Intraday Relationship Between Market Activity And Public Announcements

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ABSTRACT

This paper aims to study the relationship between public information arrival and Euronext Paris intraday activity. The information flow is measured as the number of news items recorded by Reuters and conditional volatility is modeled by an EGARCH process. Our results reveal a strong positive relationship between public information flow and trading volume and a moderate positive relation between stock returns volatility and the information flow. These results are available for the CAC40 Index as well as for individual stocks and are robust even after controlling for the impact of the intraday patterns.

Keywords: Information flow; conditional volatility; trading volume; market microstructure; intraday analysis; EGARCH

1. INTRODUCTION

The link between information and price changes is a central issue in the market microstructure literature. Indeed, one of the main objectives of microstructure models is to examine the relationship between information and market activity. The mixture of distribution hypothesis (MDH), has attempted to provide a theoretical justification for this relation. The seminal work of Clark (1973) has introduced the MDH hypothesis, which supposes that stock price changes are driven by information. This hypothesis was extended in the models of Epps and Epps (1976) and Tauchen and Pitts (1983), which highlight a strong relationship between the information flow and market activity. These models consider the information flow as a latent common factor that affects both of trading volume and stock prices. Thus, price changes and trading volume may be correlated as they depend jointly on the intensity of the information flow (Li and Wu, 2006). Empirically, this means that trading volume and stock prices react contemporaneously in response to information releases. In fact, the arrival of new information to the market induces a price adjustment process through the sequence of trades. This hypothesis is also confirmed by event studies and market efficiency literature[1].

The aim of our study is to examine the relationship between intraday market activity and the rate of public information flow. However, the literature highlights the difficulty to measure the information flow. Lamoureux and Lastrapes (1990) and Maillet and Michel (1997) propose to use the trading volume as a proxy for information arrival. In this study, we prefer the measure proposed by Berry and Howe (1994). They quantify the information flow as the number of news items published by Reuters per unit of time. The authors break down the trading day into 13 half-hourly intervals and regress the absolute returns against the number of news items published by Reuters during each period. The authors show that the coefficient of the variable "number of news items" is not significant for the 13 regressions. Berry and Howe (1994) conclude to an insignificant relationship between price volatility and the intraday information flow. However, as mentioned by Kalev, Liu, Pharm and Jarnecic (2004), the use of realised volatility measures such as absolute returns can generate biased results regarding the well-known conditional heteroskedasticity of volatility time series. Kalev et al. (2004) focus on the relationship between the information flow and conditional volatility in the Australian market. Using a GARCH model, the authors highlight a strong positive relationship between public information arrival and stock price volatility.

[1] For more details see Fama (1991).

In this paper, we propose to shed light on the intraday relationship between the information flow and market activity in Euronext Paris. To measure price movements, we consider the conditional volatility instead of the realized volatility. Unlike, Kalev et al. (2004) we propose to distinguish between overnight announcements and news releases published during the continuous market. This treatment allows us to take into account the specific rules of Euronext Paris at the opening period and at the closing period. Our results reveal a strong positive relationship between the trading volume and the number of news items published by Reuters. But, we find a moderate positive relation between the conditional volatility and the information flow. The remainder of the paper is organised as follows. Section 2 presents the organisation of Euronext Paris, specifies the research methodology and gives a description of the data. Section 3 exposes our empirical results. The last section concludes.

2. ORGANISATION OF EURONEXT PARIS AND METHODOLOGY

2.1 Euronext Paris microstructure

Euronext was created in September 2000 from the merger of the Amsterdam, Brussels and Paris stock exchanges[2]. Recently, the Euronext group merged with the New York Stock Exchange (NYSE). Euronext Paris operates through a single electronic trading system (Nouveau Système de Cotation: NSC). Traders' orders are conveyed to a central order book. A transaction takes place when a new order is placed and if a matching order exists on the other side of the book. The trading day begins at 7:15 a.m. with a preopening period where traders can place, modify or cancel orders. The market opens at 9:00 a.m. with a call auction, which determines the opening price. From 9:00 a.m. to 5:25 p.m. the market is in its continuous period. In the same way as the opening, the market closes with a preclosing period from 5:25 p.m. to 5:30 p.m. The closing price is determined at 5:30 p.m. with a call auction. A "trading at last" period was introduced to give investors the opportunity to trade after 5:30 p.m. at the closing price. The CAC40 index is the main benchmark for Euronext Paris. It is comprised of the 40 largest and most liquid stocks trading on the exchange.

2.2. Conditional stock price volatility

2.2.1. The EGARCH model

The clustering pattern of volatility is a well-known phenomenon in the financial literature. In fact, several empirical studies show that volatility time series are characterized by the presence of conditional heteroskedasticity. The family of ARCH[3] models accounts for the volatility persistence effect and tries to capture conditional heteroskedasticity patterns. In these models, the current idiosyncratic variance depends on its past levels and past innovations. In this study, we propose using the EGARCH (exponential general auto regressive conditional heteroskedasticity) model proposed by Nelson (1991). The EARCH (1,1) can be presented as follows:

$$r_t = \mu + \varepsilon_t \tag{1}$$

$$Log\left(Var\left[\varepsilon_t \middle| \varepsilon_{t-1}\right]\right) = Log\left(\delta_t^2\right) = Log\left(h_t\right)$$

And

$$Z_{t-1} = \frac{\varepsilon_{t-1}}{\delta_{t-1}}$$

$$Log\left(h_t\right) = \omega + \gamma Z_{t-1} + \alpha\left(\left|Z_{t-1}\right| - \sqrt{\frac{2}{\pi}}\right) + \beta Log\left(h_{t-1}\right) \tag{2}$$

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[2] Lisbon, Porto and the LIFFE joined the group later.
[3] For more details about these models, see Engle (1982) and Bollerslev (1986).

Where r_t is the level of stock returns at the interval t and μ is a constant. The coefficient γ accounts for the asymmetry effects. The errors (innovations) ε_t are assumed to be identically and independently distributed. In order to account for this constraint, we compute the variance-covariance matrix using the algorithm of Bollerslev and Wooldridge[4] (1992). In this case, our estimate will be robust even if returns are not normally distributed. Expression (2) is the equation of the conditional volatility h_t. The model supposes that the volatility of the current period depends upon the conditional volatility of the former period h_{t-1} and innovation ε_{t-1}.

