What drives the volume-volatility relationship on Euronext Paris?

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Abstract

The goal of this paper is to shed light on the relationship between volume and volatility. More specifically, it aims to determine which component of trading volume (trade size or number of transactions) drives this relation. Our intraday analysis reveals several results. Firstly, we confirm the strong positive relationship between volume and volatility. Secondly, including volume in the conditional variance of stock returns significantly reduces the persistence of volatility. Thirdly, in line with Jones et al. (1994), we show that the well-known positive relationship between volatility and volume is generated by the number of trades. These results are robust, even after controlling for the impact of the intraday patterns. Finally, our findings are available for the CAC40 Index as well as for individual stocks.

Keywords: Volume, conditional volatility, number of transactions, size of trades, market microstructure, Euronext Paris

JEL classification codes: G12; G14

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Abstract

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1. INTRODUCTION

A Wall Street adage says "*It takes volume to make prices move*." This saying is confirmed by several empirical studies documented in the survey paper of Karpoff (1987). The author provides an interesting literature review of papers studying the relationship between price changes and volume. Most papers cited by Karpoff (1987) conclude that there is a strong positive correlation between volatility (measured as absolute or squared price changes) and trading volume. Recently, Chuang et al. (2009) use quantile regressions to show that volume has a positive effect on return volatility. These results mean that volatile returns are associated with high trading volume.

Various microstructure models have attempted to provide theoretical justification for the well-known positive relationship between price changes and trading volume. The competing explanations are the mixture of distribution hypothesis and the asymmetric information hypothesis.

The seminal work of Clarck (1973) has introduced the mixture of distribution hypothesis (MDH), which supposes that asset 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 information flow and market activity. These models consider 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 information flow (Li and Wu, 2006). Empirically, this means that volume and stock price 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. The mixture distribution hypothesis has also been used to explain the well-known autoregressive conditional heteroskedasticity (ARCH) process that volatility follows. Lamoureux and Lastrapes (1990) use data from the US market and show that persistence in volatility is diminished when volume is introduced in the conditional variance equation of the GARCH model. This result is confirmed in the Korean market (Pyun et al., 2000) and in the Polish market (Bohl and Henke, 2003). These findings show that volume is driven by the same factors that generate the ARCH effects. In general, the mixture distribution hypothesis supports a strong, contemporaneous and positive relationship between volume and volatility.

Despite the interesting explanation given by the mixture distribution hypothesis, the models described above do not allow us to determine the component of trading volume that generates this relation. In fact, trading volume is composed of two components: the number of trades and size of trades. Thus, it would be interesting to test whether the volume-volatility relationship is driven by either one or both components. The asymmetric information hypothesis has focused on this issue. The microstructure literature distinguishes two groups of models: competitive asymmetric information models and strategic asymmetric information models. Competitive models suppose that informed investors prefer to trade large amounts and conclude that there is a positive relationship between price changes and trade size (Pfleiderer, 1984; Easley and O'Hara, 1987; Grundy and McNichols, 1989; Holthausen and Verrecchia, 1990; and Kim and Verrechia, 1991). Empirically this assumption leads to our first hypothesis:

Hypothesis 1: the well-known volume-volatility relationship is driven by the size of trades.

However, strategic models predict that informed traders may camouflage their private information by splitting large trades into several small trades (Kyle, 1985; Foster and Vishwanathan, 1990; Holden and Subrahmanyam, 1992). Empirically this intuition leads to the following second hypothesis:

Hypothesis 2: the number of trades generates the well-known positive relationship between price changes and volume.

Despite the abundant literature on the volume-volatility relationship, few papers have focused on its origin. Jones et al. (1994) use daily data on NASDAQ-NMS firms and ordinary least squares (OLS) technique to test whether number of transactions per se or their size generates volatility. The authors show that the positive daily relationship between volatility and volume is due to the positive daily relationship between volatility and the number of transactions. Jones et al. (1994) conclude that the average size of trades has no incremental information content beyond that contained in the number of trades. Using data from the New York Stock Exchange (NYSE), Xu and Wu (1999) investigate the relationship between price changes, average trade size and the number of transactions. The authors confirm the information role of the frequency of transactions. However, contrary to Jones et al. (1994), they show that the average size of trades contains nontrivial information for return volatility. Chan and Fong (2000) consider a sample of stocks listed on the NASDAQ and New York Stock Exchange. Their findings are in line with those of Xu and Wu (1999). They support the significance of average trade size in the volume-volatility relationship in both markets.

