Tools for Rounding Up the Herd: The Role of the Trading Volume *

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Abstract

This paper presents three new tools to detect herding behavior and information cascades at very early stages by considering the information content in trading volumes and prices. These new instruments can help investors to maintain the value of their portfolios and provide monetary authorities with new tools to react in time to extreme market reactions. The basic idea behind the new model that supports these instruments is that there exists a certain threshold upon which agents do not follow their own pricing rules but they follow the market stream to avoid being trapped in their initial positions as in an episode of herding or information cascade.

The first instrument, the strength of the market movement calculates the degree of support for a given market trend. Then, the distribution of strength across returns reports the strength for each possible market outcome. Next, we present the market strength weighted return as it completes the information content and improves the robustness of existing measures of returns for tracking the market evolution. As an additional step, we test the behavior of the volume weighted market return compared to the traditional indicator of market evolution to analyze the impact on the Spanish market of shocks from emerging and developed markets in 2003-2004.

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1 Introduction

Financial market crises have highlighted that the assumptions made by asset pricing models on nonexistent transaction costs, market efficiency and agents' rational behavior are systematically violated. Non rational behavior of agents, at least in the pricing of risks when assessing the value of financial assets, is among the main causes of the current global financial crisis. The implications of these violations are crucial for market confidence and the current malfunctioning of markets is, to a greater extent, due to the lack of confidence that all agents have on each other. This justifies a deeper research on the factors that cause this type of behavior and on the possibility of detecting abnormal behavior patterns in time, so that market participants and authorities could react in the best possible way.

Indeed, the literature on behavioral finance focuses on agents' nonrational behavior in financial markets and contributes to explain and predict the systematic implications of these cognitive processes of decision making (Olsen, 1996; Thaler, 1999). This literature began as a response to the increasing interest of practitioners on the impact that cognitive processes exert on decision criteria , and argue that certain financial phenomena are better understood by introducing non-rational agents on the asset pricing models (Slovic, 1972; and Tversky and Kahneman, 1974). The two main pillars of the behavioral finance literature are (Shleifer and Summers, 1990): first, limits to arbitrage, whereby a substantial impact might exist if there is any interaction between rational and non-rational agents (Mullainathan and Thaler, 2000); the second pillar is cognitive psychology, which catalogues the kind of deviations from the rational behavior assumed by the market efficiency hypothesis (Fromlet, 2001).

The propositions made by this literature are useful for the individual investor since they widen the perspective on her environment and provide a deeper knowledge of the consequences on asset prices derived from certain behavior patterns can exert on asset prices. From the authorities' perspective, the advances in this research field facilitate the adoption of ex-ante measures that avoid abrupt endings associated to non-rational behavior such as a stock market crash originated by herding behavior and non supported by the economic situation.

This paper contributes to the literature by providing three new tools to detect episodes of herding or information cascades right at the beginning. Unluckily, in the absence of a complete information set, it is extremely complicated to differentiate between these two types of events. We focus on the importance of its detection right at the beginning, and leave for further research the distinction among the two, on the belief that these instruments could be very useful to agents with rich information sets, as monetary and financial market authorities. Hereinafter, this paper refers to both events as herding behavior keeping in mind that they might be information cascades. As said, the key of this paper is the detection of these events and not its classification.

In sum, these new instruments can help investors to maintain the value of their portfolios, and would be also helpful for monetary authorities, would have new tools to react in time to extreme market reactions. These new tools are based on a new simple model for herding behavior. The basic idea behind the model is that there exists a certain threshold upon which agents do not follow their own pricing rules, but the market stream to avoid being trapped in their initial positions, as in episode of herding information cascades. As an additional step, we test the behavior of one of the new instruments, the volume weighted market return, by analyzing its behavior and comparing it to the traditional indicator of market evolution, the return based on closing prices.

Therefore, this article aims to contribute to the psychological perspective in four ways: first, it develops a new indicator for the strength of the market movement that accounts for the information content in volumes and prices and identifies the degree of market support to a certain trend. Second, we use this new indicator of movement strength to calculate the distribution of strength across returns, which offers a global perspective of the importance associated to each possible return at any point in time. Third, we propose the market strength weighted return built on the basis of intraday data on prices and trading volumes to calculate a new representative market return that aims to complete the information content and the robustness of the measures for the evolution of the market.

As a further step, this paper analyzes the impact of external shocks in the Spanish stock market taking into account the fact that daily financial market returns may be significantly biased due to operations with low trading volume and big changes in prices, frequently traded at market closing times. In this sense, the various specifications of the volume weighted return provide valuable information on what the impact can be using indicators of market evolutions with a greater information content, as the volume weighted return.

It should be emphasized that the goal of this paper is not identifying the relation between prices and volumes but analyzing what happens when assuming that both variables are important to assess the market evolution. Therefore, this paper should be distinguished from others that have analyzed such relationship as, for instance, Hiemstra and Jones (1994), who find evidence of significant bidirectional nonlinear causality between both variables. Similarly, and analyzing the role of trading volume on international financial markets studying the links between stock market returns, Avouyi-Dovi and Jondeau (2000) suggest that the unexpected trading volume has a strong positive impact on all market returns and volatilities, although unexpected volume appears to have asymmetric effects on return as well as on volatility.

This paper's findings indicate that in days of relative calmness the closing price seems to be a good indicator of what has happened during the day. However, when there is an important discount of relevant information and herding behavior appears in the market, the return based on closing prices may not be representative of what has happened during the day due to odd operations with low trading volume and big changes in prices that frequently take place at the market closing times.

In addition, our results suggest that the market strength weighted return is a more robust estimate of the market evolution during the day. This way of computing the market return can improve the information used in the financial analysis and can help to mitigate the jumps in the series originated by punctual trading operations with small volume and big changes in prices at market closing times.

Moreover, the findings suggest that the three new tools, the strength of market movement, the distribution of the strength and the volume weighted return can be helpful in identifying the market opinion about the evolution of prices in the very short term. Besides, the four different specifications for the volume weighted return can provide more moderate estimates than the return based on closing prices when assessing the impact of spillovers from developed and emerging markets countries to the Spanish stock market. These results could be relevant from a monetary policy perspective provided that the use of the volume weighted return, as a more accurate measure of the market evolution, could shed some light on the understanding of the links between financial markets among countries. Besides, a deeper knowledge on the linkages among different markets could be also helpful for private investors in designing diversification strategies for multi-country portfolios.

The remainder of the paper is organized as follows. Section 2 presents an overview of the literature, Section 3 presents the model of agents' behavior, develops the three new tools and the methodology applied, then Section 4 details the empirical analysis and, finally, Section 5 contains the main conclusions.

2 Literature Review

Behavioral Finance studies certain reactions of financial markets that are contrary to the conventional theory. This literature provides an important contribution to the avoidance of serious mistakes working on financial market related issues (Fromlet, 2001). Considering the psychology approach (Barberis and Thaler, 2003), it typifies the various deviations from rational behavior observed in human actions. Some examples of these deviations are: imitation processes (Scharfstein and Stein, 1990; Bannerjee, 1992); disposition effect (Shefrin and Statman, 1985), heuristics dealing with information, varying availability of information, preference for certain news, differences in interpretation, and the psychology of sending messages and anchoring (Fromlet, 2001); gender and overconfidence (Barber and Odean, 1998); control illusion (Shiller, 1999; Gervais and

Odean, 2001); disposition effect (Odean, 1998); and following the herd (Eguiluz and Zimmermann, 2000). In addition, the literature on Prospect theory initiated by Kahneman and Tversky (1979) analyzes, among others, loss aversion (Kahneman and Tversky, 1992) and mental accounting (Shiller, 1999). These are some of the behavior patterns observed in financial markets that systematically violate the rational assumptions made by the neoclassical school and that create severe problems especially in times of financial stress.

