believed to change with little or no apparent movement in the market itself. The use of linear factor models can also provide additional insights into other directions towards which the market may herd based on different factors in addition to the market factor, such as growth and value, country- or sector-specific factors [24].

To test this proposition we first subdivide our sample into sub samples according to microstructural criteria. We obtain sub samples of banking and non banking firms, small and big size companies, high and low value book to market companies or liquid and illiquid companies. Then, we estimate coefficients of linear regressions between returns of each sub sample and our herding measure.

- *Proposition 2:* 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.

If market participants tend to follow aggregate market behavior and ignore their own priors during periods of large average price movements, then the linear and increasing relation between herding and market return will no longer hold. Instead, the relation can become non-linearly increasing [7].

The underlying intuition behind our approach is as follows. We show that when herding exists, rational asset pricing models predict not only that dispersion is an increasing function of the market returns but also that the relation is linear. Furthermore, an increased tendency on the part of market participants to herd around the market consensus during periods of large price movements is sufficient to convert the linear relation into a non-linear one [46].

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 ([17], [27] and [6]). We use this model to capture any possible non-linear relation between herding and the market return

- *Proposition 3:* 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.

The asymmetric property stipulates that herding is more prevalent in the extreme down markets than the extreme up. These observations are consistent with the behavior theory that some investors panic and sell their positions during the extreme market declines [28].

The results reveal the presence of herd behavior in stock market in which it is more prevalent in the lower market stress and bearish periods. Investors are perceived irrational as they are unwilling to make their own decisions. Instead, they follow the collective actions of the market. This behavior further implies that the violation of the rational people assumption in which standard modern finance is based. Reference [39] suggests that the need for market participants to understand the impact of psychology has on them and those around them. If they ignore psychology, they do so at their own risk. This is consistent with the intuition of [7] and [9] that during these periods of extreme market movements, individuals suppress their own beliefs in favour of the market consensus.

To test this proposition we shed light on the extent of herd behavior across trading month with average, extreme upward and downward price movements. We separate our sample returns according to the media criteria. We consider average returns those close to the mean and extreme returns those far from the both in up and down tails. Then, we estimate the linear regression between these returns and our herding measure.

➢ *Relationship between herding behavior and Returns according to microstructural factors (proposition 1)*

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.

The size effect is calculated from the stock exchange capitalization. A company which has a lower capitalisation than the average capitalisation of the total sample is considered as a small size company and vice versa.

For the book to market effect, we use a ratio that compares the book value of a firm to its market value. Book value is calculated from the firm's historical costs, or an accounting value. Market value is determined in the stock market through its market capitalization.

For liquidity we apply a measure of [1]. According to this author, the illiquidity of an action I for one month T is measured by the following formula:

$$ILLIQ_t^i = \frac{1}{N_t^i} \sum_{d=1}^{N_t^i} \frac{\left| R_{d,t}^i \right|}{V_{d,t}^i} \tag{15}$$

Where:

$R_{d,t}^i$: return on stock i in the day d of the month t;

$V_{d,t}^i$: trading volume of stock i in the day d of the month t;

N_t^i : A number of days of transaction of stock i in the month t.

Table II represents the statistics of our data, where the sample is subdivided into sub samples according to activity sector, size, book to market and liquidity criteria. This subdivision let us to see the degree of herding among these several classes.