2.2.2. The research model

To test the impact of public information arrival on price volatility, we introduce an informational proxy (N_t) in the conditional variance equation. This variable represents the number of news items published by Reuters during each 15-minute period t. If the coefficient λ of the variable N_t is significant, we can conclude that public information arrival has an impact on price volatility. In order to take into account the specific rules of Euronext Paris during the opening period and the closing period, we propose to distinguish between overnight announcements and the news published during the continuous market. First, we test our model during the continuous market. Next, we focus on the impact of overnight information flow on the open-to-close volatility.

The intraday U-shaped pattern of volume and volatility is a well-documented phenomenon in the microstructure literature. Jain and Joh (1985), Wood, McInish and Ord (1985) and Blau, Van Ness and Van Ness (2009) highlight heavy market activity in the beginning and the end of the trading day. To account for this phenomenon, we include two dummy variables in the conditional volatility equation. The dummy variable DO equals 1 for the first 15-minute period of the trading day and 0 otherwise. DC equals 1 for the last 15-minute period of the trading day and 0 otherwise.

The model testing the impact of the information flow on price volatility during the continuous market can be presented as follows[5]:

$$r_t = \phi_0 r_{t-1} + \phi_1 \varepsilon_{t-1} + \varepsilon_t \tag{3}$$

$$Log(h_t) = C + \gamma Z_{t-1} + \alpha(|Z_{t-1}| - \sqrt{\frac{2}{\pi}}) + \beta Log(h_{t-1}) + \lambda N_t + \theta_1 DO + \theta_2 DC$$

We compute stock price returns with the logarithm formula:

$$r_t = 100 \ \ln(P_t / P_{t-1})$$

Where P_t is the stock price at the end of each 15-minute period t.

N_t represents the number of news items published by Reuters during each 15-minute period t.

The impact of overnight information flow on open-to-close volatility is tested by the following model:

$$\bar{r}_t = \bar{\phi}_0 \bar{r}_{t-1} + \bar{\phi}_1 \bar{\varepsilon}_{t-1} + \bar{\varepsilon}_t \tag{4}$$

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[4] This routine is used to compute the quasi-maximum likelihood (QML) covariances and standard errors using the methods described by Bollerslev and Wooldridge (1992). The parameter estimates will be unchanged, only the estimated covariance matrix and p-values will be altered.
[5] Stock returns are modelled by a moving average process of order 1 to account for autocorrelation.

$$Log\left(\bar{h}_t\right) = \bar{C} + \bar{\gamma} Z_{t-1} + \bar{\alpha}\left(\left|\bar{Z}_{t-1}\right| - \sqrt{\frac{2}{\pi}}\right) + \bar{\beta} Log\left(\bar{h}_{t-1}\right) + \bar{\lambda}\bar{N}_t$$

$$\bar{r}_t = 100 \ \ln(\bar{P}_t / \bar{P}_{t-1})$$

Where $\bar{P}_t$ is the opening price of the day t and $\bar{P}_{t-1}$ is the closing price of the day t-1.

$\bar{N}_t$ is the number of overnight news items published by Reuters.

2.3. Trading volume

The mixture distribution hypothesis provides evidence that the information flow impacts stock prices as well as trading volume. Event studies conducted around public announcements confirm this intuition. Indeed, these studies show that news releases are accompanied by a significant price variation and an abnormal high trading volume (Louhichi, 2008). Blume, Easley and O'Hara (1994) investigate the usefulness of trading volume for technical analysis. The authors highlight the informational role of the volume statistic. The authors conclude that trading volume and price changes have distinct and complementary informational roles. They recommend the use of both trading volume and returns for financial forecasting.

A simple way to examine the relationship between trading volume and the information flow is to regress the trading volume against the number of news items published by Reuters during each interval t. The model testing the impact of the information flow on trading volume during the continuous market can be presented as follows:

$$Log(V_t) = C + \lambda N_t + \theta_1 DO + \theta_2 DC + \varepsilon_t \tag{5}$$

N_t is the number of news items published by Reuters during each 15-minute period t.

V_t is the trading volume during each 15-minute period t.

The impact of overnight information flow on opening trading volume is tested by the following model:

$$Log(\bar{V}_t) = \bar{C} + \bar{\lambda}\bar{N}_t + \bar{\varepsilon}_t \tag{6}$$

$\bar{N}_t$ is the number of overnight news items.

$\bar{V}_t$ is the opening trading volume.

2.4. Data

The aim of this paper is to shed light on the relationship between the public information flow and market activity using high-frequency data from Euronext Paris. The study requires two types of data: a proxy for public information arrival and quantitative information about stocks. To measure the rate of information flow, we use the proxy proposed bay Berry and Howe (1994). We quantify the information flow as the number of news items published by Reuters during each period of 15-minute. Reuters is used by most financial operators in Euronext and has the advantage of providing the time of announcement to the nearest minute. Furthermore, our proxy is used in several papers (Berry and Howe (1994), Andersen and Bollerslev (1998), Melvin and Yin (2000)) related to our study. This allows us to compare our results to those obtained in markets characterized by a different structure that of the French market. From the Reuters database, we collect all news concerning companies pertaining to the

CAC40 index and recorded from January through December 2001 in the category "Corporate News". This section contains all information which affects only a specific firm (firm specific news).

Quantitative information concerns intraday data about trades, execution date and time, price and trading volume. This information is obtained from Euronext database and covers the period from January 2001 to December 2001. During this period, we divide the trading day into thirty four 15-minute intervals.

Our sample concerns all shares pertaining to the CAC40 Index, which is the main benchmark for Euronext Paris. The composition of the CAC40 was marked by two changes during 2001. The first occurred on May 4 when "Orange" replaced "Equant". Similarly, on August 8 "Valeo" replaced "Vivendi Environment". Finally, the sample consists of 41 companies rather than 42 because we don't have all necessary information about the firm "Bouygues".