Our study is related to the empirical works mentioned above. It aims to test whether the number of trades or the size of trades drive the volume-volatility relationship on Euronext Paris. Our contributions concern the data used and the methodology adopted.

Although there are many empirical studies on the volatility-volume relation, there is no general consensus about what actually drives the relation. Moreover, most of the previous studies pertain to the U.S. market and it is unclear whether we can generalize its results to other markets. Euronext Paris is a pure automated order driven market, which has a specific microstructure that can impact the roles of the number of trades and size of trades in the volatility-volume relation. In fact, all investors can see at any time the five best limits at each side of the market, with the associated displayed depth. This transparency can incite investors to camouflage their large orders by splitting them. Market participants can also use hidden orders, i.e., orders whose some part of the quantity is not disclosed to other investors. In this case, the total order size is registered in the order book but only the disclosed quantity is displayed on the market screens. D'Hondt et al. (2003), show that hidden orders are more involved in splitting strategies than usual orders. Hence, we expect that splitting orders may increase the information content of the number of trades on Euronext Paris. On the other hand, it may attenuate the relationship between the size of trades and volatility. To test this intuition, we collect intraday data that covers the period from January through December 2007. The intraday analysis allows us to avoid aggregating variables into daily sums, as proposed by Jones et al. (1994). The aggregation can smooth variables and affect their significance.

Our methodology differs in many aspects from the mentioned studies on the topic. We consider a conditional volatility measure instead of realized volatility. The use of a GARCH (general auto regressive conditional heteroskedasticity) model is appropriate for our study for two reasons. First, the family of ARCH models has been shown to provide a good fit for financial return time series (Lamoureux and Lastrapes, 1990; Bollerslev, 1987; Baillie and Bollerslev, 1989). In fact, the autoregressive process accounts for the persistence and for the clustering pattern of volatility. It captures some statistical artefacts in stock returns as the nonstability of the distributions documented by Mandelbrot (1963) and Fama (1965). Second, the GARCH framework allows to test if returns are generated by a mixture of distributions, in which the trading volume is a stochastic mixing variable. Indeed, to study the interaction between volume and volatility, we introduce the trading volume in the conditional volatility equation. If the MDH hypothesis is validated, we expect that trading volume significantly influences the conditional volatility and reduces substantially its persistence. We apply our econometric model to 38 stocks listed on Euronext Paris and to the main Index of the French market (CAC40 Index). To test the robustness of our results, we control for the potential impact of the well-known intraday patterns.

Our research question is interesting and has several implications. First, it provides insight into the structure of financial markets. Indeed, this relation depends on the rate of information flow, information dissemination and the extent to which market prices convey the information (Karpoff, 1987). Second, this work tests if information flow is a latent common factor that affects both of trading volume and stock prices. The response to this question is important for event studies that use both returns and trading volume to investigate the market reaction around corporate disclosure (Beaver, 1968; Louhichi, 2008; etc.). If price movements and volume depend jointly on the intensity of information flow, incorporating the price-volume relation will increase the power of these tests. Third, the results given by the decomposition of volume allows us to examine if the number of trades is a sufficient statistic for trading activity. Fourth, our findings can help investors to proxy the information flow.

Our intraday analysis reveals several results. We confirm the strong positive relationship between volume and volatility. Moreover, including volume in the conditional variance of stock returns significantly reduces the persistence of conditional volatility. Furthermore, we highlight the fact that the average size of trades has no incremental information content beyond that contained in the number of trades. These results are robust even after controlling for the impact of the intraday patterns. Finally, our findings are available for the CAC40 Index as well as for individual stocks.

The remainder of the paper is organized as follows. Section 2 focuses on the integration of European exchanges and the creation of Euronext. Section 3 details the GARCH model and specifies the research methodology. Section 4 gives a description of the data and exposes the empirical results. The last section concludes.

2. European market integration and Euronext microstructure

In 1999, the euro[2] was adopted as a common currency in the European Union. This event has played a very important catalysing role for the financial integration process as documented by several studies. Jawadi et al. (2010) focus on financial integration between 10 European stock markets during the period 1970-2007. Using a nonlinear model, the authors highlight strong evidence of a structural break after 1999 indicating that European stock markets became significantly more integrated after the creation of the common currency. Furthermore, since the euro adoption, exchanges in Europe are in a process of consolidation. In this regard, Euronext was created in September 2000 from the merger of Amsterdam, Brussels and Paris stock exchanges. The three exchanges operate through a single electronic trading system (Nouveau Système de Cotation) since 2001. Lisbon and the London-based derivatives exchange LIFFE have joined the group in 2002. These mergers are in line with the European directive MiFID (Markets in Financial Instruments Directive, November 2007), which recommend a convergence towards a unified European capital markets industry.