TABLE II
DATA STATISTICS

	Name	Sector		size		Book to market		Liquidity	
		Energy	Non energy	big	little	big	little	Liquid	illiquid
AXP	Axcan Pharma Inc.		x		x	x			x
BWR	Breakwater Resources Ltd.	x		x			x	x	
AEM	Agnico Eagle Mines Ltd.	x			x		x		x
AGU	Agrium Inc.	x			x	x			x
BLD	Ballard Power Systems Inc		x		x		x	x	
BBDB	Bombardier Inc. Class BSV		x	x			x		x
BCE	BCE Inc.		x	x		x		x	
BMO	Bank of Montreal		x	x		x		x	
BNS	Bank of Nove Scotia The		x	x		x		x	
BVF	Biovail corp		x		x		x	x	
CCO	Cameco corp	x		x			x		x
CM	Canadian Imperial Bank of Commerce		x	x		x		x	
CNQ	Canadian National Railway Co.	x		x		x		x	
CNR	Canadian Natural Resources Ltd.		x	x		x		x	
COSUN	Canadian Oil Sands Trust	x			x		x		x
CAR	Canadian Apartment properties		x		x		x	x	
CMH	Compton Petroleum corporation	x			x		x	x	
CLS	Celestica Inc.		x		x		x		x
ELD	Eldorado Gold Corp.	x			x		x		x
ENB	Enbridge Inc.	x			x		x	x	
EMA	Emera Inc.	x			x		x	x	
FTS	Fortis Inc.	x			x		x	x	
FTT	Finning International Inc.		x		x		x		x
GEA	Gold Eagle Mines Ltd.	x			x		x		x
GIL	Gildan Activewear Inc.		x		x	x		x	
HSE	Husky Energy Inc.	x		x		x		x	
IMN	Inmet Mining Corp.	x			x	x		x	
IMO	Imperial Oil Ltd.	x		x			x		x
K	Kinross Gold Corp.	x		x			x	x	
L	Loblaw Companies Ltd.		x	x			x	x	
LUN	Lundin Mining Corporation	x		x		x		x	
MDS	MDS Inc.		x		x	x		x	
MFC	Manulife Financial Corp.		x	x		x		x	
MBT	Manitoba Telecom Services Inc.		x		x	x		x	
NA	National Bank of Canada		x		x		x	x	
OCX	Onex Corp.		x		x	x		x	
NCX	NOVA Chemicals Corp.		x		x		x	x	
NT	Nortel Networks Ltd.		x	x			x	x	
NXY	Nexen Inc.	x		x		x		x	
PCA	Petro-Canada Inc.	x		x		x			x
POT	Potash Corporation of Saskatchewan	x			x		x		x
PWTUN	Penn West Energy Trust	x		x			x		x

RCIB	Rogers Communications Inc.		x	x		x			x
RIM	Research In motion Ltd.		x	x		x		x	
RY	Royal bank of Canada		x	x			x	x	
SAP	Saputo Inc.		x		x	x		x	
SCC	Sears Canada Inc.		x		x		x		x
SGF	Shore Gold Inc.	x			x	x		x	
SU	Suncor Energy Inc.	x		x		x		x	
T	TELUS Corp.		x		x		x	x	
TA	TransAlta Corp.	x			x		x	x	
TCKB	Teck Cominco Ltd.	x		x			x		x
TEO	Tesco Corp.	x			x		x	x	
TIH	Toromont Industries Ltd.		x		x		x		x
TCW	Trican well service Ltd	x			x		x	x	
TOG	Tristar oil and Ltd.	x		x		x		x	
TP	TransCanada Corporation	x		x			x	x	
WN	George Weston Ltd.	x			x	x		x	
VETUN	Vermilion Energy Trust	x			x		x	x	
YRI	Yamana Gold Inc.	x		x			x		x
	Total	**32**	**28**	**26**	**34**	**25**	**35**	**41**	**19**

- *Relation between herding behavior and individual stock returns:*

To test this relation we estimate the following regression:

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

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 below.