3. RESULTS

3.1. Public information arrival and conditional volatility

The results of estimating the EGARCH model during the continuous market are summarized in Table 1. We notice that the EGARCH coefficients (α and β) are significant except for the asymmetric effects (γ). The coefficient β is always less than 1 which confirms the stationarity of the model. Moreover, the introduction of the dummy variables is justified since their coefficients are generally statistically significant. Finally, Table 1 allows us to shed light on the impact of the information flow on the price volatility. The coefficient of the informational variable N_t is significantly positive for 11 out of the 40[6] firms of our sample, which represents 27.5%. These findings are statistically significant because, with a 95% confidence interval, Type I errors expect to find 2 coefficients in each set of 40 that are significant by chance. Our results are out of this range, which show that they are robust.

Table 2 summarizes the estimation results of Eq. (4). This table confirms the results detailed above. Indeed, the EGARCH coefficients (α and β) are generally significant and ensuring the stationarity of the model. The coefficient λ is significantly positive for 18 out of the 38[7] firms of our sample, which represents 47.5%. These findings show that high opening volatility is explained by both informational causes (accumulation of public information during the closing period) and microstructure factors related to the opening protocol (the opening effect documented by Jain and Joh (1985), Wood et al. (1985) and Blau et al. (2009) among others).

We have also tested our models for the market index (CAC40). Table 1 and Table 2 show that the coefficient of the informational variable (N_t) is not significant during the continuous market as well as for overnight announcements. In conclusion, our findings show that there is a moderate positive relationship between the number of news releases recorded by Reuters and stock price volatility. Our results are different from those found by Berry and Howe (1994) on the U.S. market and those obtained by Kalev et al. (2004) on the Australian market. The first authors highlight an insignificant relationship between the number of headlines published by Reuters and price volatility. Kalev et al. (2004) show that stock price volatility increases significantly around news releases. The moderate relationship between volatility and our informational proxy can be explained by several reasons. Indeed, we have taken into account all the news published by Reuters. This means that our sample can contain some announcements which were anticipated by the market. Therefore, this category of news has no information content and has been already integrated into prices. Moreover, several significant price changes occur without informational cause. The crash of October 1987 and the studies of Fair (2002) and Culter, Poterba and Summers (1989) confirm this hypothesis.

[6] The model didn't converge for the firm Peugeot.
[7] The model didn't converge for 3 firms: Axa, Peugeot and Sodexho.

Table 1: the intraday relation between volatility and news releases during the continuous market

Titre	ϕ_0	ϕ_1	C	γ	α	β	λ	θ_1	θ_2
Accor	0.024 (0.85)	-0.119 (0.37)	-2.298 (0.00)	-0.014 (0.58)	0.445 (0.00)	0.824 (0.00)	0.706 (0.00)	1.288 (0.00)	0.534 (0.00)
AGF	0.180 (0.00)	-0.358 (0.00)	-2.793 (0.00)	-0.003 (0.90)	0.423 (0.00)	0.779 (0.00)	0.639 (0.06)	0.848 (0.00)	0.761 (0.00)
Air Liquide	0.257 (0.00)	-0.445 (0.00)	-1.633 (0.00)	0.050 (0.19)	0.328 (0.00)	0.879 (0.00)	-0.021 (0.94)	0.723 (0.00)	0.612 (0.00)
Alcatel	0.255 (0.03)	-0.283 (0.02)	-4.166 (0.00)	-0.031 (0.09)	0.398 (0.00)	0.622 (0.00)	0.155 (0.18)	2.710 (0.00)	-0.043 (0.68)
Alstom	0.004 (0.98)	-0.059 (0.82)	-1.878 (0.00)	-0.042 (0.10)	0.459 (0.00)	0.860 (0.00)	0.532 (0.00)	1.415 (0.00)	0.305 (0.02)
Aventis	0.152 (0.283)	-0.222 (0.11)	-2.440 (0.00)	-0.035 (0.05)	0.372 (0.00)	0.814 (0.00)	0.144 (0.44)	1.354 (0.00)	0.401 (0.00)
Axa	0.861 (0.01)	-0.848 (0.01)	-4.026 (0.92)	0.127 (0.93)	0.253 (0.77)	0.618 (0.88)	-0.049 (0.94)	1.636 (0.96)	0.107 (0.97)
Bnp Paribas	0.070 (0.49)	-0.189 (0.06)	-2.795 (0.00)	-0.001 (0.95)	0.410 (0.00)	0.795 (0.00)	0.231 (0.21)	1.595 (0.00)	0.363 (0.00)
Cap Gemini	-0.138 (0.35)	0.073 (0.63)	-4.512 (0.00)	0.012 (0.60)	0.454 (0.00)	0.604 (0.00)	0.826 (0.05)	2.542 (0.00)	0.120 (0.24)
Carrefour	0.248 (0.00)	-0.385 (0.00)	-1.700 (0.00)	0.000 (0.99)	0.343 (0.00)	0.875 (0.00)	0.426 (0.13)	1.064 (0.00)	0.391 (0.00)
Casino	0.163 (0.00)	-0.405 (0.00)	-2.704 (0.00)	-0.026 (0.15)	0.360 (0.00)	0.791 (0.00)	0.044 (0.86)	0.900 (0.00)	0.616 (0.00)
Crédit Lyonnais	0.211 (0.00)	-0.369 (0.00)	-3.076 (0.00)	0.062 (0.00)	0.379 (0.00)	0.761 (0.00)	-0.161 (0.48)	1.311 (0.00)	0.707 (0.00)
Dassault	0.033 (0.78)	-0.102 (0.41)	-3.708 (0.00)	0.032 (0.12)	0.417 (0.00)	0.669 (0.00)	0.061 (0.79)	2.015 (0.00)	0.310 (0.00)
Dexia	0.090 (0.65)	0.379 (0.00)	-10.254 (0.00)	-0.409 (0.24)	0.955 (0.14)	0.124 (0.40)	0.584 (0.03)	2.366 0.065	-1.378 (0.04)
Eads	0.914 (0.00)	-0.950 (0.00)	-2.614 (0.00)	-0.043 (0.27)	0.518 (0.00)	0.792 (0.00)	0.083 (0.63)	1.436 (0.00)	0.442 (0.00)
Equant	0.215 (0.59)	-0.195 (0.62)	-1.062 (0.87)	0.008 (0.97)	0.022 (0.62)	0.894 (0.19)	-0.068 (0.99)	0.174 (0.96)	0.042 (0.92)
France Télécom	-0.831 (0.00)	0.816 (0.00)	-3.119 (0.00)	0.003 (0.87)	0.371 (0.00)	0.736 (0.00)	-0.007 (0.95)	2.245 (0.00)	0.123 (0.27)
Danone	0.197 (0.00)	-0.341 (0.00)	-3.023 (0.00)	-0.030 (0.11)	0.346 (0.00)	0.763 (0.00)	0.115 (0.42)	1.500 (0.00)	0.626 (0.00)
Lafarge	0.062 (0.47)	-0.203 (0.01)	-2.901 (0.00)	-0.017 (0.34)	0.352 (0.00)	0.772 (0.00)	0.288 (0.28)	1.222 (0.00)	0.583 (0.00)
Lagardère	-0.059 (0.66)	-0.038 (0.78)	-3.390 (0.00)	-0.028 (0.17)	0.417 (0.00)	0.715 (0.00)	0.411 (0.01)	1.116 (0.00)	1.122 (0.00)
L'oréal	0.283 (0.00)	-0.383 (0.00)	-2.797 (0.00)	0.002 (0.91)	0.333 (0.00)	0.770 (0.00)	0.517 (0.20)	0.746 (0.00)	0.799 (0.00)
LVMH	-0.159 (0.26)	0.097 (0.49)	-2.942 (0.00)	0.003 (0.86)	0.411 (0.00)	0.760 (0.00)	0.514 (0.01)	1.541 (0.00)	0.589 (0.00)
Michelin	0.217 (0.00)	-0.392 (0.00)	-3.462 (0.00)	0.005 (0.84)	0.463 (0.00)	0.717 (0.00)	0.902 (0.06)	1.594 (0.00)	0.385 (0.00)