Euronext Paris operates through an electronic order driven system, in which traders' orders are conveyed to a central order book. A transaction takes place when a new order is placed and a matching order exists on the other side of the book. The trading day begins at 7:15a.m. with a pre-opening period where traders can place, modify or cancel orders. The market opens at 9:00a.m. with a call auction, which determines the opening price. From 9:00a.m. to 5:30p.m., the market is in its continuous period. In the same way as the opening, the market closes with a pre-closing period from 5:30p.m. to 5:35p.m. The closing price is determined at 5:30p.m. with a call auction. A "trading at last" period was introduced to give investors the opportunity to trade from 5:35p.m. to 5:40p.m. at the

[2] The euro was introduced to financial markets as an accounting currency on 1 January 1999. Euro coins and banknotes entered circulation on 1 January 2002.

closing price. Investors can see, at any time of the trading day, the five best limits and market sheet updates. The CAC40 index is the main market benchmark for Euronext Paris. It comprises the 40 most highly capitalized and liquid shares listed on the stock exchange.

3. METHODOLOGY

3.1. The GARCH model

The goal of this paper is to shed light on the relationship between volume and volatility. More specifically, it aims to determine which component of trading volume (trade size or number of transactions) drives this relation. Several proxies have been used to measure volatility. Jones et al. (1994) use the absolute returns to calculate the realized volatility and set their analysis in the framework of ordinary least squares (OLS) technique to model the relationship between volume and volatility. However, in this class of standard linear regression, the error of the model (ε) is assumed to have a zero mean and a constant standard deviation. Numerous studies show that the hypothesis of constant variance is not verified empirically. Engle (1982) assumes that volatility time series are characterized by the presence of conditional heteroskedasticity. The author proposes an autoregressive model (ARCH) that allows the conditional variance to change over time. Moreover, the family of ARCH[3] models accounts for the volatility persistence effect and attempts to capture the clustering pattern (volatility tends to cluster in periods of high volatility and periods of low volatility). In these models, the current idiosyncratic variance depends on its past levels and past innovations. Bollerslev (1986) proposed the GARCH (generalized ARCH) conditional variance specification that allows for a parsimonious parameterisation of the lag structure. In this study, we use the

[3] For more details about these models, see Engle (1982) and Bollerslev (1986).

GARCH model proposed by Bollerslev (1986) to model volatility. The GARCH (1,1) can be presented as follows:

$$r_t = \mu + \varepsilon_t \qquad \text{(1a)}$$

$$VAR(\varepsilon_t | \varepsilon_{t-1}) = \sigma_t^2$$

$$\sigma_t^2 = \omega + \alpha\ \varepsilon_{t-1}^2 + \beta\ \sigma_{t-1}^2 \qquad \text{(1b)}$$

Where r_t is the stock return at period t and μ is a constant. The errors (innovations) ε_t are assumed to be identically and independently distributed. The model supposes that the conditional volatility of the current period (σ_t) depends upon the conditional volatility of the former period σ_{t-1} and the innovation ε_{t-1}. The degree of volatility persistence is measured by the sum of coefficients ($\alpha + \beta$). As the magnitude of persistence approaches unity, the persistence of shocks to volatility increases.

3.2. The research model

To test the impact of volume on the price volatility, we include the trading volume (V_t) in the conditional variance equation. Trading volume (V_t) is computed as the number of shares traded during each period t. If the coefficient λ of the variable V_t is significant, we can conclude that trading volume has an impact on price volatility. Moreover, if the mixture distribution hypothesis is verified[4], then the magnitude of volatility persistence ($\alpha + \beta$) should be significantly diminished in comparison to the estimates from Eq. (1b). The model testing the relationship between price volatility and trading volume can be presented as follows:

[4] This means that trading volume is driven by the same factors that generate the ARCH effects.

$$r_t = \mu_t + \varepsilon_t \quad (2a)$$

$$\sigma_t^2 = \omega + \alpha\ \varepsilon_{t-1}^2 + \beta\ \sigma_{t-1}^2 + \lambda\ V_t \quad (2b)$$

