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Trading volume and volatility patterns across selected Central European stock markets from microstructural perspective

1. Introduction

Market microstructure can be defined as specific local rules in a given market and/or anomalies reflecting patterns in price, trading volume, or volatility and more data from a stock market that is relevant with respect to trading activity.

Nowadays, there has been a revival of this notion in the context of electronic trading and the numerical capacities of fast computers supporting trading. One of the most-important topics in empirical stock market studies in the framework of microstructure is recognizing patterns of volatility and trading volume seasonality. This is an important issue with respect to risk management, arbitrage, and speculation. Based on the patterns in the past, market participants can try to maximize their returns and minimize risk. In addition, knowledge of market microstructure can help the market governance in the establishment of new rules of trading in order to support the creation of a more-efficient trading system. This type of empirical research has been conducted for several developed stock markets; however, to the best of our knowledge, there are no studies on the issue for emerging stock markets, especially for the stock markets in CEE countries.

Another advantage of this study is that it utilizes high-frequency data. This kind of data is very important in order to analyze questions related to the negotiation process and trading patterns (comp. Wood, 2000; Tsay, 2010) that are seldomly used in the Polish market for a historic perspective of high-frequency data.

The variables investigated in this contribution are trading volume and volatility. The timeframe of this work comprises trading sessions over several months in

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2016. We use this timeframe due to the availability of data. In light of the empirical studies for developed stock markets, the U and L patterns can be considered as stylized fact on these stock markets.

We are looking out for patterns during the trading session of the selected CEE stock markets, trying to match the results of stock markets around the world that display similar behavior (a U- or L-shaped pattern).

As the opening is the most-volatile time of the trading day, easing throughout the day and bumping up at the end results in a U-shaped pattern of trading. The other observable pattern is opening high and simmering down throughout the day until closing (as the L-shaped designation suggests). With respect to trading volume, some authors point to peculiar characteristics when analyzing several-minute intervals. A similar picture is expected for the most-traded stocks in the stock exchanges of Austria, Germany, and Poland.

A simple approach has been utilized to model volatility and trading volume. We consider 5-minute absolute logarithmic returns as a measure of volatility and sum of trading volumes within each 5-minute period during the day. Anticipating some of the results found, we stress that volatility follows more of an L-shaped pattern, with daily highs in the opening and declining throughout the day (with a bit of a bump after lunch time). In the case of trading volume, the pattern detected in our study and reported in the literature is U-shaped, with high activity in the beginning and at the end of the trading day.

This study is justified by the absence of this sort of investigation (and comparative studies) for the selected stock markets in Central Europe. Even though the topic has received great attention in developed markets such as the NYSE, London Stock Exchange, and Tokyo Stock Exchange, there is a lack of similar studies – especially regarding smaller stock markets like the Austrian or Polish markets.

The findings of this research will help answer some questions; e.g., do trading volume and volatility exhibit U-shaped or L-shaped patterns, respectively, and behave similar to other especially-developed markets? Do they influence each other? Before answering these questions, we overview the selected contributions concerned with the shape of trading volume and volatility in Section 2 of this paper. The methodology used in this contribution is presented in Section 3. The empirical results and their evaluation are provided in Section 4. Section 5 concludes.

2. Literature overview

The investigation of market microstructure has been done several times for developed markets, in many forms, and by several methods.

In one of the earliest studies on market microstructure, Wood et al. (1985) analyzed the behavior of returns and trading volume at the micro level of the New York Stock Exchange. They found higher returns and higher variance in the first 30 minutes after the start of trading.

In a study by Jain and Joh (1988) (also based on data from the New York Stock Exchange), the authors showed that returns depend on the trading hours. Moreover, during some hours of the day, a rise in trading volume can be detected. They supplied empirical evidence on the joint characteristics of hourly common stock trading volume and returns. Average trading volume exhibits significant differences across the trading hours of the day and across the days of the week. In addition, the average returns depend not only on the hours of the day but also on the days of the week.

Different patterns of volatility have been found in several contributions in the financial literature, such as the work of Lockwood and Linn (1990). The authors examined the variance of hourly market returns on the NASDAQ. They found that return volatility falls from the opening hour until early afternoon and rises thereafter and is significantly greater for intraday versus overnight periods.

Andersen and Bollerslev (1997) supplied evidence of strong intraday periodicity and seasonality of two different asset classes (foreign exchange and securities) traded under widely varied market structures.