Actually, in panic situations, certain decisions that are rational at an individual level cause an irrational result at an aggregate level. A classical example is a cinema fire in which the individual rational decision of "leaving among the firsts" becomes chaotic and irrational if a relatively big group of people try to "leave among the firsts" at the same time. This type of group-chaotic thought individually-rational decisions also take place in financial markets. As will be explained later in detail, under certain circumstances, the rational individual decision of selling a certain asset when noticing the end of an Irrational Exuberance episode might trigger the massive sale of such asset at any price(Greenspan, 1996; Shiller, 2000). In this sense, herding behavior is an indication of the imitation processes that take place in the market and can be observed in both upward and downward trends. Information cascades are similar to the former in that there is an important imitation process behind, with the main difference that some relevant pieces of news underlie the movement in prices. In the beginning of an upward trend, just a few investors consider that some assets are underpriced, thus they buy these assets at higher prices targeting a new equilibrium price. Meanwhile, other investors observe the upward trend, which shows up little by little, and do not want to lose the opportunity of making profits even if they do not believe that the asset is cheap. Thus, even if they are not sure about the reasons for the increase in prices, they will follow it to make more profits.

Herding behavior is more interesting in downward trends. In these cases some analysts will justify the fall in prices due to certain causes while other analysts will not be able to justify the movement. If the downward movement strengthens, both types of analysts (supporters and non-supporters of the trend) will tend to adjust their portfolios. Fromlet (2001) distinguishes two different types of herding behavior: voluntary and enforced. The voluntary herding corresponds to those agents whose assessments are in line with the herd (supporters), while the enforced herding is the one related to those who cannot fight the herd and follow it to avoid being trampled in their initial positions. In this sense, counter-tendency investors can mitigate the downward trend, although it is very unlikely that they could invert it. The difficulties in differentiating between information cascades and herding behavior do not affect the analysis implemented here. The purpose of this paper is to provide tools to detect episodes of information cascades or herding right at the start, but not distinguishing between two, which should be tackled by future research. In addition, institutional investors could enhance the herding behavior by the signals that uninformed investors could get from them. However, the role of institutional investors should be taken carefully as they accede to a better quality information, and thus, can contribute to the information cascades rather than to herding behavior.

Going one step forward, herding behavior in a downward trend is reinforced by two phenomena that are of interest for this paper's findings: the varying availability of information and the preference for certain news. Information is not easily available to all agents in the market and it may be misleading for less skilled agents (Fromlet, 2001). In this sense, if only a few investors knew about a very negative piece of news (such as a Government inability to pay its debt) they would discreetly start selling those certain Government bonds hold in their portfolios. As long as the trading volume increased and the price decreased in the process of getting rid of these "dangerous" assets, some sharp uninformed agents would perceive the discreet flight. They would follow the flight, making this movement even more evident to other market participants until prices finally tumble.

The second phenomena that boosts herding behavior is the preference for certain news. Some times agents are reluctant to change their predictions and recommendations, thereby they may underestimate the relevance of new information, particularly in the presence of relatively unimportant pieces of news that support their old assessment (Fromlet, 2001). In this sense, the formation of speculative bubbles is closely related to the preference for certain news. If neither specialists nor authorities perceive in time the divergence among the real economy indicators and the evolution of market prices, or even if they cannot act effectively to reduce this divergence, then financial market stability might be jeopardized. On the bubble limit, some agents will revise their positions and expectations and they will start selling at perceptibly lower prices. If the volume of these operations at lower prices increases and a herding behavior shows up, the probability of the bubble to burst increases.

Thus, the availability of new tools to detect in time herding behavior can help market authorities in fostering financial stability by monitoring potential severe price movements that are not backed by real data. Recall that statements and remarks by monetary and financial authorities already proved to work out in supporting the functioning of financial markets in the recent financial crisis.

3 The Model

This section presents a new model for herding behavior that serves as the basis for computing an indicator of the strength of the market movement. This new indicator can detect herding behavior in the very short run, therefore it can be useful to avoid at the very last minute the possible extreme outcomes of such behavior.

Herding behavior is highly noticeable during stock market crashes. When this herding behavior becomes evident, asset prices are severely depreciated and trading volumes are quite high since most investors pretend to escape from that asset as soon as possible and at any cost. If the market movement responds to an information cascade, there is not much to do for authorities, except procuring an orderly adjustment of the market. However, if the movement clearly responds to herding behavior, there is a role for competent authorities to transmit tranquility to the market. The set of instruments that this paper provides, can be of help to detect herding or information cascades in the very short run when the sharp market movement is still noticeable only for a few participants.

The next subsection presents a model that considers the individual decision making process to evaluate asset prices and the following subsection explains the functioning of the market as a result of the aggregation of these individual patterns. Afterwards develop the set of new indicators: strength of the market movement, distribution of strength across returns, and market strength weighted return.

3.1 Behavior of the individual investor

The model presented here allows tracking the strength of the market movement for each possible tendency of market prices. As a first step, in order to explain the asset pricing model it is necessary to make certain assumptions on the criteria that agents use.

We consider a market including N investors, where each investor has her own criteria so that the price of an asset can be decomposed on a reference value plus a second component, ψ_i, that considers all the individual factors that correct the reference value. Then, the asset price is given by

$$p_i = \nu + \psi_i, \quad i = 1, \cdots, N \tag{1}$$

where

- $p_i \in \mathbb{R}$ is the price assigned by the investor i to the asset.
- $\nu \in \mathbb{R}$ denotes the reference value, a key element of the model.
- $\psi_i \in \mathbb{R}$ indicates the adjustment to the reference value made by the investor i.

The selection of the reference value, ν, is a fundamental issue in the model. Among the different possibilities to assess the reference value, ν,we discuss just three of them:

a) The present value of all future cash flows, the ideal reference if one could knew accurately the flows and the discount factors. Unfortunately, it is not possible to know any of these magnitudes correctly and its estimation is subject to significant biases.

b) The asset value determined by the fundamental analysis, which is also subject to severe estimation biases given that the frequency of the data included in this analysis is much lower than the appropriate in technical analysis. In the same line, the asset value determined by the technical analysis would be subject to an estimation bias depending on the considerations of the analyst.

c) The last option is to consider a neutral price, for instance, the opening price for the trading day. The main advantage of this alternative is the absence of estimation bias. Also, and comparing to the closing price of the previous day, this opening price is consistent with the calculation of the relative volume.

The second element in the pricing formula, the adjustment to the reference value applied by each agent, ψ_i, captures all subjective components considered by the individual investor in her valuation rule. Among these components, those of special relevance are characterized for being non-rational such as the preference for certain news, overconfidence and control illusion, imitation processes, and herding behavior or information cascades. Among other factors, this individual adjustment term depends on the following variables:

- The asset price during a given period, π_i, which might vary among agents.
- The evolution of other asset prices used as benchmark for valuation, κ_i.
- The interpretation of news, η_i.
- The fact that the portfolio is running profit or losses at that time, d_i.
- The individual's risk preferences, λ_i.