TABLE III
CONTEMPORARY RELATION OF INDIVIDUAL STOCK RETURNS AND HERDING BEHAVIOR

	Alpha	Beta		Alpha	Beta
AXP	-0.023*	7.944**	LUN	0.290**	-26.34**
BWR	-0.034	10.20***	MDS	-0.010	2.564**
AEM	0.005**	3.840**	MFC	0.029**	-2.963*
AGU	0.031*	-2.563	MBT	0.003*	1.471
BLD	-0.072	14.42**	NA	0.019**	-0.654
BBDB	-0.043**	6.147**	OCX	-0.066*	12.28**
BCE	-0.045*	7.581**	NCX	0.031**	-4.977**
BMO	0.005**	0.376	NT	-0.348	90.42***
BNS	0.035	-4.974	NXY	0.009**	*1.017*
BVF	-0.027*	4.126**	PCA	0.072	*-11.00**
CCO	0.076**	-10.44***	POT	0.043**	*-5.440**
CM	0.010*	0.608	PWTUN	0.033*	*-4.458**
CNQ	0.032**	-3.423*	RCIB	-0.066**	*14.01*
CNR	0.046*	-7.225**	RIM	-0.124*	*31.04**
COSUN	7.5691*	-1170.5**	RY	0.008**	*-0.921*
CAR	6.510*	-1006.0*	SAP	0.039	-6.576**
CMH	-0.050	10.72***	SCC	-0.037**	*7.6184**
CLS	-0.037	5.108**	SGF	-0.050*	*24.974**
ELD	0.046*	-1.759	SU	-0.004**	*3.273**
ENB	0.032*	-4.808**	T	-0.025*	*6.978**
EMA	0.009	-0.698	TA	0.029**	*-3.966*
FTS	0.030*	-4.172*	TCKB	0.028*	*-0.176*
FTT	0.034**	-3.262**	TEO	0.025**	*-1.423*
GEA	-0.018**	21.56***	TIH	0.036*	*-5.175**
GIL	-0.033*	9.681**	TCW	0.044**	*-3.651*
HSE	0.031*	-1.605	TOG	-0.002**	*1.275*
IMN	-0.076**	19.38**	TP	0.052*	*-7.068**
IMO	0.025*	-2.573**	WN	0.046*	*-7.787**
K	0.069	-5.249*	VETUN	0.053	*-4.925*
L	0.039*	-6.562**	YRI	1.144	*7.944**

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

The reading of Table III 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.

- *Relation between herding behavior and stock returns according to assets sort:*

The loss of significance of the relation between herding and individual stock returns for some companies pushes us to question if there are common characteristics between companies which can influence this relation. For this reason, 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:*

$$R_{si,t}=\alpha+\beta VH_{si,t}+\varepsilon_t \qquad (17)$$

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:*

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

$$R_{low\ Book,t}=\alpha+\beta VH_{low\ Book,t}+\varepsilon_t \qquad (19)$$

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:

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

$$R_{illiquid,t}=\alpha+\beta VH_{illiquid,t}+\varepsilon_t \qquad (21)$$

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 IV gathers the results of these regressions.

TABLE IV
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, we might argue that stocks from different sectors have experienced similar herding behavior. So the relation between herding and returns is insensitive to the type of activity.

Concerning the size effect we record almost the same value of beta. Therefore, 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 a range of results including evidence of significant herding towards different levels of book to market value. This later 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.

According to our preceding study, at the aggregate and individual level, and even according to different criteria activity sector, size, book to market and liquidity, beta of the herding measure is significant, so we reject our first proposition which stipulate that the non stability of the relation between herding behavior and returns is due to microstructural data.

> ### Herding behavior and returns under non linear relation (Proposition 2)

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 ([17], [27] and [6]). In what follows, we employ a standard asymmetrical GJR-AGARCH (1,1)-in-mean model:

$$R_{m,t} = \varphi_0 + \varphi_1 \sigma_t + \varphi_2 VH_{m,t} + \varepsilon_t \qquad (22)$$

$$\sigma_t^2 = \omega + \alpha \varepsilon_{t-1}^2 + \beta \sigma_{t-1}^2 + \lambda I[\varepsilon_{t-1} < 0] \varepsilon_{t-1}^2 \qquad (23)$$

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

Equation (22) represents the mean, where (23) 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. So every type of news has a special impact on conditional variance where α measures impact of good news measures, and $\alpha + \lambda$ captures the effect of bad news. When λ is positive, the volatility is increased by worse information's. In the case where λ is not null, any information has the same impact.

In (22), a significance test of $\varphi_1 = 0$ examines the hypothesis of return-risk trade-off, which need a positive coefficient. To take into consideration the incremental efficiency of $VH_{m,t}$, we put the augmented mean equation:

$$R_{m,t} = \varphi_0 + \varphi_1 \sigma_t + \varphi_2 VH_{m,t} + \varepsilon_t \qquad (24)$$

This equation contains an incremental variable, $VH_{m,t}$, 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 V
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,

This table reports estimation of mean equation under two forms: $R_{m,t} = \varphi_0 + \varphi_1\sigma_t + \varepsilon_t$ (equation 1) and $R_{m,t} = \varphi_0 + \varphi_1\sigma_t + \varphi_2 VH_{m,t} + \varepsilon_t$ (equation 2).