Trading volume is composed of two components: the number of trades and the size of trades. In fact, trading volume V_t (number of shares traded in a period t) can be defined as the number of trades in period t (NT_t) multiplied by the average size of trades of the period t (ST_t). The goal of the following analysis is to determine whether the number of transactions or the size of trades drives the relationship between volume and volatility. The significance of the coefficients δ and γ in the following model provides empirical evidence of whether the number of transactions and the size of trades impact volatility:

$$r_t = \mu_t + \varepsilon_t \quad (3a)$$

$$\sigma_t^2 = \omega + \alpha\ \varepsilon_{t-1}^2 + \beta\ \sigma_{t-1}^2 + \delta\ NT_t + \gamma\ ST_t \quad (3b)$$

The intraday U-shaped pattern of volume and volatility is a well-documented phenomenon in the microstructure literature. Jain and Joh (1985), Wood et al. (1985) and Blau et al. (2009) highlight heavy market activity in the begging 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_t equals 1 for the first 30-minute period of the trading day and 0 otherwise. DC_t equals 1 for the last 30-minute period of the trading day and 0 otherwise. To check the robustness of our results, we also estimate the following model:

$$r_t = \mu_t + \varepsilon_t \quad (4a)$$

$$\sigma_t^2 = \omega + \alpha\ \varepsilon_{t-1}^2 + \beta\ \sigma_{t-1}^2 + \delta\ NT_t + \gamma\ ST_t + \theta\ DO_t + \phi\ DC_t \quad (4b)$$

4. DATA AND RESULTS

4.1. Data

The aim of this paper is to shed light on the relationship between trading volume and price volatility using high-frequency data from Euronext Paris. The study requires intraday data about trades, execution date and time, size, price, best limits and number of transactions. This information is obtained from Euronext database and covers the period from January through December 2007. During this period, Euronext Paris was open from 9:00 a.m. to 5:30 p.m. Transaction data in each day are divided into seventeen 30-minute intervals.

Our sample concerns all shares pertaining to the CAC40 Index, which is the main benchmark for Euronext Paris. The sample consists of 38 companies rather than 40 because the GARCH model has encountered convergence[5] problems with 2 companies (Essilor and Veolia Environment). Table 1 reports descriptive statistics across the individual stocks in our sample. The table contains each company name, the CVALBDM code[6], the average trading volume, the average number of transactions and the average trade size. All reported numbers are based on half-hourly data.

[Take in Table 1]

We compute CAC40 Index returns with the logarithm formula:

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

Where P_t is the price of the CAC40 Index at the end of each 30-minute interval. However, in lieu of transacted price, we use the mid-quotes at the end of each 30-minute interval for individual stocks. Using mid-quotes avoids the estimation bias caused by bid-ask bounce. For each stock of our sample, returns are calculated by the following formula:

[5] This kind of problems is typical of GARCH model.
[6] The CVALBDM is a specific code assigned to each stock recorded in the Euronext database.

$r_t = 100 \ \ln(MQ_t / MQ_{t-1})$

Where $MQ_t = (Bid_t + Ask_t)/2$

Bid_t and Ask_t are the best limits at the end of the 30-minute interval t.

In addition to returns, our database provides volume time series. For every 30-minute interval, we count the number of shares traded, the number of transactions and the average size of trades[7] for each firm of our sample.

4.2. Empirical results

[Take in Table 2]

Table 2 summarizes the estimation results of Eq. (1b). The table contains the estimated coefficients α and β as well as the sum $\alpha+\beta$ to evaluate the magnitude of persistence of volatility. The results show that the ARCH coefficient α and the GARCH coefficient β are significant for the CAC40 Index and for all the stocks of our sample. Moreover, for the CAC40 Index and for 25 out of the 38 firms of our sample, the sum $\alpha+\beta$ is higher than 0.93 and close to the constraint ensuring the stationarity of the model ($\alpha+\beta$ < 1). The high degree of persistent provides an explanation for the well-known clustering pattern of volatility i.e. the current idiosyncratic variance depends on its past levels and past innovations. These finding highlight the fact that intraday stock returns can be characterized by a GARCH (1,1) specification.

[Take in Table 3]

Table 3 allows us to shed light on the impact of volume on the price volatility. The coefficient λ is significantly positive (at the 1% level) for all the stocks of our sample and for the

[7] The average size of trades is defined as the number of shares traded divided by the number of transactions.