It should be noted that the importance of each component might vary among agents. Moreover, the relation between the factors provided by $f(\cdot)$ might be non-linear:

$$\psi_i = f(\pi_i, \kappa_i, \eta_i, d_i, \lambda_i). \tag{2}$$

Then, assume each individual investor expects the market price to remain between an upper and a lower bound. Therefore, the agent's own interval for the asset price is given by:

$$p_t \in [p_i^{low}, p_i^{up}]. \tag{3}$$

Any time the condition in (3) is not satisfied, the investor will revise her expectations and try to justify the change in the thresholds. If she succeeds, she will establish new upper and lower bounds for the threshold. Nonetheless, if she finds no explanation for the price variation, then she will probably follow the market trend at some point to avoid being trapped in her initial position.

3.2 Market behavior

We assume that each agent follows her own pricing rule as long as the market price remains between the upper and lower bounds of the agent's valuation interval. However, according to the literature on herding behavior, as soon as the price falls out of the valuation interval, the agent will follow the market dominant trend to avoid being trapped in her initial position, that is:

$$p_i = \begin{cases} \nu + \psi_i & if\ p_t \in [p_i^{low}, p_i^{up}] \\ \nu + \psi_{market} & otherwise \end{cases}, \tag{4}$$

where ψ_{market} is the adjustment to the reference value observed in the market.

We consider two possibilities in this model:

1. A balanced market behavior in which agents maintain their valuation rules:

$$\psi_{market} = \sum_{i=1}^{N} \psi_i \approx \varepsilon, \tag{5}$$

   where ε denotes a smooth market movement based on the public and private information available. The idea is that the corrections made by some agents in one direction would be compensated by similar corrections in the opposite direction by other agents. As a result the aggregate behavior reflects a smooth market movement.

2. However, in some cases when a negative piece of news arrives in the market, asset prices may fall below the lower bound, and agents could follow the market trend even if the information publicly available is not sufficient to explain such a big change. In this way, the strongest market trend, labeled *dominant*, ψ_d, would dominate the weakest one, *non dominant*, ψ_{nd}. One can measure the trend by considering the corrections from the reference value made in each operation. Therefore, the adjustment to the reference value will be given by the sum of the corrections of the operations supporting the dominant market trend, plus the sum of the corrections made by the operations that do not support the market trend (non dominant).

$$\psi_{market} = \sum_{i=1}^{n} \psi_i^d + \sum_{i=n+1}^{N} \psi_i^{nd} \not\approx \varepsilon, \tag{6}$$

The spillover of the dominant trend among agents is as follows: each individual has a different interval where the upper and lower bounds are given by $[p_i^{low}, p_i^{up}]$. Then, herding behavior takes place on a sequential basis provided that not all the agents detect at the same time this behavior. Concretely, as long as the market prices go beyond investor's thresholds, more and more agents will follow the dominant market trend.

Taking into account the above mentioned factors, we propose to calculate the strength of the market movement (i.e. the proportion of the market following a certain trend), $\vartheta_{d,\tau}$, as the ratio of the correction in the reference value of trading operations that follow the market trend (i.e. ψ_i^d) relative to the correction in the reference value of the market, ψ_{market}:

$$\vartheta_{d,\tau} = \frac{\sum_{i=1}^{n} \psi_i^d}{\psi_{market}} = \frac{\sum_{i=1}^{n} \psi_i^d}{\sum_{i=1}^{n} \psi_i^d + \sum_{i=n+1}^{N} \psi_i^{nd}}. \tag{7}$$

How to measure the corrections ψ_i? Agents' preferences regarding risk, the period and prices used as reference, or the benchmark assets used are not easy to model and, this target would go beyond the scope of this paper. However, if we assume that all agents behave in a similar manner, all those aspects may be well reflected (although probably not completely) on the trading prices and volumes. The obvious indicator to assess ψ_i is the price change with respect to the reference value. However, this calculation would omit the information content in the trading volume. This is valid for either ψ_i^d and $\psi_i^n d$.

Then, one can calculate ψ_i as the product of the price change with respect to the reference price times the trading volume of the operation. Besides, to avoid that positive and negative price changes compensate each other, we calculate the absolute value of the price changes. Therefore, the correction of the reference value observed in each trading operation is given by

$$\psi_i = \left| \ln \left(\frac{p_i}{reference\_price} \right) \right| \times volume_i. \tag{8}$$

To calculate the strength of the market movement for each return interval, d, and time interval, τ, we use equations (7) and (8) to get the following expression:

$$\vartheta_{d,\tau} = \frac{\sum_{i=1}^{d} |return_{i,\tau}| \times volume_{i,\tau}}{\sum_{i=1}^{D} |return_{i,\tau}| \times volume_{i,\tau}} \times 100, \tag{9}$$

where the sequence $i = 1, \cdots, d, \cdots, D$ identifies the operations ordered according to their associated return, so that the d first operations support the analyzed trend (let's call it, *dominant*) and D represents the total number of operations recorded in the time interval, τ. The parameter $\vartheta_{d,\tau}$ measures the strength of the market movement and ranges from 0 (indicating there are no operations supporting that trend) to 100 (where all operations support the trend). Returns are calculated as the percentage change of the price with respect to the reference value.

For illustrative purposes, Table 1 presents a very simple example, which shows the daily reference value (opening price), quoted price, and trading volume for a given asset between 9.30am and 10.30am. To calculate the strength of the market movement supporting certain trend (for instance, a decrease in prices by more than X%, then $r \leq X\%$), we have to compute the coefficient $\vartheta_{d,\tau}$ defined above:

[INSERT TABLE 1 AROUND HERE]

- Example 1: Decrease larger than 2%. The above Table contains seven operations, out of which, four of them indicate a decrease in the market greater or equal to -2%. According to this Table, the strength of this movement is computed as follows:

$$\vartheta_{r \leq -2\%, 9:30-10:30} = \frac{6+72+6+6}{110} \times 100 = 81.82\%$$

- Example 2: Decrease greater than 6%. In this case, just two of the seven operations support this movement. However, the volume traded in these operations is important and, then, the impact on the movement strength is significant. In fact, the result says that the 70.91% of the volume traded in the market is associated to a return smaller than 6%. The computation is as follows:

$$\vartheta_{r \leq -6\%, 9:30-10:30} = \frac{6+72}{110} \times 100 = 70.91\%$$

The above examples are exaggerated but they help to understand the empirical exercise developed in the next section.

As a later step, we propose a new measure for tracking the evolution of the market that complements the return based on closing prices. Concretely, from the indicator of market strength (equation (9)), it can be derived a market strength weighted return by adding intraday returns weighted by their associated strength. For simplicity, we will name it *volume weighted return*, W. That is:

$$W\_r_{t,t+1} = \sum_{return=k}^{K} return_{(t,t+1]} \times \vartheta_{r,(t,t+1]} \qquad (10)$$

Where $k = 1, ..., K$ denotes all operations in the time interval $(t, t+1]$.