Table V reports parameters of AGARCH(1,1)-in-mean model with the corresponding z-statistics of using $VH_{m,t}$ as a measure of herding. Coefficients of the variance equation are well significant in all cases, which is consistent with the past results of AGARCH estimation, and which show that volatility is characterized by a heteroscedastic process. The coefficient of asymmetric shock term indicates that the trading volume react more deeply to bad information. Concerning the coefficient of conditional standard deviation in (23), it is statistically insignificant and provides different signs. So, we can't confirm the volume-risk trade-off which is consistent with existing researches ([5], [34], [27] and [31]).

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. This result is reasonable since the herding term can provide some information about the

market dynamic. This variable can also include risk relating to market fluctuations caused by portfolio adjustments.

The coefficient α in the conditional variance equation is considerably smaller than the β in all cases, implying that small market surprises induce relatively large revisions in future volatility. Using the GARCH model, the coefficients of regressing returns on herding measure are positive and significant. So, the positive relationship between herding and return preserves after taking heteroskedasticity into account.

> ***Herding behavior and returns according to asymmetric effect (Proposition 3)***

In our study, we find that there is a strongly significant contemporary relation between the herding behavior and stock returns. However, this relation misses stability. In this paragraph, we study our third proposition which assumes that the instability of this relation is due asymmetric effect. For this purpose, we study this relation at two levels: extreme and average returns.

Majority of papers assumes that an extreme return occurs if market movements exceed some predetermined threshold value (for example 1% or 5%) on either side of a probability distribution of equity return. This threshold is arbitrary and can't be generalizing on all the stock markets. In our case, 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:

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

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

$$R_{m,t}^{average\ down} = \alpha + \beta VH_{m,t} + \varepsilon_t \qquad (27)$$

- At the individual level:

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

$$R_{i,t}^{average\ up} = \alpha + \beta VH_{i,t} + \varepsilon_t \qquad (29)$$

$$R_{i,t}^{average\ down} = \alpha + \beta VH_{i,t} + \varepsilon_t \qquad (30)$$

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.

The results of this decomposition are shown in Tables VI, VII and VIII.

TABLE VI
RELATIONSHIP BETWEEN HERDING BEHAVIOR AND AVERAGE RETURN

	Alpha	Beta		Alpha	Beta
AXP	0,214	11,683	LUN	0,310	-16,067
BWR	-0,0371	13,400	MDS	-0,013	3,696
AEM	0,0047	4,436	MFC	0,0375	-4,406
AGU	0,041**	-3,456*	MBT	0,003**	0,942
BLD	-0,066	13,793	NA	0,0219*	-0,822*
BBDB	-0,048	7,575	OCX	-0,049	15,997
BCE	-0,0580	8,1738	NCX	0,029	-4,5906
BMO	0,0053	0,3873	NT	-0,2737	131,908
BNS	0,0517	-4,315*	NXY	0,0068	*1,0907*
BVF	-0,0301	4,2636	PCA	0,065	*-11,861*
CCO	0,1049	-8,1399	POT	0,046	*-3,4127*
CM	0,0143**	0,5730**	PWTUN	0,0446	*-2,826*
CNQ	0,0169	-4,1328	RCIB	-0,064	*19,49*
CNR	0,0431	-5,8484	RIM	-0,1552	*25,124*
COSUN	3,923	-1068,049	RY	0,0113	*-0,791*
CAR	9,6766	-924,098	SAP	0,0560	*-9,679*
CMH	-0,0299	10,298	SCC	-0,0442	*5,132*
CLS	-0,0270	4,6441	SGF	-0,030*	*32,646***
ELD	0,0496**	-2,0195*	SU	-0,0055	*3,5101*
ENB	0,0386	-5,4069	T	-0,0282	*5,2226*
EMA	0,0121	-0,5512	TA	0,0393	*-2,4904*
FTS	0,0268	-6,0443**	TCKB	0,0154	*-0,136*
FTT	0,0277	-4,5346	TEO	0,0379	*-1,483*
GEA	-0,01629	17,651	TIH	0,0239	*-3,559*
GIL	-0,0447	14,033	TCW	0,0308	*-3,398*
HSE	0,0274*	-1,032**	TOG	-0,0024*	*0,7160**
IMN	-0,0782	15,674	TP	0,0648	*-5,1080*
IMO	0,0154	-3,1926	WN	0,0520	*-6,8620*
K	0,0391	-3,0160	VETUN	0,046	*-4,342*
L	*0,0230*	*-3,8932*	*YRI*	*1,5498*	*9,0083*