CAC40 Index. This result confirms the well-known positive relationship between volume and volatility (Karpoff, 1987; Alsubaie and Najand, 2009; Chuang et al., 2009). Moreover, Table 3 shows that the inclusion of trading volume (V_t) in the conditional variance equation significantly diminished the level of persistence in volatility, as measured by the sum ($\alpha + \beta$). For the CAC40 Index the persistence in volatility is reduced from 0.996 to 0.229. This means that the persistence of volatility is mostly absorbed by the trading volume effect. These findings highlight the significant information content of trading volume and confirm the mixture distribution hypothesis, which predicts that volume and volatility depend on the same latent underling information (Lamoureux and Lastrapes, 1990; Pyun et al., 2000; Bohl and Henke, 2003).

[Take in Table 4]

In the following analysis, we propose an exploration of the volume-volatility relationship by accounting for the 2 components of trading volume: the number of trades and the size of trades. The goal of this analysis is to determine which component drives the positive relationship between volume and volatility. Table 4 gives the estimation results from Eq. (3b). These results confirm the findings detailed above. Indeed, including informational variables (number of trading and trade sizes) significantly reduces the persistence of volatility. Moreover, the coefficient of the number of trades (δ_t) is positive and significant for each company and for the CAC40 Index. However, the coefficient of the size of trades (γ_t) is insignificant for all the stocks of our sample. This means that the well-known positive relationship between volatility and volume is generated by the number of trades. In fact, the average size of trades has no incremental information content beyond that contained in the number of trades. Our findings are in line with the daily results of Jones et al. (1994), but are different from those of Xu and Wu (1999) and Chan and Fong (2000). Thus, we support the strategic asymmetric information models (Kyle, 1985; Foster and Vishwanathan, 1990; Holden and Subrahmanyam, 1992), which predict that informed traders may camouflage their private information by splitting large trades into several small trades. On one hand, this phenomenon may increase the information content of the number of trades. On the other hand, it may attenuate the relationship between the size of trades and volatility.

[Take in Table 5]

To check the robustness of our results, we have estimated Eq. (4b), which controls for the intraday patterns of volume and volatility. Table 5 indicates that the coefficient of the dummy variable θ is significantly positive for all stocks in our sample and for the CAC40 Index. This means that market activity is significantly higher in the opening 30-minute period. However, the coefficient ϕ of the dummy variable accounting for the closing 30-minute period is significant only for 2 cases. Furthermore, the estimation of Eq. (4b) gives similar results as Eq. (3). In fact, the coefficient of the number of trades (δ_t) is positive and significant for all the stocks of our sample. Nevertheless, the coefficient of the size of trades (γ_t) is significant for only 2 out of the 38 companies in our sample. This means that our results are robust even after controlling for the intraday patterns of volume and volatility.

5. CONCLUSION

This paper aims to shed light on the relationship between return volatility and trading volume. Unlike the existing literature, we consider conditional volatility measure instead of realized volatility. We decompose trading volume into two components: the number of trades and the size of trades. Using intraday data from Euronext Paris, we test if the volume-volatility relationship is driven by one or both components. Our empirical study highlights the fact that the average size of trades has no incremental information content beyond that contained in the number of trades. These results are available for the CAC40 Index as well as for individual stocks, even after controlling for the impact of the intraday patterns. Our findings support the strategic asymmetric information hypothesis, which predicts that informed traders may behave strategically and camouflage their private information by splitting large trades into several small trades. On one hand, this phenomenon may increase the information content of the number of trades. On the other hand, it may attenuate the relationship between the size of trades and volatility. Finally, our study remains purely empirical, future research should develop a market microstructure model that endogenizes both the size and the number of trades.

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Table1

This table reports descriptive statistics across the individual stocks in our sample. The table contains each company, the CVALBDM code, the average trading volume, the average number of transactions and the average trade size. All reported numbers are based on half-hourly data.