Table 1 (continued)

Titre	ϕ_0	ϕ_1	C	γ	α	β	λ	θ_1	$\theta 2$
Orange	0.080 (0.34)	-0.187 (0.02)	-2.554 (0.00)	0.013 (0.50)	0.341 (0.00)	0.795 (0.00)	0.074 (0.73)	1.563 (0.00)	0.282 (0.02)
Peugeot	—	—	—	—	—	—	—	—	—
Pinault-PR	0.003 (0.97)	-0.136 (0.18)	-2.234 (0.00)	-0.020 (0.24)	0.385 (0.00)	0.830 (0.00)	-0.174 (0.33)	1.147 (0.00)	0.546 (0.00)
Renault	0.127 (0.25)	-0.228 (0.03)	-2.462 (0.00)	-0.032 (0.16)	0.416 (0.00)	0.806 (0.00)	0.280 (0.14)	1.051 (0.00)	0.805 (0.00)
Saint-Gobain	0.168 (0.04)	-0.303 (0.00)	-2.462 (0.00)	0.002 (0.90)	0.380 (0.00)	0.811 (0.00)	-0.145 (0.53)	0.916 (0.00)	0.838 (0.00)
Sanofi Synthelabo	0.185 (0.04)	-0.275 (0.00)	-3.180 (0.00)	-0.025 (0.46)	0.369 (0.00)	0.744 (0.00)	0.067 (0.80)	1.149 (0.00)	0.636 (0.00)
Schneider	0.256 (0.64)	-0.230 (0.67)	-1.457 (0.97)	0.005 (0.99)	0.008 (0.98)	0.860 (0.85)	-0.011 (0.99)	0.030 (0.99)	0.130 (0.87)
Sociéte Générale	-0.127 (0.38)	0.030 (0.83)	-2.468 (0.00)	-0.022 (0.25)	0.367 (0.00)	0.806 (0.00)	-0.023 (0.94)	1.220 (0.00)	0.551 (0.00)
Sodexho	0.347 (0.00)	-0.484 (0.00)	-6.534 (0.59)	0.036 (0.97)	0.408 (0.72)	0.424 (0.69)	0.424 (0.26)	2.643 (0.87)	1.654 (0.00)
ST-Microelectronics	0.548 (0.00)	-0.504 (0.00)	-3.013 (0.11)	0.052 (0.74)	0.069 (0.69)	0.715 (0.00)	-0.243 (0.58)	0.695 (0.59)	-0.232 (0.14)
Suez Lyon.Des Eaux	0.007 (0.95)	-0.142 (0.30)	-4.325 (0.00)	-0.124 (0.12)	0.657 (0.00)	0.656 (0.00)	0.450 (0.13)	3.032 (0.00)	-0.826 (0.36)
Tf1	0.092 (0.49)	-0.114 (0.40)	-2.542 (0.00)	-0.009 (0.72)	0.388 (0.00)	0.786 (0.00)	0.609 (0.09)	1.564 (0.00)	0.563 (0.00)
Thales	0.168 (0.16)	-0.268 (0.02)	-4.008 (0.00)	-0.022 (0.26)	0.412 (0.00)	0.657 (0.00)	0.979 (0.03)	1.197 (0.00)	0.432 (0.00)
Thomson	-0.208 (0.09)	0.156 (0.21)	-3.105 (0.00)	-0.011 (0.66)	0.382 (0.00)	0.729 (0.00)	1.175 (0.02)	1.930 (0.00)	0.536 (0.00)
Total Fina Elf	-0.280 (0.08)	0.210 (0.20)	-3.095 (0.00)	-0.016 (0.35)	0.341 (0.00)	0.759 (0.00)	0.095 (0.53)	1.238 (0.00)	0.801 (0.00)
Valeo	0.149 (0.04)	-0.336 (0.00)	-3.081 (0.00)	0.025 (0.27)	0.374 (0.00)	0.746 (0.00)	0.290 (0.41)	1.012 (0.00)	1.053 (0.00)
Vivendi Environement	0.398 (0.00)	-0.542 (0.00)	-4.139 (0.00)	-0.006 (0.82)	0.470 (0.00)	0.671 (0.00)	-0.175 (0.50)	1.412 (0.00)	0.699 (0.00)
Vivendi Universal	-0.100 (0.00)	0.033 (0.26)	-2.368 (0.00)	-0.029 (0.14)	0.406 (0.00)	0.819 (0.00)	0.183 (0.29)	1.610 (0.00)	0.521 (0.00)
CAC40	0.394 (0.19)	-0.376 (0.22)	-3.286 (0.00)	-0.011 (0.54)	0.411 (0.00)	0.762 (0.00)	-0.090 (0.90)	2.296 (0.00)	0.155 (0.28)