This new measure allows computing four specifications of volume weighted return depending on two alternatives for the reference price (previous day closing price vs. same day opening price), and for the time frequency used to calculate the return (tick data vs.5-minutes interval data).[1] Concretely, we define:

$$
\begin{aligned}
WO\_tick_t &= \sum_{n=1}^{N} \frac{v_n}{V_t} \ln\left(\frac{F_{n,t}}{F_{1,t}}\right) \times 100, & (11)\\
WO\_5min_t &= \sum_{i5=1}^{I} \frac{v_{i5}}{V_t} \ln\left(\frac{F_{i5,t}}{F_{1,t}}\right) \times 100, & (12)\\
WC\_tick_t &= \sum_{n=1}^{N} \frac{v_n}{V_t} \ln\left(\frac{F_{n,t}}{F_{N,t-1}}\right) \times 100, & (13)\\
WC\_5min_t &= \sum_{i5=1}^{I} \frac{v_{i5}}{V_t} \ln\left(\frac{F_{i5,t}}{F_{N,t-1}}\right) \times 100, & (14)
\end{aligned}
$$

where

- WO_tick_t and WO_5min_t stand for the volume weighted return based on the same day opening price using tick-data and 5-minute interval data respectively.
- WC_tick_t and WC_5min_t denote volume weighted return based on the previous day closing price using tick-data and and 5-minute interval data respectively.
- N is the number of trading operations during the day, and I is the number of 5-minute intervals during the day,
- V_t is the trading volume in the day t, v_n denotes the trading volume on the n-th intraday trading operation, v_{i5} denotes the cumulated trading volume within the i-th 5-minute interval.
- $F_{n,t}$ is the futures price of the n-th intraday trading operation, $F_{i5,t}$ is the last futures price of the i-th 5-minute interval, and $F_{N,j}$ $(F_{1,j})$ is the closing (opening) price at day j
- Finally, as reference, we calculate the return based on closing prices, U_t as the log difference in closing prices: $U_t = \ln(\frac{F_{N,t}}{F_{N,t-1}}) \times 100$

In the analysis of the market evolution we compare the performance of the four specifications of the volume weighted return to that of the return based on closing prices. Namely, we analyze the representative market return as a function of the shocks from developed markets, using the shocks from the US

[1] The authors gratefully acknowledge V.Golosnoy for suggesting the use of 5-minutes interval data to avoid microstructure problems.

as a main global market driver and, also, as a function of shocks coming from emerging markets countries where Spain has economic interests. Concretely, we estimate a GARCH (1,1) model of the form:

$$return_t = \beta_0 + \sum_{c=i}^{I} [\beta_{positive} \cdot D\_P_{i,t} + \beta_{negative} \cdot D\_N_{i,t}] + e_t \qquad (15)$$

where,

$$\sigma^2_{e,t} = \alpha_0 + \alpha_1 \cdot \sigma^2_{e,t-1} + \alpha_2 \cdot e^2_{t-1},\ e_t = \sigma_{e,t} \cdot u_t,\ u_t \sim white\, noise.$$
$$i = \{Developed,\ Latin\ America,\ Eastern\ Europe,\ Asia\}.$$

$D\_P_{i,t}$ are positive shocks from region i at time t, and $D\_N_{i,t}$ are negative shocks from region i at time t. We consider shocks from the US from emerging markets where Spain has economic interests.[2] Concretely, we identify and classify shocks according to the following procedure: first, we selected the emerging market countries where Spain has economic interests: main trading partners and main net recipients of foreign direct investment, both in terms of flows and stocks. Then we classify shocks between positive and negative according to the local market reaction in the country of origin of the shock. That is, a news release in Argentina that caused a positive (negative) reaction of the Latin American stock market index, is classified as a positive (negative) shock in Latin America. Finally, we only consider those shocks that exceed certain thresholds to avoid the inclusion of irrelevant shocks in the database. In this sense, we test different thresholds to provide a deeper insight into the behavior of the volume weighted return.

This is a delicate procedure since the various possible definitions of thresholds might distort the analysis. Thus, we proceed to define several thresholds to ensure the reliability of the results. Namely, we define the release of news (threshold=0%) and 6 different fixed thresholds to determine whether there is a shock or not. We do this by considering the cases in which the return exceeds (in absolute terms) 0.5%, 1%, 1.5%, 2%, 2.5% or 3%. The argument for these criteria is that they are easy to handle and they are somehow comparable to standard references as the normal distribution assumed for the asset returns. In the following section, we will describe in detail the dummies obtained by applying these criteria.

[2]Namely, in Latin America we consider Argentina, Brazil, Colombia, Chile, Mexico, Peru, and Venezuela; in Eastern Europe: Czech Republic, Hungary, Poland, Russia and Turkey; finally, in Asia we include South Korea, China, India and Indonesia. Data on trade and FDI has been collected from the Spanish Ministry of Industry, Tourism and Trade.

4 Empirical application

4.1 Data

The empirical analysis is based on the Spanish futures market on IBEX-35, using data from Mercado Español de Futuros Financieros de Renta Variable (MEFF-RV) from August, 2003 to September, 2004. The idea is that a stock index future reflects the market evolution and, in contrast to the index, the future is traded and thus, there are data available on the trading volume. In more detail, we consider the price and trading volume for the nearest contract expiration, as they are more liquid assets.

As for the dummys on shocks, news stories were collected from Bekaert and Harvey (2000, 2004), unluckily, their database has not been updated sin July 2004. Then, we have a shorter period in the analysis of the impact of shocks in the Spanish stock market. In addition, for those news stories for which these authors do not indicate the exact date, we assign a date on them using several newspapers' libraries and other Internet sources (BBC, Factiva, Comisión Andina de Juristas, and the Spanish newspapers El Mundo and El País, among others).

4.2 Empirical results

This section presents the analysis for the strength of the market movement, the distribution of strength across returns, and the volume weighted return as a complementary measure that improves the robustness of the return based on closing prices. As a further step, we also present the impact that shocks from countries where Spain has economic interests have on the Spanish stock market according to the different specifications of volume weighted return and the return based on closing prices.

4.2.1 Strength of the Market Movement

By computing the strength of the market movement, we obtain an indicator that reflects the information content in prices and volumes traded, thus, incorporates further information than classical methods in technical analysis. For illustrative purposes, Figure 1 presents a candlestick chart including representative prices (open, high, low and last price) as well as the total trading volume for each time period within a trading date. This figure is quite representative, since this was the first trading date after the unexpected result of the general elections after the terrorist attack in Madrid (March, 11^{th}). Thus, there were lots of uncertainty and a bulk of information to incorporate to prices during the day, and the behavior of the market within the day was not smooth (see table 2). Unluckily, using the aggregate volume and prices every 30 minutes as the candlestick chart does, on cannot distinguish the proportion of the market that supports each potential market trend. For instance, on March 15^{th}, 2004, in the time period between 9:00am and 9.30am, more than 4,524 contracts with prices between 7,778 and 7,914 were traded. However, Figure 1 does not help to identify the trading volume related to each price movement. However, as will be shown later, the strength of the market movement can provide this information.