Stock	CVALBDM	Company name	Volume	Number of trades	Size of trades
1	4170	ACCOR	79934.673	272.556	279.797
2	272	AIR FRANCE -KLM	114810.3	298.875	368.381
3	4150	AIR LIQUIDE	46894.408	317.734	139.179
4	4438	ALCATEL-LUCENT	1031408	412.750	2295.044
5	38371	ALSTOM	50278.157	375.244	131.199
6	4187	AXA	524481	550.396	904.571
7	26990	BNP PARIBAS	277265.9	709.840	382.570
8	4178	BOUYGUES	76385.718	279.367	268.634
9	4340	CAP GEMINI	94694.553	298.522	297.816
10	4154	CARREFOUR	220534.3	414.391	492.616
11	72275	CREDIT AGRICOLE	278857.9	407.183	648.887
12	4188	DANONE	119716.2	373.311	285.327
13	45057	DEXIA	135388.3	140.425	897.116
14	49388	EADS	198558.7	289.914	636.839
15	123032	EDF	74255.395	328.838	217.185
16	36064	FRANCE TELECOM	642460	492.441	1247.537
17	118139	GAZ DE FRANCE	76422.927	231.530	314.095
18	4181	LAFARGE	58557.996	346.101	165.025
19	4448	LAGARDERE S.C.A.	34599.972	152.876	224.005
20	4166	L'OREAL	69004.446	287.094	236.929
21	4213	LVMH	80423.608	316.714	246.545
22	4234	MICHELIN	60421.234	260.581	227.354
23	4192	PERNOD RICARD	22841.754	211.266	101.659
24	4252	PEUGEOT	90045.578	282.410	313.627
25	4250	PPR	32751.663	218.336	145.995
26	29512	RENAULT	91141.582	374.024	241.978
27	4322	SAINT GOBAIN	136945.9	417.477	305.762
28	4157	SANOFI-AVENTIS	268578.3	501.898	509.224
29	4292	SCHNEIDER ELECTRIC	75199.306	366.230	202.776
30	4462	SOCIETE GENERALE	173609.6	621.134	268.971
31	29636	STMICROELECTRONIC	279904.2	151.572	1729.855
32	4180	SUEZ	289668.4	458.005	611.561
33	44540	THOMSON	86652.183	136.178	582.120
34	4161	TOTAL	539560.2	705.071	751.835
35	20928	UNIBAIL	22274.660	198.180	107.372
36	4168	VALLOUREC	39700.087	442.212	84.522
37	4351	VINCI	117006.7	427.795	255.655
38	4245	VIVENDI	305812	388.505	751.469

Table 2

This table presents the estimation results of the GARCH (1,1) model. α and β represent the estimated parameters of the variance equation: $\sigma_t^2 = \omega + \alpha\ \varepsilon_{t-1}^2 + \beta\ \sigma_{t-1}^2$ *.* σ_t^2 *is the conditional variance of the error process* ε_t *. The significance at 10% level is marked by (*), 5% level by (**) and 1% level by (***).*

Stock	α	β	$\alpha+\beta$
1	0.264***	0.427***	0.691
2	0.019***	0.976***	0.995
3	0.273***	0.500***	0.773
4	0.613***	0.028***	0.642
5	0.324***	0.475***	0.799
6	0.013***	0.981***	0.994
7	0.033***	0.953***	0.986
8	0.035***	0.947***	0.982
9	0.025***	0.963***	0.988
10	0.262***	0.327***	0.588
11	0.039***	0.950***	0.989
12	0.290***	0.209***	0.499
13	0.019***	0.979***	0.999
14	0.030***	0.956***	0.986
15	0.241***	0.438***	0.679
16	0.118***	0.523***	0.641
17	0.033***	0.928***	0.961
18	0.011***	0.987***	0.998
19	0.045***	0.922***	0.967
20	0.344***	0.347***	0.692
21	0.135***	0.529***	0.663
22	0.050***	0.925***	0.974
23	0.794***	0.156***	0.950
24	0.172***	0.173***	0.345
25	0.045***	0.937***	0.982
26	0.028***	0.961***	0.988
27	0.031***	0.952***	0.983
28	0.025***	0.965***	0.990
29	0.041***	0.946***	0.987
30	0.048***	0.945***	0.992
31	0.200***	0.457***	0.656
32	0.038***	0.925***	0.963
33	0.406***	0.527***	0.933
34	0.178***	0.434***	0.612
35	0.063***	0.922***	0.985
36	0.014***	0.963***	0.978
37	0.073***	0.876***	0.950
38	0.018***	0.975***	0.993
Index (CAC40)	0.017***	0.979***	0.996

Table 3

This table presents the estimation results of the GARCH (1,1) model. α, β, and δ *represent the estimated parameters of the variance equation:* $\sigma_t^2 = \omega + \alpha\ \varepsilon_{t-1}^2 + \beta\ \sigma_{t-1}^2 + \lambda V_t$. σ_t^2 *is the conditional variance of the error process* ε_t *and* V_t *is the trading volume. The significance at 10% level is marked by (*), 5% level by (**) and 1% level by (***).*