$$r_t = \phi_0 r_{t-1} + \phi_1 \varepsilon_{t-1} + \varepsilon_t$$

$$Log(h_t) = C + \gamma Z_{t-1} + \alpha|Z_{t-1}| + \beta log(h_{t-1}) + \lambda N_t + \theta_1 D_O + \theta_2 D_F$$

Table 1 – This table presents the results of the estimation of model (3) which tests the intraday relation between volatility and news releases during the continuous market. Volatility is estimated with the EGARCH model proposed by Nelson (1991). r_t and h_t are respectively the return and the conditional volatility during the 15-minute period t. N_t is the number of news items published by Reuters during each 15-interval t. DO and DC are two dummy variables accounting respectively for the first 15-minute period of the trading day and for the last 15-minute period. P-values (in parentheses) are calculated using Bollerslev and Wooldrige's (1992) robust standard errors.

Table 2: the relation between volatility and overnight announcements

Titre	ϕ_0	ϕ_1	C	γ	α	β	λ
Accor	1.001 (0.00)	-0.989 (0.00)	-0.704 (0.15)	0.128 (0.12)	0.212 (0.00)	0.936 (0.00)	0.088 (0.85)
AGF	-0.775 (0.00)	0.805 (0.00)	-7.495 (0.00)	0.187 (0.18)	0.747 (0.00)	0.244 (0.17)	0.114 (0.74)
Air Liquide	0.986 (0.00)	-0.926 (0.00)	-8.270 (0.04)	0.065 (0.49)	0.010 (0.97)	0.104 (0.82)	-0.356 (0.14)
Alcatel	-0.490 (0.15)	0.490 (0.16)	-3.957 (0.22)	-0.101 (0.30)	0.272 (0.08)	0.490 (0.26)	0.045 (0.48)
Alstom	0.928 (0.00)	-0.848 (0.00)	-0.899 (0.16)	-0.037 (0.56)	0.179 (0.11)	0.918 (0.00)	0.386 (0.01)
Aventis	-0.009 (0.96)	-0.016 (0.93)	-6.058 (0.06)	-0.043 (0.69)	0.359 (0.00)	0.388 (0.26)	0.186 (0.24)
Axa	—	—	—	—	—	—	—
Bnp Paribas	-0.997 (0.00)	0.992 (0.00)	-2.265 (0.18)	0.075 (0.77)	0.214 (0.41)	0.791 (0.00)	0.139 (0.45)
Cap Gemini	-0.513 (0.01)	0.581 (0.00)	-14.572 (0.00)	-0.027 (0.22)	0.447 (0.00)	-0.867 (0.00)	0.491 (0.00)
Carrefour	0.395 (0.26)	-0.433 (0.22)	-8.037 (0.00)	-0.150 (0.13)	-0.140 (0.58)	0.154 (0.55)	0.561 (0.00)
Casino	0.752 (0.00)	-0.631 (0.00)	-12.603 (0.00)	0.105 (0.12)	0.587 (0.00)	-0.279 (0.00)	1.550 (0.00)
Crédit Lyonnais	0.997 (0.00)	-0.989 (0.00)	-9.493 (0.18)	0.144 (0.13)	-0.740 (0.29)	-0.084 (0.92)	-0.433 (0.07)
Dassault	-0.522 (0.00)	0.710 (0.00)	-5.032 (0.15)	0.117 (0.27)	0.155 (0.24)	0.374 (0.40)	0.693 (0.03)
Dexia	0.005 (0.99)	0.005 (0.99)	-3.859 (0.00)	0.010 (0.99)	0.010 (0.99)	0.010 (0.98)	0.000 (1.00)
Eads	0.858 (0.00)	-0.751 (0.00)	-2.760 (0.00)	0.198 (0.05)	0.470 (0.00)	0.710 (0.00)	0.250 (0.37)
Equant	-0.328 (0.00)	0.549 (0.00)	-9.257 (0.00)	1.134 (0.00)	1.567 (0.00)	-0.108 (0.012)	0.691 (0.02)
France Télécom	0.472 (0.02)	-0.602 (0.00)	-3.297 (0.05)	0.113 (0.15)	-0.250 (0.07)	0.568 (0.00)	0.025 (0.74)
Danone	0.545 (0.00)	-0.445 (0.00)	-4.143 (0.00)	-0.158 (0.01)	0.037 (0.76)	0.578 (0.00)	0.724 (0.00)
Lafarge	0.997 (0.00)	-0.993 (0.00)	-17.843 (0.00)	0.029 (0.46)	0.113 (0.01)	-0.938 (0.00)	0.435 (0.04)
Lagardère	-0.298 (0.59)	0.421 (0.42)	-0.940 (0.16)	-0.102 (0.17)	0.279 (0.26)	0.913 (0.00)	0.009 (0.96)
L'oréal	0.779 (0.00)	-0.783 (0.00)	-8.549 (0.00)	0.016 (0.90)	0.153 (0.45)	0.075 (0.83)	1.405 (0.01)
LVMH	0.922 (0.00)	-0.922 (0.00)	-12.753 (0.00)	0.189 (0.17)	0.416 (0.01)	-0.450 (0.00)	0.718 (0.00)
Michelin	0.750 (0.00)	-0.564 (0.00)	-2.560 (0.00)	-0.027 (0.73)	0.265 (0.02)	0.742 (0.00)	0.939 (0.01)

Table 2 (continued)