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

TABLE VII
RELATIONSHIP BETWEEN HERDING BEHAVIOR AND EXTREME UP RETURN

	Alpha	Beta		Alpha	Beta
AXP	0,001	7,038**	LUN	0,336**	-26,854**
BWR	-0,04489	11,921***	MDS	-0,0128	1,7827**
AEM	0,0054**	4,5309	MFC	0,0192**	-3,9260*
AGU	0,0373*	-1,3093	MBT	0,0020*	0,7736
BLD	-0,1077	18,457	NA	0,0107**	-0,76884
BBDB	-0,02584**	3,1034**	OCX	-0,0914	18,377**
BCE	-0,0617	8,9199**	NCX	0,0250	-2,9399
BMO	0,0029**	0,41726	NT	-0,2174	119,13***
BNS	0,0476	-3,0094	NXY	0,0097**	*0,5947*
BVF	-0,02573*	3,13955**	PCA	0,0810	*-7,6199**
CCO	0,0802**	-14,141***	POT	0,0495	*-7,1747*
CM	0,0115	0,8367	PWTUN	0,0237*	*-4,1682**
CNQ	0,0351**	-2,59148*	RCIB	-0,055**	*10,284*
CNR	0,02591*	-7,44354	RIM	-0,0873*	*42,510**

	Alpha	Beta		Alpha	Beta
COSUN	11,095*	-1174,6**	RY	0,0077**	-1,03631*
CAR	9,5533*	-955,25*	SAP	0,02878	-5,2875**
CMH	-0,0532	11,807***	SCC	-0,054**	9,481**
CLS	-0,02497	3,732	SGF	-0,0446	32,539**
ELD	0,06354*	-0,9206	SU	-0,004**	4,546**
ENB	0,03462*	-3,3400**	T	-0,0202*	8,7288
EMA	0,01173	-0,68614	TA	0,020**	-2,02409*
FTS	0,0373*	-2,8033*	TCKB	0,0174*	-0,1668*
FTT	0,0487**	-2,4940**	TEO	0,034**	-1,95653
GEA	-0,0234**	13,054***	TIH	0,0387*	-6,4823**
GIL	-0,04690*	6,3583**	TCW	0,029**	-4,69451
HSE	0,02261*	-1,0978	TOG	-0,002**	0,79915*
IMN	-0,0685**	21,3975**	TP	0,037*	-3,6859**
IMO	0,03067*	-1,39613	WN	0,0304**	-9,3620**
K	0,068651	-6,26921*	VETUN	0,07374	-6,66019*
L	0,04897*	-6,8358**	YRI	0,85576	4,892209**