Stock	α	β	$\alpha+\beta$	λ*10^6
1	0.046***	0.382***	0.428	1.075***
2	0.031***	0.106***	0.136	1.418***
3	0.062***	0.274***	0.335	1.363***
4	0.036***	0.103***	0.138	0.154***
5	0.108***	0.197***	0.305	2.989***
6	0.012	0.068***	0.080	0.212***
7	0.046***	0.105***	0.151	0.444***
8	0.092***	0.280***	0.373	1.190***
9	0.066***	0.268***	0.335	1.325***
10	0.087***	0.329***	0.416	0.342***
11	0.067***	0.237***	0.304	0.303***
12	0.056***	0.288***	0.344	0.649***
13	0.079***	0.316***	0.395	0.678***
14	0.088***	0.287***	0.375	0.559***
15	0.137***	0.320***	0.457	0.893***
16	0.041***	0.177***	0.218	0.125***
17	0.103***	0.312***	0.415	0.932***
18	0.054***	0.313***	0.367	1.347***
19	0.071***	0.547***	0.618	1.022***
20	0.085***	0.359***	0.444	0.682***
21	0.051***	0.303***	0.354	0.690***
22	0.094***	0.220***	0.314	2.216***
23	0.048***	0.233***	0.281	3.252***
24	0.056***	0.280***	0.336	1.401***
25	0.160***	0.346***	0.506	1.550***
26	0.092***	0.240***	0.333	1.392***
27	0.109***	0.320***	0.429	0.610***
28	0.114***	0.169***	0.283	0.251***
29	0.064***	0.280***	0.344	1.217***
30	0.064***	0.045***	0.109	0.809***
31	0.033***	0.183***	0.216	0.286***
32	0.059***	0.098***	0.158	0.353***
33	0.223***	0.308***	0.531	0.719***
34	0.045***	0.121***	0.166	0.142***
35	0.128***	0.376***	0.505	4.961***
36	0.037***	0.064***	0.101	4.911***
37	0.045***	0.183***	0.229	0.981***
38	0.087***	0.252***	0.339	0.186***
Index (CAC40)	0.036***	0.193***	0.229	0.211***

Table 4

This table presents the estimation results of the GARCH (1,1) model. α, β, δ, and γ *represent the estimated parameters of the variance equation:* $\sigma_t^2 = \omega + \alpha\ \varepsilon_{t-1}^2 + \beta\ \sigma_{t-1}^2 + \delta NT_t + \gamma ST$. σ_t^2 *is the conditional variance of the error process* ε_t , NT_t *is the number of trades and* ST_t *is the size of trades. The significance at 10% level is marked by (*), 5% level by (**) and 1% level by (***).*

Stock	α	β	$\alpha+\beta$	$\delta * 10^3$	$\gamma * 10^3$
1	0.040***	0.251***	0.291	0.367***	0.000
2	0.042***	0.000	0.042	0.577***	0.000
3	0.047***	0.196***	0.243	0.214***	0.000
4	0.047***	0.000	0.047	0.387***	0.000
5	0.067***	0.057**	0.124	0.451***	0.000
6	0.016	0.015	0.031	0.205***	0.000
7	0.045***	0.064**	0.109	0.174***	0.000
8	0.081***	0.245***	0.327	0.332***	0.000
9	0.076***	0.190***	0.266	0.442***	0.000
10	0.075***	0.282***	0.358	0.182***	0.000
11	0.058***	0.162***	0.220	0.222***	0.000
12	0.064***	0.266***	0.330	0.196***	0.000
13	0.062***	0.203***	0.265	0.744***	0.000
14	0.078***	0.192***	0.270	0.411***	0.000
15	0.138***	0.163***	0.301	0.264***	0.000
16	0.028**	0.052**	0.080	0.178***	0.000
17	0.113***	0.170***	0.283	0.374***	0.000
18	0.048***	0.265***	0.313	0.240***	0.000
19	0.043***	0.569***	0.612	0.232***	0.000
20	0.095***	0.359***	0.454	0.161***	0.000
21	0.055***	0.323***	0.378	0.167***	0.000
22	0.067***	0.192***	0.259	0.513***	0.000
23	0.022**	0.129***	0.150	0.402***	0.000
24	0.033***	0.309***	0.342	0.424***	0.000
25	0.140***	0.371***	0.511	0.216***	0.000
26	0.073***	0.321***	0.394	0.303***	0.000
27	0.103***	0.245***	0.347	0.215***	0.000
28	0.093***	0.134***	0.227	0.137***	0.000
29	0.065***	0.274***	0.338	0.247***	0.000
30	0.076***	0.002	0.078	0.236***	0.000
31	0.024**	0.152***	0.176	0.519***	0.000
32	0.050***	0.007	0.058	0.233***	0.000
33	0.222***	0.185***	0.407	0.520***	0.000
34	0.027**	0.046**	0.073	0.114***	0.000
35	0.119***	0.383***	0.502	0.514***	0.000
36	0.033***	0.000	0.033	0.424***	0.000
37	0.052***	0.053**	0.106	0.280***	0.000
38	0.073***	0.214***	0.287	0.149***	0.000
Index (CAC40)	0.050***	0.225***	0.275	0.104***	0.000