In further contributions by Andersen and Bollerslev (1998) (who investigated Deutsche mark-dollar volatility) and in McInish and Wood (1992) (who investigated the bid-ask patterns of stocks from the New York Stock Exchange), a U-shaped pattern is visible.

Andersen et al. (2000) analyzed the intraday volatility of 5-minute Nikkei 225 returns and found a double U-shaped pattern related to the opening and closing of the separate morning and afternoon trading sessions.

Nishimura et al. (2012) found that the volatility pattern is U-shaped in Shanghai and W-shaped in the Tokyo Stock Exchange (in their framework of investigations of spillover effects between China and Japan using 5-minute high-frequency data).

In a more-recent contribution, Agarwalla and Pandey (2013) focused on a developing stock market (Bombay Stock Exchange). They check the expiration day effect on intraday volatility and find that the volatility of the stocks increases in the last half hour of trade on the expiry day but not during the other time intervals in this stock exchange. Tilak et al. (2013) established a U-shaped pattern based on intraday data for the main index (CAC40) for the Paris Stock Exchange. Also in the case of trading volume, the pattern found was U-shaped with high trading activity in the beginning and at the end of the trading day.

Buckle et al. (1998) established the L-shape pattern and other significant patterns in their framework of investigations of the Short Sterling interest rate and FTSE 100 stock index future contracts traded on the London International Financial Futures and Options Exchange (LIFFE).

Analyzing securities listed on the Shanghai Stock Exchange, Tina and Guo (2007) found that volatility follows more of an L-shaped pattern, with daily peaks in the opening and easing throughout the day (with a bit of a bump after lunchtime).

Chan et al. (1995) and Abhyankar et al. (1997) reported U-shaped and M-shaped volatility patterns for NASDAQ and the UK stocks, respectively.

While searching for intraday patterns on the Tokyo Grain Exchange (TGE) and announcements of public information, Eaves and Williams (2010) found that intraday volume is U-shaped and intraday volatility is closer to L-shaped. The contributors found that, after accounting for the public information in preceding auctions for the same commodity, for earlier trading in other commodities, and for trading on overseas markets open overnight in Tokyo, the intraday patterns are by and large flat.

Hussain (2011) takes into account the strong intraday seasonal pattern in return variability before attempting to model the conditional volatility. His study provides intraday evidence on the relationship between return volatility, trading activity, and market liquidity variables at the aggregate level for DAX30 constituents. The author detects a reverse-J-shaped pattern of intraday bid-ask spreads with the exception of a major bump following the intraday auction at 13:05 CET. According to the author, the aggregate trading volume exhibits L-shaped pattern for the German blue chip index, while German index volatility displays a somewhat reverse-J-shaped pattern with two major bumps at 14:30 and 15:30 CET. These results are contrary to the U-shaped pattern found in previous studies. His empirical findings demonstrate that contemporaneous and lagged trading volume and bid-ask spreads have a numerically small but statistically significant effect on return volatility. In addition, his results also indicate asymmetry in the effects of volume on conditional volatility.

Będowska-Sójka (2013) investigated the averages of absolute DAX and CAC40 returns within five-minute periods and examined the reaction of these indices to the macro surprises from two economies (the German and the American).

In one of the most-recent contributions, Silva Da Costa et al. (2015) analyzed market microstructure with high-frequency data for all stocks that participate in the Ibovespa index, a traditional and influential Latin American index. They modeled volatility with a straightforward method using standard deviation as a proxy, and classified the volume traded of all Ibovespa stocks in every 10-minute interval of the trading days sampled. They found similarities and dissimilarities of their results with previous investigations documented in the financial literature, such as the stylized facts: L-shaped pattern for volatility and U-shape for trading volume. One interesting finding is that, during the most-active trading time, volatility slumps in the interval that comprises the closing call; on the other hand, the second-most-active trading time (the opening) displays extreme volatility.

The rest of the article is organized as follows: the next section describes the methodology applied. The fourth chapter contains the described dataset and subsequent results. The last section concludes the paper.