Titre	ϕ_0	ϕ_1	C	γ	α	β	λ
Orange	-0.807 (0.00)	0.788 (0.00)	-17.705 (0.00)	0.160 (0.00)	0.165 (0.00)	-0.964 (0.00)	0.507 (0.00)
Peugeot	—	—	—	—	—	—	—
Pinault-PR	-0.998 (0.00)	0.995 (0.00)	-18.535 (0.00)	-0.138 (0.02)	0.056 (0.31)	-0.983 (0.00)	0.093 (0.40)
Renault	-0.357 (0.54)	0.448 (0.45)	-3.117 (0.37)	0.188 (0.48)	0.455 (0.17)	0.677 (0.07)	-0.005 (0.95)
Saint-Gobain	0.857 (0.00)	-0.800 (0.00)	-1.246 (0.04)	0.244 (0.01)	0.101 (0.19)	0.872 (0.00)	0.318 (0.35)
Sanofi Synthelabo	-0.738 (0.56)	0.739 (0.56)	-4.201 (0.14)	0.033 (0.73)	0.377 (0.02)	0.582 (0.05)	0.49 (0.05)
Schneider	0.400 (0.16)	-0.172 (0.55)	-4.342 (0.00)	-0.349 (0.04)	0.430 (0.02)	0.553 (0.00)	1.218 (0.00)
Société Générale	-0.618 (0.00)	0.713 (0.00)	-6.814 (0.01)	0.011 (0.92)	0.010 (0.97)	0.245 (0.43)	-1.230 (0.00)
Sodexho	—	—	—	—	—	—	—
ST-Microelectronics	-0.543 (0.01)	0.571 (0.01)	-0.650 (0.01)	-0.097 (0.20)	0.092 (0.26)	0.922 (0.00)	-0.738 (0.02)
Suez Lyon.Des Eaux	-0.220 (0.95)	0.218 (0.95)	-4.613 (0.01)	0.180 (0.91)	-0.432 (0.45)	0.011 (0.97)	0.051 (0.99)
Tf1	-0.598 (0.00)	0.676 (0.00)	-0.717 (0.11)	-0.202 (0.09)	0.032 (0.62)	0.922 (0.00)	0.455 (0.00)
Thales	-0.462 (0.42)	0.461 (0.42)	-7.617 (0.03)	0.115 (0.21)	-0.088 (0.51)	0.154 (0.70)	0.674 (0.00)
Thomson	-0.488 (0.11)	0.500 (0.10)	-4.384 (0.00)	0.089 (0.47)	0.403 (0.04)	0.462 (0.00)	-5.444 (0.00)
Total Fina Elf	0.159 (0.62)	-0.222 (0.48)	-0.372 (0.02)	-0.070 (0.03)	-0.065 (0.08)	0.960 (0.00)	0.277 (0.00)
Valeo	0.945 (0.00)	-0.820 (0.00)	-7.560 (0.00)	0.413 (0.00)	0.712 (0.00)	0.203 (0.17)	0.614 (0.00)
Vivendi Environment	0.752 (0.00)	-0.602 (0.00)	-1.244 (0.31)	0.283 (0.00)	0.222 (0.17)	0.881 (0.00)	0.071 (0.65)
Vivendi Universal	-0.504 (0.11)	0.518 (0.10)	-0.554 (0.13)	-0.013 (0.84)	0.298 (0.13)	0.962 (0.00)	-0.047 (0.21)
CAC40	-0.472 (0.29)	0.532 (0.21)	-9.261 (0.00)	0.156 (0.28)	0.311 (0.02)	0.053 (0.87)	-0.419 (0.55)

$$\bar{r}_t = \bar{\phi}_0 \bar{r}_{t-1} + \bar{\phi}_1 \bar{\varepsilon}_{t-1} + \bar{\varepsilon}_t$$
$$Log(\bar{h}_t) = \bar{C} + \bar{\gamma}\bar{Z}_{t-1} + \bar{\alpha}|\bar{Z}_{t-1}| + \bar{\beta} log(\bar{h}_{t-1}) + \bar{\lambda}\bar{N}_t$$

Table 2 – This table presents the results of the estimation of model (4) which tests the relation between volatility and overnight announcements. Volatility is estimated with the EGARCH model proposed by Nelson (1991). $\bar{r}_t$ and $\bar{h}_t$ are respectively the overnight return and conditional volatility. $\overline{N}_t$ is the number of overnight news items published by Reuters. P-values (in parentheses) are calculated using Bollerslev and Wooldrige's (1992) robust standard errors.

Table 3: the intraday relation between volume and news releases during the continuous market