[INSERT FIGURE 1 and TABLE 2 AROUND HERE]

The result in (9)allows for the computation of the strength of the market movement for each return interval on March 15^{th} 2004, on each 30 minutes interval (see Table 3). Note that when trading started over a large interval of returns, due to all relevant information being published that morning related to the unexpected result of the Spanish general elections and to the confusion created by the terrorist attack that happened in Madrid 4 days before. Between 9:00am and 9.30am, most of the trading operations had positive returns. However, one can see a small proportion of trading operations with associated negative returns. Some herding behavior arose as the market was assimilating the news. In a way, on that date the market was continuously correcting the initial positions. At the closing time, the decrease was close to 2%.

[INSERT TABLE 3 AROUND HERE]

4.2.2 Distribution of strength across returns

The distribution of strength across returns provides a general overview of what the market considers each time period. Hence, one can see the price interval where the market is trading and obtain a relevant measure of the trading volume related to each price. Figure 2 shows the distribution of the market strength across returns for some time intervals in March 15^{th}, 2004. It provides valuable information on market activity. For instance, the curve observed between 9:00am and 9.30am is especially interesting as one can identify a number of trading operations whose prices are much lower than the average price over this time interval.

In presence of herding behavior or information cascades, we expect a different shape for the distribution of strength across returns, as the case presented before. For instance, between 9:00am and 9:30am, the distribution of strength across returns seems to reflect that a certain group of investors was closing positions or arriving at a lower new equilibrium price. Moreover, these operations pointed to a significant drop in prices (see Figure 2).

[INSERT FIGURE 2 AROUND HERE]

A quiet behavior in the market is related to a smooth movement of the prices, and it is also associated to an homogeneous distribution of strength across returns. This is the case of September 21^{st}, 2004, when all the contracts were traded in a rather narrow interval of returns (between -0.2% and 0.3%) (see Figure 3).

[INSERT FIGURE 3 AROUND HERE]

In contrast to a tranquil day, some other days are characterized by high uncertainty and a significant discount of information, as in March 11^{th}, 2004 (see Figure 4). On this date, the city of Madrid (Spain) suffered an impressive terrorist attack, three days before the Spanish general elections. Although this trading day started with very different opinions, with returns varying between -0.8% and +0.3%, the distribution of strength across returns between 12pm and 12.30pm is highly significant. The reason is probably related to the first official release of the number of victims, which caused a drop in returns to the interval $[-2.0\%, -0.6\%]$.

[INSERT FIGURE 4 AROUND HERE]

In summary, there is relevant information embedded in the trading volume that is underused by the traditional methods of financial analysis. This information helps to complete the views provided by existing measures of market performance, as the return based on closing prices. Using previous and new methods for tracking market performance, allows obtaining a clearer view of the potential trends that the investors are considering. Thus, by using the new methodology introduced in this paper, an investor could assess whether her strategy equates goes in line with the market trend and then, take later decisions.

4.2.3 Volume weighted returns

Summarizing daily facts in a single price (opening, maximum, minimum or closing) is frequently misleading. The market strength weighted return shows a very similar evolution during tranquil days than the return based on closing prices. Nonetheless, the volume weighted return mitigates the impact of trading operations with extreme prices and small trading volumes that frequently take place at market closing times. This type of operations could occur in days with high degree of uncertainty and correspond to potentially non-representative data (see Figure 5). Indeed, the return based on closing prices tends to be more extreme than the market strength weighted return.[3]

[3]This is an important issue to obtain an objective measure of the market behavior in a certain date.

[INSERT FIGURE 5 AROUND HERE]

Moreover, Figure 6 reports the accumulated probability distributions for the market strength weighted return and for the return based on closing prices, and it shows the presence of more extreme values when considering the return based on closing prices, while the market strength weighted return decreases the impact of the extreme outcomes if their volume is relatively small with respect to the total daily trading volume.

[INSERT FIGURE 6 AROUND HERE]

Considering the importance that must be given to trading operations with small volume, it seems reasonable to use the market strength weighted return as a daily representative return provided that this indicator takes into account not just the impact of the price change but also, the relative size of the operation. In this way, an extreme closing price with a small volume traded would have little impact on the representative return. Then, the representative price of the day is closer to that of the trading operations with a significant trading volume in relation to the total daily trading volume.

Using equations (11)-(14) we calculate four different specifications of the volume weighted return and, for illustrative purposes, we compare them to the return based on closing prices using scatter plots (see Figures 7 to 10). The volume weighted return reduces the impact of the extreme prices if their associated volume is relatively small with respect to the total daily trading volume. Thus, the assessment of the impact of certain events on the market could be overestimated when using the return based on closing prices as the representative market return.

[INSERT FIGURES 7 TO 10 AROUND HERE]

To test this issue, we test the behavior of the volume weighted return compared to the return based on closing prices using a standard GARCH (1,1), and we check the impact os shocks from emerging and developed countries in the Spanish stock market over the period August, 2003 to July, 2004. Table 4 summarizes the main statistical properties of the data on returns.

[INSERT TABLE 4 AROUND HERE]

We propose the volume weighted return as a daily representative market return given that it considers the impact on prices weighted by the relative volume of the operation within the trading date. Hence, the assessment of the market evolution depends more on the trading operations with higher trading volume relative to the total daily trading volume.

Regarding the definition of the dummy variables, some countries seem to be over represented in the sample of news stories, as Mexico. We transform the news into shocks to ensure that the news stories included in the database are important for the domestic market where they were released, at least, to a certain extent. Therefore, we reject the news stories that do not have a significant impact in their local market. As explained before, we use seven different threshold criteria, ranging from 0% to 3%. Table 5 shows the number of shocks that we obtain after applying these thresholds to filter news stories and delete those that are not relevant in the local market where they were released.

[INSERT TABLE 5 AROUND HERE]

The empirical results confirm our intuition that the volume weighted return produces more moderate estimates of the impact of news from other countries on the Spanish market. The results also show an improvement in the significance of the dummies' parameters. The regional analysis also shows different reactions to the different regions, which are explained in detail in the next section (see Table 6).

[INSERT TABLE 6 AROUND HERE]

Moreover, we find that there are no significant differences when using tick data or 5-minute interval data so that the results based on tick data seem to be robust to the possible microstructure problems. Besides, we also find a stronger impact when considering the previous day closing price as reference price for the calculation of the volume weighted return. This makes sense provided that the volume weighted return measures based on the opening price are not accounting for the information released overnight, and thus, may provide a smaller impact than that obtained when using also the overnight information. Therefore, and for simplicity on the discussion of the results, we will compare the results based on the use of the tick data.

4.3 Discussion

This subsection deals with the linkages between the Spanish market and other economies that are found on the empirical results, according to the different measures of the volume weighted returns based on tick data (see Tables 3 to 6).

As expected, relevant news stories from the US affect the Spanish market. However, the size and the impact of positive an negative news differ in the following aspects:

(i) Shocks from ths US: positive news from the US are always relevant. The size of the impact increases as the impact on the US market also increases.

These results also suggest that using the volume weighted return as the representative market return, the average impact is about 58% of the average impact calculated using the return based on closing prices. Negative news also affect the Spanish market if the impact on the US market is at least -1.0%. Unfortunately, the model does not contain enough information to derive a consistent conclusion when comparing to the return based on closing prices.

(ii) Latin America: shocks from Latin America always affect the Spanish market. Although the asynchrony of trading between the Latin American and the Spanish markets may play an important role in the different behavior of the market returns, as more "odd" operations can take place in the Spanish market at closing times if there is a shock in Latin America, the impact of negative news is larger than the impact of positive news. On average, for positive shocks the volume weighted return provides an impact of 29bp, whereas the return based on closing prices indicates 53bp. As for negative news, the impact of the volume weighted return indicates -67bp, smaller than the -110bp of the return based on closing prices.