3. Methodology

Flexible Fourier Form (FFF regression) introduced by Gallant (1981) and later used by Andersen and Bollerslev (1997, 1998), Laakkonen (2014), and Będowska-Sójka (2013) seems to be the most-frequently-used method of modeling periodicity in high frequency data. Let T be the number of days in a sample and the number of equally spaced periods in one day. The volatility of logarithmic return $r_{t,n}$ ($t = 1, \ldots, T$, $n = 1, \ldots, N$). The volatility of logarithmic return $r_{t,n}$ ($t = 1, \ldots, T$, $n = 1, \ldots, N$) divided into daily volatility component σ_t, intraday volatility component $s_{t,n}$, and random error term $Z_{t,n}$, so $r_{t,n}$ is expressed as:

$$r_{t,n} - E\left(r_{t,n}\right) = \frac{\sigma_t}{N^{1/2}} s_{t,n} Z_{t,n} \tag{1}$$

The component $E(r_{t,n})$ is replaced with unconditional mean $\bar{r}$ and the σ_t can be estimated with various methods. In this paper we use robust to price jumps estimator medRV (Andersen, 2012) which is defined as

$$\hat{\sigma}_t^2 = \frac{\pi}{6 - 4\sqrt{3} + \pi}\left(\frac{M}{M-2}\right)\sum_{i=2}^{M-1} \text{med}\left(\left|r_{t,i-1}\right|, \left|r_{t,i}\right|, \left|r_{t,i+1}\right|\right)^2$$

The daily component is eliminated, both sides are squared, and logarithms are taken. After this, Equation (1) becomes

$$2\ln\frac{\left|r_{t,n} - \bar{r}\right|}{\hat{\sigma}_t / N^{1/2}} = 2\ln\left(s_{t,n}\right) + 2\ln\left(Z_{t,n}\right)$$

We are interested in modeling component for intraday volatility $s_{t,n}$.

For this purpose trigonometric functions are used:

$$f_{t,n} = \delta_1 \frac{n}{N_1} + \delta_2 \frac{n^2}{N_2} + \sum_{p=1}^{P} \left(\theta_p \cos\left(\frac{2\pi p}{N} n \right) + \varphi_p \sin\left(\frac{2\pi p}{N} n \right) \right) + \sum_{k=1}^{K} \gamma_k D_{k,t,n} + \varepsilon_{t,n} \tag{2}$$

where $f_{t,n} = 2 \ln \frac{\left| r_{t,n} - \bar{r} \right|}{\frac{\hat{\sigma}_t}{N^{\frac{1}{2}}}}$, $N_1 = \frac{(N+1)}{2}, N_2 = \frac{(N+1)(N+2)}{6}$ are normalizing factors and $D_{k,t,n}$ are indicator variables. An estimate of intraday volatility is obtained as $\hat{s}_{t,n} = \exp\left(\frac{\hat{f}_{t,n}}{2} \right)$, and the normalized seasonality estimate is:

$$\tilde{s}_{t,n} = \frac{T \cdot \hat{s}_{t,n}}{\sum_{t=1}^{T} \sum_{n=1}^{N} \hat{s}_{t,n}}$$

In the regression above, we use indicator variables for day-of-the-week-effect testing. We test the null that there is no day-of-the-week effect at the company level. For this purpose, we estimate the regression models twice: first without dummy variables (restricted model) and next with dummy variables (unrestricted). Then, we test if there is a day-of-the-week effect. Formally, null hypothesis H_0: $\gamma_1 = \gamma_2 = \gamma_3 = \gamma_4 = \gamma_5 = 0$ is verified with an F-test.

A similar method of modeling and testing can be applied to series of raw trading volumes (we insert values of trading volumes in the place of $f_{t,n}$). Similarly, Manganelli (2005) models the daily periodicity of series of volatilities, volumes, and durations (although using piecewise linear spline functions).

4. The data and empirical results

4.1. Descriptive statistics and autocorrelation patterns

We take into account three sets of high-frequency data with five-minute sampling frequency: all companies listed in DAX, 19 companies (without ATS) of the ATX index, and all from the WIG20 index. The prices of the DAX and ATX companies come from 2016-01-11 to 2016-07-01 and WIG20 from 2014-01-02 to 2014-06-30. As a measure of volatility, we use absolute logarithmic returns. In addition, we take into account volumes over five-minute periods to investigate the intensity of trading. In Tables 1, 2, and 3, we present descriptive statistics of the variables under study.