Titre	C	λ	θ_1	θ_2	Fisher	R^2
Accor	9.477 (0.00)	0.391 (0.00)	-0.887 (0.00)	1.037 (0.00)	160.550 (0.00)	0.053
AGF	8.414 (0.00)	0.359 (0.17)	-0.937 (0.00)	1.403 (0.00)	192.930 (0.00)	0.063
Air liquide	8.375 (0.00)	0.679 (0.00)	-0.510 (0.00)	1.095 (0.00)	167.380 (0.00)	0.055
Alcatel	12.182 (0.00)	0.327 (0.00)	0.394 (0.00)	0.620 (0.00)	79.440 (0.00)	0.027
Alstom	10.031 (0.00)	0.880 (0.00)	-0.550 (0.00)	0.881 (0.00)	81.460 (0.00)	0.027
Aventis	10.662 (0.00)	0.091 (0.34)	-0.320 (0.00)	0.774 (0.00)	116.310 (0.00)	0.039
Axa	10.967 (0.00)	0.659 (0.00)	-0.316 (0.00)	0.838 (0.00)	73.510 (0.00)	0.025
Bnp Paribas	10.293 (0.00)	0.473 (0.00)	-0.414 (0.00)	0.814 (0.00)	124.330 (0.00)	0.041
Cap Gemini	9.490 (0.00)	0.905 (0.00)	0.063 (0.00)	0.861 (0.30)	89.920 (0.00)	0.030
Carrefour	10.343 (0.00)	0.366 (0.00)	-0.424 (0.00)	0.952 (0.00)	153.440 (0.00)	0.051
Casino	8.051 (0.00)	0.537 (0.00)	-0.718 (0.00)	1.165 (0.00)	134.900 (0.00)	0.045
Crédit Lyonnais	9.237 (0.00)	0.601 (0.00)	-0.378 (0.00)	1.248 (0.00)	125.990 (0.00)	0.042
Danone	9.165 (0.00)	0.527 (0.00)	-0.678 (0.00)	0.966 (0.00)	172.810 (0.00)	0.057
Dassault	8.350 (0.00)	0.48678 -0.010	-0.310 (0.00)	1.202 (0.00)	110.470 (0.00)	0.037
Dexia	8.801 (0.00)	0.916 (0.00)	-0.467 (0.00)	1.077 (0.00)	49.220 (0.00)	0.017
Eads	10.015 (0.00)	0.637 (0.00)	-0.350 (0.00)	1.145 (0.00)	122.840 (0.00)	0.041
Equant	9.471 (0.00)	0.547 (0.02)	-0.320 (0.00)	1.181 (0.00)	90.810 (0.00)	0.031
France Télécom	11.294 (0.00)	0.261 (0.00)	0.214 (0.00)	0.713 (0.00)	69.590 (0.00)	0.023
Lafarge	9.126 (0.00)	0.534 (0.00)	-0.785 (0.00)	0.998 (0.00)	154.830 (0.00)	0.051
Lagardère	8.856 (0.00)	0.563 (0.00)	-0.495 (0.00)	1.464 (0.00)	184.730 (0.00)	0.060
L'oréal	9.782 (0.00)	0.299 (0.08)	-0.381 (0.00)	0.878 (0.00)	134.080 (0.00)	0.044
LVMH	10.012 (0.00)	0.358 (0.00)	-0.515 (0.00)	0.993 (0.00)	148.780 (0.00)	0.049
Michelin	8.606 (0.00)	0.821 (0.00)	-0.671 (0.00)	1.364 (0.00)	142.74 (0.00)	0.047

Table 3 (continued)

titre	C	λ	θ_1	θ_2	Fisher	R^2
Orange	11.748 (0.00)	0.584 (0.00)	-0.266 (0.00)	0.754 (0.00)	46.890 (0.00)	0.018
Peugeot	8.943 (0.00)	0.501 (0.01)	-0.829 (0.00)	1.013 (0.00)	91.580 (0.00)	0.031
Prinault-PR	8.539 (0.00)	0.718 (0.00)	-0.618 (0.00)	1.191 (0.00)	163.080 (0.00)	0.054
Renault	9.500 (0.00)	0.339 (0.00)	-0.434 (0.00)	1.117 (0.00)	140.270 (0.00)	0.046
Saint-Gobin	8.403 (0.00)	0.580 (0.00)	-0.704 (0.00)	1.076 (0.00)	149.620 (0.00)	0.049
Sanofi Synthelabo	10.347 (0.00)	0.340 (0.00)	-0.347 (0.00)	0.852 (0.00)	117.310 (0.00)	0.039
Schneider	9.536 (0.00)	0.880 (0.00)	-0.925 (0.00)	0.994 (0.00)	167.880 (0.00)	0.056
Société Générale	10.069 (0.00)	0.182 (0.29)	-0.411 (0.00)	1.048 (0.00)	155.040 (0.00)	0.051
Sodexho	8.427 (0.00)	0.901 (0.00)	-0.943 (0.00)	1.357 (0.00)	123.650 (0.00)	0.041
ST-Microelectronics	11.573 (0.00)	0.475 (0.01)	0.030 (0.58)	0.571 (0.00)	37.960 (0.00)	0.013
Suez Lyon.Des Eaux	10.241 (0.00)	0.042 (0.75)	-0.661 (0.00)	0.905 (0.00)	91.320 (0.00)	0.031
TF1	9.450 (0.00)	0.260 (0.00)	-0.422 (0.00)	1.065 (0.00)	119.300 (0.00)	0.040
Thales	8.313 (0.00)	0.646 (0.00)	-0.729 (0.00)	1.295 (0.00)	139.100 (0.00)	0.046
Thomson	9.485 (0.00)	0.752 (0.02)	-0.100 (0.12)	1.042 (0.00)	88.350 (0.00)	0.030
Total Fina Elf	10.645 (0.00)	0.072 (0.40)	-0.076 (0.10)	1.031 (0.00)	165.120 (0.00)	0.054
Valeo	8.304 (0.00)	0.601 (0.00)	-1.004 (0.00)	1.425 (0.00)	158.280 (0.00)	0.053
Vivendi Environment	8.810 (0.00)	0.791 (0.00)	-1.030 (0.00)	1.321 (0.00)	120.140 (0.00)	0.040
Vivendi Universal	11.140 (0.00)	0.237 (0.00)	-0.111 (0.02)	1.096 (0.00)	166.450 (0.00)	0.055
CAC40	10.853 (0.00)	0.060 (0.00)	0.021 (0.55)	0.811 (0.00)	188.02 (0.00)	0.062

$$Log(V_t) = C + \lambda N_t + \epsilon_t + \theta_1 D_O + \theta_2 D_F$$

Table 3 – This table presents the results of the estimation of model (5) which tests the intraday relation between trading volume and news releases during the continuous market. V_t is the trading volume the 15-minute period t. N_t is the number of news items published by Reuters during each 15-interval t. DO and DC are two dummy variables accounting respectively for the first 15-minute period of the trading day and for the last 15-minute period.