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

TABLE VIII
RELATIONSHIP BETWEEN HERDING BEHAVIOR AND EXTREME DOWN RETURN

	Alpha	Beta		Alpha	Beta
AXP	0,0010**	7,8404**	LUN	0,3679**	-40,169**
BWR	-0,04677	14,8641***	MDS	-0,0123	2,5316**
AEM	0,00423**	3,527502**	MFC	0,01589**	-4,77235*
AGU	0,03835*	-1,22149	MBT	0,00186*	0,8789*
BLD	-0,07497	13,8549**	NA	0,01214**	-0,6894**
BBDB	-0,01919**	2,32331**	OCX	-0,11343	25,063**
BCE	-0,07073*	12,1209**	NCX	0,03364**	-3,870***
BMO	0,00312**	0,29191*	NT	-0,19325	96,582*
BNS	0,0421234	-3,12614**	NXY	0,00626**	0,55586**
BVF	-0,01379*	1,66943**	PCA	0,11651	-8,7235**
CCO	0,04186**	-19,092***	POT	0,0325**	-7,8285**
CM	0,00774*	0,62773	PWTUN	0,03071*	-4,2577*
CNQ	0,02514**	-2,847482*	RCIB	-0,0595**	8,83808**
CNR	0,03549*	-9,39986**	RIM	-0,08118*	43,858*
COSUN	10,2962*	-1755,36**	RY	0,00943**	-1,2222**
CAR	5,74535*	-1002,26*	SAP	0,0384	-6,4147**
CMH	-0,03558	8,31470***	SCC	-0,0296**	11,2584**
CLS	-0,016401	5,28754**	SGF	-0,05893*	42,2518**
ELD	0,03752*	-1,19199	SU	-0,0046**	5,12235**
ENB	0,03431*	-3,94860**	T	-0,01663*	7,61688*
EMA	0,00663	-0,36044*	TA	0,0138**	-1,19717*
FTS	0,02185*	-3,52922**	TCKB	0,02441*	-0,16597
FTT	0,04505**	-2,97586**	TEO	0,0361**	-1,7686**
GEA	-0,02347**	13,784***	TIH	0,0539*	-5,6623**
GIL	-0,0283*	5,8178**	TCW	0,0369**	-4,11662
HSE	0,03048	-1,4346**	TOG	-0,0021**	0,82725**
IMN	-0,0512**	17,2795**	TP	0,0552*	-3,1047**
IMO	0,04472*	-1,1272**	WN	0,03899**	-13,7754*
K	0,0738	-5,18001*	VETUN	0,097511	-9,3505**
L	0,02749*	-9,12818**	YRI	0,452170	5,4033**

*** , ** , * 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.

From table (VI) we record that only 9 betas are significant 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.

From tables (VII) and (VIII), we conclude that betas are highly significant compared to those of table 6. 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. It affirms, in another way, that the herding behavior has an impact on the prices dynamics only when for extreme returns; i.e., when asset price moves away from the fundamental value, which consequently implies the market inefficiency.

The existence of herding behavior during extreme up market is confirmed by the work of [9] 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 ([7] and [24]).

These observations are consistent with the behavior theory that some investors panic and sell their positions during the extreme market declines. So, herd behaviors could be more prevalent in the extreme down market because of investors' psychological panics. Reference [28] finds the same evidence that evidence of herding behavior of Malaysian market participants is prevalent in extreme lower market stress context and financial crisis (bearish) period. Reference [47] pointed out that when human beings are in doubt, they tend to look to others for answers. It is quite easy to imagine when an investor sees stock prices continue to fall; the investor likes to use other people's judgement as the basis for his or her decisions. Investors as a whole prefer to follow the opinion of others rather than form their own opinions.

This can be seen from the survey conducted by [40] on nearly 900 investors within a few days after the October 1987 crash. Two thirds of the respondents indicated that investor psychology was more responsible for the stock market crash than fundamental changes. Investors viewed the declining stock prices as important information when compared to economic fundamental factors such as corporate earnings and interest rates. During the market downturn, the investors herd around and followed the crowd, hence, causing the stock

prices to plunge even further. References [26], [32] and [37] had explained that investors may be reluctant to act according to their own information and beliefs, fearing that their contrarian behavior will damage the reputation as sensible decision makers.

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.

V. CONCLUSION

The concept of herding has attracted considerable attention on behalf of the research community following the advent of Behavioural Finance in the 1980s. In this paper, we examine the investment behavior of market participants within the Canadian stock market, specifically with regard to their tendency to conform with aggregate market behavior, i.e., exhibit herding.

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 [24] and based on trading volume rather than 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. 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.

In order to test the robustness of our new measure, we tend to examine the relationship between the herding phenomenon and the three principle elements of the market: the return, volatility and trading volume. From these tests we conclude 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. The results of our study shows microstructural factor such: activity sector, size effect, book to market and liquidity effect are not responsible of the non stability of the relation between herding behavior and returns. We find also evidence of asymmetric effect in the extreme down returns which can explain the non stability of the relation herding/returns.

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