(iii) Eastern European countries seem to affect the Spanish market only in the case of positive news and only if the impact of the shock on the Eastern European local market is quite high (at least 2.5%). This result could be explained by the favorable performance of these countries during the process of integration on the European Union that took place over the sample period. In this case, the impact of positive shocks calculated using the volume weighted return is 6bp compared to the 12bp reported by the return based on closing prices. Unluckily, there is not enough information to assess the impact of negative news in this subsample.

(iv) Shocks from Asia present a similar pattern to those of Latin America and US in the following aspects: first, positive shocks from Asia do impact more on the Spanish market the stronger the impact on the Asian market is. On average, the impact provided by the volume weighted return is quite similar to that of the return based on closing prices for positive shocks (19bp vs. 17bp). Unluckily, as in the case of Eastern Europe, there is not enough information to accurately assess the impact of negative shocks.

Concerning the asymmetry between positive and negative shocks from the regions analyzed, we find that according to the new indicators, the news stories from the US have the strongest and most symmetric effect on the Spanish market if we use the opening price as reference (around 45bp for positive and -0.45bp for negative shocks on average), although the impact becomes asymmetric if we account for the overnight information (103bp for positive and -16bp for negative news). Then, Latin America is the emerging region with the strongest impact on the Spanish market, which also presents asymmetries between positive and negative news (27bp and -51bp when using the same day opening price as reference price and 31bp and -78bp when using the previous day closing price as reference). The impact of shocks arising in Eastern Europe is more moderate than in US and Latin America (14bp and -8bp, opening price; and 15bp and -17bp, closing price). Also, Asia presents a similar moderate impact of shocks on the Spanish market (10bp and -12bp, opening price; and 23bp and -16bp, closing price) present, on average, much more moderate impacts on the Spanish market for both positive and negative shocks.

In sum, this paper findings support that the volume weighted returns, as representative measures of market evolution, provide more moderate estimates of the impact of the relevant news coming from abroad. In this sense, the difference on the impact of news from abroad estimated using the return based on closing prices instead of the volume weighted returns - depending on the specification of the volume weighted return - range between 1.2 to 1.5 (1.6 to 1.9) for news from Eastern Europe and positive news from Asia (from US and Latin America).

5 Conclusions

Investors' opinion on the market evolution is reflected not just in prices but also in trading volumes. However, the information embedded in trading volumes is frequently underused by the traditional methods of financial market analysis. For instance, non-representative operations with low trading volumes and big changes in prices at market closing times frequently distort the return based on closing prices, taken usually as an indicative of the representative market return. This paper has analyzed the effect of adjusting daily returns by volume information to minimize this distortion.

This paper has presented an indicator that combines the information content in prices and trading volumes, labeled strength of the market movement, which constitutes a helpful instrument to identify the degree of market support for a certain trend. The second tool proposed in this paper, the distribution of strength across returns is very helpful in quickly identifying the opinion of investors on the price trends per time interval, which is quite interesting to capture episodes of herding behavior or information cascades at very early stages. Then, this paper has also introduced the volume weighted return -in four different specifications- as the representative market returns. As a later step, the paper tested the behavior of the volume weighted return in assessing the impact on the Spanish market of shocks coming from developed and emerging markets countries using a standard GARCH(1,1) model.

The empirical analysis has been performed on the Spanish futures market on IBEX-35 over the period August 2003 to September 2004. The results confirm that there is relevant information embedded in the trading volume, and that this information may be relevant to assess the evolution of the market. The distribution of strength across returns behaves differently on calm and nervous trading dates and helps to detect the market opinion about the evolution of prices in the very short term.

Besides, the market strength weighted return seems to be more robust than the return based on closing prices in analyzing the evolution of the market. Using four different specifications of the volume weighted return, the results support that the volume weighted returns provide more moderate estimates than the (traditional) return based on closing prices when analyzing spillovers from other countries. In this sense, our main findings suggest that the use of the return based on closing prices could provide misleading conclusions about the sensitivity of financial markets, and that this problem could be mitigated using the volume weighted return as the representative market return. Using these new indicators of market evolution, we have found that the most influential regions for the Ibex-35 futures market are the US and Latin America, followed by Eastern Europe and Asia, in line with the results obtained using the return based on closing prices.

All in all, the tools presented in this paper could help investors to obtain information on the market aggregate opinion and to design diversification strategies if they are specially interested in building multi-country portfolios. These tools can also be useful for the monetary authorities in sustaining market stability by signalling an incipient episode of herding behavior that could intervene to calm down investors. Besides, the new tools proposed in this paper contribute to a deeper knowledge on the linkages among financial markets in different countries. This is especially relevant in the case of countries where Spain has important economic interests and therefore, has a higher exposition to their domestic shocks as it is the case of many Latin American countries.

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Tables and Figures

Table 1
Market support to a certain trend

This table illustrates the calculation of the market strength indicator for a given date and time interval. The first columns contains the time, the second contains the reference value for the day, ν, which in this case is the daily opening price. The third column shows the quoted price, p_t, and the fourth presents the trading volume, V. The last two columns contain the correction for the reference value, ψ_i, calculated as the percentage deviation of the quoted prices from the reference value, the final column presents the product of the price correction times the trading volume for each operation.

Time	Ref. value	Price	Volume	ψ_m	$\|\psi_m \times V\|$	$ret \leq -2\%$	$ret \leq -6\%$
9:30	5,000	4,950	3	-1.0	3		
9:40	5,000	4,900	3	-2.0	6	6	
9:50	5,000	5,075	10	1.5	15		
10:00	5,000	4,700	12	-6.0	72	72	72
10:10	5,000	5,100	1	2.0	2		
10:20	5,000	4,850	2	-3.0	6	6	
10:30	5,000	4,700	1	-6.0	6	6	6
TOTAL					110	90	78
$\vartheta_{r \leq X\%, 9:30-10:30}$						81.82%	70.91%

Table 2
Market Evolution on March 15^{th}, 2004

This Table shows the market evolution in terms of trading volume, opening price, maximum and minimum prices, and closing price for each 30 minutes time interval on March 15^{th}, 2004.

Time interval	Trading Volume	Opening price	Maximum	Minimum	Closing price
09.00-09.30	4,524	7,830	7,914	7,778	7,871
09.30-10.00	2,757	7,870	7,872	7,845	7,852
10.00-10.30	1,741	7,853	7,862	7,838	7,838
10.30-11.00	1,315	7,838	7,840	7,806	7,820
11.00-11.30	1,218	7,820	7,820	7,800	7,809
11.30-12.00	1,642	7,811	7,816	7,792	7,797
12.00-12.30	2,080	7,794	7,796	7,772	7,772
12.30-13.00	1,290	7,773	7,784	7,748	7,761
13.00-13.30	855	7,761	7,786	7,760	7,779
13.30-14.00	988	7,778	7,781	7,758	7,768
14.00-14.30	551	7,770	7,786	7,761	7,781
14.30-15.00	869	7,780	7,796	7,771	7,785
15.00-15.30	903	7,785	7,808	7,784	7,796
15.30-16.00	970	7,795	7,798	7,777	7,784
16.00-16.30	1,355	7,783	7,784	7,764	7,773
16.30-17.00	4,029	7,772	7,772	7,727	7,728
17.00-17.30	5,058	7,727	7,727	7,683	7,691
17.30-18.00	1,654	7,688	7,690	7,647	7,679

Table 3
Distribution of strength across returns, March 15^{th}, 2004

This Table reports the strength of the market movement for each return interval and for each 30 minutes interval. When considering one single time interval, we obtain the Distribution of strength across returns.