Table 4: the relation between volume and overnight announcements

Titre	C	λ	Fisher	R^2
Accor	9.036 (0.00)	0.524 (0.00)	8.620 (0.00)	0.033
AGF	8.159 (0.00)	0.088 (0.71)	0.140 (0.71)	0.001
Air liquide	8.169 (0.00)	0.140 (0.13)	0.800 (0.13)	0.003
Alcatel	11.858 (0.00)	0.141 (0.00)	11.250 (0.00)	0.043
Alstom	9.588 (0.00)	0.778 (0.00)	26.270 (0.00)	0.095
Aventis	10.093 (0.00)	0.078 (0.36)	0.830 (0.36)	0.003
Axa	10.640 (0.00)	0.041 (0.81)	0.050 (0.81)	(0.00)
Bnp Paribas	9.663 (0.00)	0.255 (0.05)	3.750 (0.05)	0.015
Cap Gemini	9.138 (0.00)	0.513 (0.00)	15.900 (0.00)	0.060
Carrefour	9.978 (0.00)	0.302 (0.00)	6.820 (0.00)	0.027
Casino	7.667 (0.00)	0.614 (0.00)	8.620 (0.00)	0.033
Crédit Lyonnais	9.516 (0.00)	0.358 (0.00)	7.430 (0.00)	0.029
Danone	8.576 (0.00)	0.296 (0.00)	9.970 (0.00)	0.038
Dassault	8.424 (0.00)	0.578 (0.00)	7.650 (0.00)	0.030
Dexia	8.774 (0.00)	-0.379 (0.22)	1.460 (0.22)	0.006
Eads	9.991 (0.00)	0.174 (0.23)	1.440 (0.23)	0.006
Equant	9.329 (0.00)	0.326 (0.14)	2.160 (0.14)	0.002
France Télécom	10.914 (0.00)	0.151 (0.02)	5.240 (0.02)	0.021
Lafarge	8.512 (0.00)	0.435 (0.00)	16.470 (0.00)	0.002
Lagardère	8.939 (0.00)	0.141 (0.53)	0.380 (0.53)	0.002
Loréal	9.532 (0.00)	0.874 (0.00)	14.760 (0.00)	0.056
LVMH	9.553 (0.00)	0.230 (0.05)	3.580 (0.05)	0.014
Michelin	8.677 (0.00)	0.459 (0.01)	6.130 (0.01)	0.024

Table 4 (continued)

Titre	C	λ	Fisher	R^2
Orange	11.068 (0.00)	0.443 (0.01)	6.420 (0.01)	0.028
Peugeot	8.323 (0.00)	0.291 (0.34)	0.890 (0.34)	0.004
Prinault-PR	8.070 (0.00)	0.225 (0.09)	2.830 (0.09)	0.011
Renault	9.151 (0.00)	0.100 (0.17)	1.820 (0.17)	0.007
Saint-Gobin	8.081 (0.00)	0.464 (0.00)	10.710 (0.00)	0.041
Sanofi Synthelabo	9.781 (0.00)	0.536 (0.00)	9.360 (0.00)	0.036
Schneider	8.740 (0.00)	0.539 (0.00)	24.820 (0.00)	0.091
Société Générale	9.418 (0.00)	0.051 (0.76)	0.090 (0.76)	(0.00)
Sodexho	8.015 (0.00)	0.476 (0.04)	4.120 (0.04)	0.016
ST-Microelectronics	10.800 (0.00)	1.333 (0.00)	17.950 (0.00)	0.067
Suez Lyon.Des Eaux	9.915 (0.00)	-0.175 (0.30)	1.050 (0.30)	0.004
TF1	9.116 (0.00)	0.335 (0.01)	5.880 (0.01)	0.023
Thales	8.333 (0.00)	0.487 (0.00)	6.920 (0.00)	0.027
Thomson	9.535 (0.00)	0.102 (0.85)	0.030 (0.85)	(0.00)
Total Fina Elf	10.117 (0.00)	0.071 (0.60)	0.270 (0.60)	0.001
Valeo	7.702 (0.00)	0.566 (0.00)	15.710 (0.00)	0.059
Vivendi Environment	8.364 (0.00)	0.457 (0.00)	13.460 (0.00)	0.051
Vivendi Universal	10.781 (0.00)	0.085 (0.16)	1.920 (0.16)	0.008
CAC40	10.319 (0.00)	0.039 (0.00)	9.71 (0.00)	0.037

$$Log(\bar{V}_t) = \bar{C} + \bar{\lambda}\bar{N}_t + \bar{\epsilon}_t$$

Table 4 – This table presents the results of the estimation of model (6) which tests the relation between trading volume and overnight announcements. $\overline{V_t}$ is the opening trading volume at the day t. $\overline{N_t}$ is the number of overnight news items published by Reuters.

3.2. Public information arrival and trading volume

Table 3 summarizes the results of the estimation of model (5). We observe that the coefficients of the dummy variables are generally significant which confirm the intraday U-shaped pattern of volume. Moreover, the results show that the coefficient of our informational proxy is significantly positive for 36 firms out of 41, which represents 88%. This finding highlights a strong relationship between the rate of public information flow and trading volume, which confirms the MDH hypothesis.

The results of the estimation of model (6) are given in Table 4. The linear regression reveals that the coefficient of the informational variable N_t is positive and significant for 26 out of the 41 firms of our sample, which represents 64%. The results for the CAC40 index confirm this strong positive relationship between trading volume and the information flow. This finding show that the number of news items published during the closing period impacts significantly the trading volume at the opening.

In conclusion, the relationship between the information flow and trading volume seems stronger than the relationship between the information flow and stock price volatility. This result can be explained by the fact that the trading volume may be abnormally high even around “no news” announcements which do not cause a significant price change. Indeed, several empirical studies highlight an abnormal trading volume even in the absence of price changes (Beaver (1968), Bamber and Cheon (1995), Kandel and Pearson (1995), etc.). Theoretically, Blume et al. (1994) explain this empirical result by the fact that volume has a limit distribution that is nondegenerate. The difference in investors’ expectations, the difference in the degree of risk aversion among investors, the differential interpretation of information and the publicity effect can explain this phenomenon.

4. CONCLUSION

The goal of this paper is to examine the relationship between the information flow and market activity. The information flow is measured as the number of news items recorded by Reuters. Our results reveal a strong relation between trading volume and public information flow and a moderate relation between the information flow and stock returns volatility. These results are available for the CAC40 Index as well as for individual stocks. Moreover, our findings show that high opening market activity is explained by both microstructure factors (Euronext opening protocol) and informational causes i.e. accumulation of public information during the closing period.

Our study confirms partially the mixture distribution hypothesis. However, the moderate relationship between the information flow and stock price volatility can be attributed to the choice of our informational proxy which focuses only on public information. Further research should develop more sophisticated information measure in order to take into account private information.

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