Table 5

This table presents the estimation results of the GARCH (1,1) model. α, β, δ, γ, θ and Φ *represent the estimated parameters of the variance equation:* $\sigma_t^2 = \omega + \alpha\ \varepsilon_{t-1}^2 + \beta\ \sigma_{t-1}^2 + \delta NT_t + \gamma ST + \theta DO_t + \phi DC_t$. σ_t^2 *is the conditional variance of the error process* ε_t *,* NT_t *is the number of trades and* ST_t *is the size of trades.* DO_t *and* DC_t *are two dummy variables accounting respectively for the first 30-minute period of the trading day and for the last 30-minute period. The significance at 10% level is marked by (*), 5% level by (**) and 1% level by (***).*

Stock	α	β	$\alpha+\beta$	δ*10^3	γ*10^3	θ	ϕ
1	0.062***	0.077***	0.138	0.318***	0.000	0.763***	0.000
2	0.072***	0.046***	0.118	0.397***	0.000	0.918***	0.000
3	0.057***	0.044***	0.101	0.187***	0.000	0.475***	0.000
4	0.053***	0.000	0.053	0.307***	0.000	0.905***	0.000
5	0.089***	0.027**	0.116	0.330***	0.000	1.044***	0.000
6	0.035***	0.035***	0.070	0.146***	0.000	0.666***	0.000
7	0.024**	0.000	0.024	0.142***	0.000	0.722***	0.000
8	0.080***	0.066***	0.146	0.305***	0.000	0.675***	0.000
9	0.118***	0.033***	0.151	0.356***	0.000	1.068***	0.000
10	0.105***	0.087***	0.192	0.176***	0.000	0.459***	0.000
11	0.077***	0.042***	0.119	0.182***	0.000	0.632***	0.000
12	0.072	0.035	0.107	0.192***	0.007	0.459***	0.000
13	0.093***	0.029***	0.122	0.633***	0.000	0.881***	0.000
14	0.102***	0.097***	0.199	0.333***	0.004	0.650***	0.000
15	0.127***	0.169***	0.296	0.178***	0.015*	0.474***	0.000
16	0.026*	0.053***	0.079	0.145***	0.000	0.354***	0.000
17	0.097***	0.055***	0.153	0.338***	0.009	0.398***	0.000
18	0.046***	0.049***	0.095	0.223***	0.000	0.684***	0.000
19	0.090***	0.089***	0.180	0.265***	0.000	0.512***	0.010***
20	0.099***	0.048***	0.147	0.174***	0.000	0.484***	0.000
21	0.068***	0.056***	0.124	0.174***	0.000	0.403***	0.000
22	0.089***	0.075***	0.164	0.399***	0.000	1.019***	0.000
23	0.057***	0.024***	0.080	0.205***	0.000	1.416***	0.000
24	0.086***	0.125***	0.211	0.354***	0.002	0.957***	0.000
25	0.116***	0.108***	0.224	0.222***	0.025**	0.422***	0.000
26	0.084***	0.072***	0.157	0.314***	0.000	0.860***	0.000
27	0.107***	0.049***	0.156	0.178***	0.000	0.888***	0.010*
28	0.095***	0.025	0.120	0.120***	0.000	0.396***	0.000
29	0.077***	0.048***	0.126	0.224***	0.006	0.787***	0.000
30	0.052***	0.008	0.059	0.169***	0.000	0.958***	0.000
31	0.068***	0.016	0.084	0.448***	0.000	0.485***	0.000
32	0.055***	0.010	0.065	0.189***	0.000	0.370***	0.000
33	0.199	0.066***	0.265	0.494***	0.000	0.410***	0.000
34	0.028***	0.004	0.031	0.095***	0.000	0.337***	0.000
35	0.119***	0.153***	0.272	0.424***	0.000	1.220***	0.035***
36	0.056***	0.011	0.066	0.310***	0.000	1.108***	0.000
37	0.062***	0.042***	0.104	0.207***	0.000	0.751***	0.000
38	0.080***	0.013	0.093	0.145***	0.000	0.378***	0.000
CAC40	0.035***	0.000	0.035	0.085***	0.000	0.417***	0.000