Table 4
Summary statistics for market returns

This Table contains the main summary statistics for the return indexes used on the empirical analysis over the period between August, 2003 and July, 2004. The first two rows contain, respectively, the summary statistics for the volume weighted return based on the same day opening price using tick-data (WO_tick) and using 5-minute interval data (WO_5min). Rows 3 and 4 show, respectively, the results for the volume weighted return based on the previous day closing price using tick-data (WC_tick) and 5-minute interval data (WC_5min). The next row contains the statistics for the return based on closing prices (U). Rows 6 to 9 contain the summary statistics for the regions and aggregates used in the analysis.

	Obs.	Mean	Median	Std. Dev.	Min	Max.	Skew.	Kurt.
Volume Weighted Returns								
WO_ tick	261	0.014	0.052	0.491	-1.449	1.691	0.062	3.242
WO_ 5min	261	0.005	0.016	0.438	-1.132	1.223	-0.053	3.049
WC_ tick	261	0.051	0.104	0.717	-3.063	1.880	-0.632	4.520
WC_ 5min	261	0.051	0.105	0.721	-3.057	1.883	-0.628	4.492
R. based on closing prices	261	0.057	0.160	0.916	-4.432	2.333	-0.630	5.030
Regions and aggregates								
Developed markets	261	0.056	0.107	0.624	-2.360	2.044	-0.344	3.865
Latin America	261	0.114	0.192	1.268	-5.194	4.471	-0.676	5.637
Eastern Europe	261	0.116	0.209	1.483	-6.442	5.807	-0.419	5.225
Asia	261	0.077	0.150	0.826	-3.911	3.085	-0.783	6.162

Table 5
Number of news / shocks per region and impact on the local market

This Table contains the number of news / shocks recorded over the period August, 2003 to July, 2004. The conditions for the dummy Shock=1 are: (a) news are released in that day, and (b) the daily return on the region where the domestic news is released is bigger (in absolute terms) than {0.5%, 1%, 1.5%, 2%, 2.5%, 3%}.

	News	Shocks					
	$\geq$ 0%	$\geq$ 0.5%	$\geq$ 1%	$\geq$ 1.5%	$\geq$ 2%	$\geq$ 2.5%	$\geq$ 3%
Positive shocks							
Developed markets	10	2	1	0	0	0	0
Latin America	49	30	16	7	2	2	0
Eastern Europe	36	27	22	11	4	1	1
Asia	25	7	3	1	0	0	0
Negative shocks							
Developed markets	6	3	1	1	0	0	0
Latin America	34	21	14	9	4	2	2
Eastern Europe	32	24	14	8	6	4	3
Asia	21	13	7	3	1	0	0

Table 6
Impact of news / shocks on Volume Weighted Returns

The table contains the regression results for robust standard GARCH(1,1) model in equation (15) for the cases where the impact of the news stories on the local market of origin is (in absolute terms) greater than 0.0% and 0.5%. The first column contains the result for the volume weighted return based on the same day Opening price using tick-data (WO_tick), the second column contains volume weighted return based on the same day Opening price using 5 minute interval data (WO_5min); column 3 shows the results for the volume weighted return based on the previous day Closing price using tick-data (WC_tick), column 4 column contains volume weighted return based on the previous day Closing price using 5 minute interval data (WC_5min); finally, the regression results for column 5 contains the return based on closing prices (U). ***, **, * indicate significantly different from zero at the 1, 5, and 10 percent level, respectively.

	$\|$local return$\|$ $\geq$ 0%					$\|$local return$\|$ $\geq$ 0.5%				
Dependent variable	WO_tick	WO_5min	WC_tick	WC_5min	U	WO_tick	WO_5min	WC_tick	WC_5min	U
Mean equation										
DP US	0.232**	0.239**	0.484***	0.486***	0.582***	0.493***	0.393***	1.055***	1.061***	1.284***
DN US	-0.017	-0.041	0.277	0.284	0.001	-0.235	-0.183	0.493	0.496	0.233
DP Latin America	0.163**	0.084	0.183**	0.186**	0.208*	0.337***	0.265***	0.317***	0.323***	0.428**
DN Latin America	-0.261***	-0.220***	-0.453***	-0.456***	-0.674***	-0.383***	-0.332***	-0.584***	-0.587***	-0.915***
DP Eastern Europe	-0.050	0.014	0.045	0.046	0.102	-0.064	-0.003	0.010	0.010	0.154
DN Eastern Europe	-0.002	0.025	-0.116	-0.118	-0.056	-0.058	-0.012	-0.155	-0.156	-0.047
DP Asia	0.112	0.114	0.193*	0.194*	0.037	0.130	0.191	0.067	0.070	-0.050
DN Asia	-0.104	-0.067	-0.191	-0.190	-0.170	-0.157	-0.135	-0.289*	-0.289*	-0.277
Constant	0.025	0.007	0.073	0.072	0.124	0.035	0.013	0.102**	0.101**	0.120*
Variance equation										
L.arch	0.096*	0.063*	0.133*	0.132*	0.164*	0.144*	0.076*	0.173*	0.173*	0.223*
L.garch	0.765***	0.794***	0.726***	0.729***	0.682***	0.630***	0.765***	0.582***	0.583***	0.547***
Constant	0.031	0.026	0.063	0.062	0.118*	0.048**	0.027*	0.107**	0.108*	0.172**
Regression statistics										
Observations	261	261	261	261	261	261	261	261	261	261
Akaike IC	362.9	310.1	535.2	537.9	670.3	344.9	294.0	531.3	534.0	660.4
Schwarz C	405.7	352.9	578.0	580.7	713.1	387.6	336.8	574.0	576.8	703.2
Wald-test(chi2)	27.31	18.22	62.14	62.89	50.33	135.63	56.76	76.89	77.48	68.89
p-value	0.001	0.020	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Log-likelihood	-169.4	-143.0	-255.6	-256.9	-323.1	-160.4	-135.0	-253.6	-255.0	-318.2

Table 6
Impact of news / shocks on Volume Weighted Returns (*Cont'd*)

This table contains the regression results for robust standard GARCH(1,1) model in equation (15) for the cases where the impact of the news stories on the local market of origin is (in absolute terms) greater than 1.0% and 1.5%. The first column contains the result for the volume weighted return based on the same day Opening price using tick-data (WO_tick), the second column contains volume weighted return based on the same day Opening price using 5 minute interval data (WO_5min); column 3 shows the results for the volume weighted return based on the previous day Closing price using tick-data (WC_tick), column 4 column contains volume weighted return based on the previous day Closing price using 5 minute interval data (WC_5min); finally, the regression results for column 5 contains the return based on closing prices (U). ***, **, * indicate significantly different from zero at the 1, 5, and 10 percent level, respectively.

	$\lvert$local return$\rvert \geq 1\%$					$\lvert$local return$\rvert \geq 1.5\%$				
Dependent variable	WO_tick	WO_5min	WC_tick	WC_ 5min	U	WO_tick	WO_5min	WC_tick	WC_5min	U
Mean equation										
DP US	0.632***	0.534***	1.537***	1.546***	1.986***					
DN US	-0.768***	-0.827***	0.542	0.569	-0.217	-0.771***	-0.833***	-1.947*	0.553	-2.346
DP Latin America	0.342***	0.326***	0.382***	0.388***	0.462***	0.326**	0.179	0.459**	0.476***	0.504*
DN Latin America	-0.482***	-0.413***	-0.705***	-0.711***	-1.045***	-0.550***	-0.483***	-0.583***	-0.588***	-0.878***
DP Eastern Europe	-0.060	-0.009	0.042	0.042	0.125	0.028	0.092	0.184	0.179	0.241
DN Eastern Europe	-0.157	-0.147	-0.346*	-0.349*	-0.344	-0.303*	-0.288	-0.482	-0.484	-0.384
DP Asia	0.130**	0.165***	0.444**	0.445**	0.515**	0.045	0.126***	0.214***	0.217***	0.298***
DN Asia	-0.112	-0.034	-0.013	-0.011	-0.029	0.046	0.094	0.353	0.359	0.394
Constant	0.045	0.023	0.091**	0.090**	0.109*	0.048	0.030	0.085**	0.084**	0.103*
Variance equation										
L.arch	0.118	0.061	0.178	0.180	0.135	0.146	0.062	0.195	0.196	0.140
L.garch	0.694***	0.789***	0.471	0.464	0.619**	0.617***	0.746***	0.575**	0.575**	0.694***
Constant	0.041*	0.025	0.155	0.158	0.178	0.054*	0.034	0.112	0.113	0.136
Regression statistics										
Observations	261	261	261	261	261	261	261	261	261	261
Akaike IC	351.2	291.9	534.8	537.6	666.2	357.1	300.2	553.1	553.8	686.0
Schwarz C	386.9	327.6	574.0	576.8	705.4	389.2	332.3	592.3	589.5	721.6
Wald - test (chi2)	825.12	900.99	1714.27	1713.94	1848.92	719.95	1139.50	54.84	52.39	60.04
p-value	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Log-likelihood	-165.6	-136.0	-256.4	-257.8	-322.1	-169.5	-141.1	-265.5	-266.9	-333.0

Table 6

Impact of news / shocks on Volume Weighted Returns (*Cont'd*)

This table contains the regression results for robust standard GARCH(1,1) model in equation (15) for the cases where the impact of the news stories on the local market of origin is (in absolute terms) greater than 2.0% and 2.5%. The first column contains the result for the volume weighted return based on the same day Opening price using tick-data (WO_tick), the second column contains volume weighted return based on the same day Opening price using 5 minute interval data (WO_5min); column 3 shows the results for the volume weighted return based on the previous day Closing price using tick-data (WC_tick), column 4 column contains volume weighted return based on the previous day Closing price using 5 minute interval data (WC_5min); finally, the regression results for column 5 contains the return based on closing prices (U). ***, **, * indicate significantly different from zero at the 1, 5, and 10 percent level, respectively.

	|local return| ≥ 2%					|local return| ≥ 2.5%				
Dependent variable	WO_tick	WO_5min	WC_tick	WC_ 5min	U	WO_tick	WO_5min	WC_tick	WC_5min	U
Mean equation										
DP US										
DN US										
DP Latin America	0.231***	0.111***	0.392***	0.397***	0.777***	0.239***	0.118***	0.403***	0.409***	0.795***
DN Latin America	-0.921***	-0.783***	-1.089***	-1.101***	-1.458***	-0.810***	-0.634***	-1.002***	-1.007***	-1.353***
DP Eastern Europe	0.200	0.276	0.060	0.058	-0.025	0.448***	0.413***	0.339***	0.350***	0.432***
DN Eastern Europe	-0.185	-0.212	-0.174	-0.172	-0.176	0.017	-0.004	0.026	0.026	-0.064
DP Asia										
DN Asia	0.456*	0.507**	0.307	0.317	0.507					
Constant	0.038	0.020	0.086**	0.086**	0.097*	0.030	0.014	0.077**	0.076*	0.087*
Variance equation										
L.arch	0.122*	0.060	0.123	0.121	0.114	0.118*	0.078*	0.128*	0.127*	0.126
L.garch	0.638***	0.712***	0.698***	0.703***	0.749***	0.694***	0.753***	0.725***	0.728***	0.746***
Constant	0.055**	0.041	0.087	0.086	0.113*	0.045	0.032	0.073	0.073	0.107*
Regression statistics										
Observations	261	261	261	261	261	261	261	261	261	261
Akaike IC	364.0	306.4	554.7	559.6	688.1	370.7	311.8	558.6	559.5	688.4
Schwarz C	392.5	334.9	583.2	591.7	716.6	399.2	336.7	587.1	584.5	713.3
Wald - test (chi2)	532.69	2723.16	1033.07	1005.29	604.67	388.88	799.17	3829.87	3037.68	158.07
p-value	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Log-likelihood	-174.0	-145.2	-269.4	-270.8	-336.1	-177.4	-148.9	-271.3	-272.8	-337.2

Table 6
Impact of news / shocks on Volume Weighted Returns ($Cont'd$)

Notes: this table contains the regression results for robust standard GARCH(1,1) model in equation (15) for the case where the impact of the news stories on the local market of origin is (in absolute terms) greater than 3.0% . The first column contains the result for the volume weighted return based on the same day Opening price using tick-data (WO_tick), the second column contains volume weighted return based on the same day Opening price using 5 minute interval data (WO_5min); column 3 shows the results for the volume weighted return based on the previous day Closing price using tick-data (WC_tick), column 4 column contains volume weighted return based on the previous day Closing price using 5 minute interval data (WC_5min); finally, the regression results for column 5 contains the return based on closing prices (U). ***, **, * indicate significantly different from zero at the 1, 5, and 10 percent level, respectively.

	$\lvert$local return$\rvert \geq 3\%$				
Dependent variable	WO_tick	WO_5min	WC_tick	WC_ 5min	U
Mean equation					
DP US					
DN US					
DP Latin America					
DN Latin America	-0.870***	-0.724***	-1.012***	-1.019***	-1.398***
DP Eastern Europe	0.448***	0.414***	0.336***	0.348***	0.430***
DN Eastern Europe	0.142	0.189	0.042	0.045	0.025
DP Asia					
DN Asia					
Constant	0.030	0.013	0.079**	0.079**	0.089*
Variance equation					
L.arch	0.118*	0.080*	0.131*	0.130*	0.130
L.garch	0.694***	0.759***	0.719***	0.723***	0.741***
Constant	0.045	0.030	0.075	0.075	0.109*
Regression statistics					
Observations	261	261	261	261	261
Akaike IC	368.8	309.4	557.2	560.2	689.6
Schwarz C	393.7	330.8	582.1	585.1	714.6
Wald - test (chi2)	718.96	877.62	7285.55	5850.68	175.73
p-value	0.000	0.000	0.000	0.000	0.000
Log-likelihood	-177.4	-148.7	-271.6	-273.1	-337.8