Table 1

Descriptive statistics of five-minute-frequency logarithmic returns

ATX					
statistic	**min**	**1st quartile**	**median**	**3rd quartile**	**max**
mean	−0.0107	−0.0038	−0.0014	−0.0014	0.0018
s.d	0.1620	0.2220	0.2676	0.2756	0.3261
kurtosis	6.1790	29.7100	226.2000	1274.0000	1497.0000
skewness	−71.9000	−13.3100	−0.1890	−11.3800	1.1680
LB	10.6500	74.5700	88.1900	103.4000	153.3000
DAX					
statistic	**min**	**1st quartile**	**median**	**3rd quartile**	**max**
mean	−0.0047	−0.0008	0.0000	0.0000	0.0009
s.d	0.1305	0.1463	0.1599	0.1784	0.1910
Kurtosis	2.8760	5.4400	9.2180	12.0400	14.1400
skewness	−0.6317	−0.1953	0.0147	0.0612	0.2306
LB	11.7300	25.7000	32.7300	33.8800	39.0300
WIG20					
statistic	**min**	**1st quartile**	**median**	**3rd quartile**	**max**
mean	−0.0049	−0.0013	−0.0010	−0.0002	0.0008
s.d	0.1459	0.2352	0.2656	0.2652	0.2932
Kurtosis	6.3970	14.1900	47.4300	958.8000	1087.0000
skewness	−37.5200	−3.3880	−0.4188	1.5360	0.2844
LB	16.6000	106.5000	149.3000	250.6000	395.8000

Source: own elaboration

Table 2

Descriptive statistics of five-minute-frequency absolute logarithmic returns

ATX					
statistic	**min**	**1st quartile**	**median**	**3rd quartile**	**max**
mean	0.0962	0.1251	0.1409	0.1424	0.1621
s.d	0.1304	0.1782	0.2166	0.2334	0.2952
Kurtosis	15.2600	52.1200	601.0000	1868.0000	2079.0000
skewness	2.7070	4.4850	13.4000	23.9600	31.3300
LB	83.3700	864.8000	1389.0000	1638.0000	2242.0000

Table 2 cont.

DAX					
statistic	**min**	**1st quartile**	**median**	**3rd quartile**	**max**
mean	0.0922	0.1017	0.1082	0.1249	0.1350
s.d	0.0924	0.1029	0.1173	0.1273	0.1350
kurtosis	7.2880	12.8500	24.6800	32.6200	40.8900
skewness	2.0280	2.6300	3.0920	3.3650	3.7060
LB	1822.0000	3579.0000	4423.0000	4171.0000	4655.0000
WIG20					
statistic	**min**	**1st quartile**	**median**	**3rd quartile**	**max**
mean	0.0923	0.1164	0.1336	0.1336	0.1472
s.d	0.1130	0.1865	0.2236	0.2275	0.2557
kurtosis	9.6920	25.9300	92.1000	1358.0000	1803.0000
skewness	2.2680	3.1920	4.9910	18.8900	28.0400
LB	117.8000	808.4000	1629.0000	1515.0000	2284.0000

Source: own elaboration

Table 3

Descriptive statistics of volumes over five-minute periods

ATX					
statistic	**min**	**1st quartile**	**median**	**3rd quartile**	**max**
mean	242.00	1450.00	2283.00	4088.00	3912.00
s.d	500.40	2252.00	4595.00	6769.00	7608.00
kurtosis	39.59	100.40	237.50	375.80	514.30
skewness	4.55	7.28	9.48	11.61	12.95
LB	669.70	1895.00	4703.00	6482.00	9785.00
DAX					
statistic	**min**	**1st quartile**	**median**	**3rd quartile**	**max**
mean	2331.00	5002.00	14230.00	26200.00	34730.00
s.d	3529.00	6929.00	18110.00	32390.00	43060.00
kurtosis	63.15	402.20	902.90	1142.00	1680.00
skewness	5.37	12.28	20.43	20.94	27.60
LB	1305.00	5463.00	8724.00	11390.00	15080.00

Table 3 cont.

WIG20					
statistic	**min**	**1st quartile**	**median**	**3rd quartile**	**max**
mean	287.50	1432.00	4883.00	10580.00	15360.00
s.d	1078.00	3525.00	18920.00	37600.00	49740.00
kurtosis	61.13	174.10	797.50	1119.00	2022.00
skewness	5.71	10.29	26.62	25.28	36.52
LB	6.96	138.30	977.30	1909.00	3259.00

Source: own elaboration

The descriptive statistics (kurtosis and skewness) indicate a departure from normality for all companies under study. This is confirmed with the Jarque-Bera test. For all series from ATX, a null hypothesis of the Ljung-Box test is strongly rejected. This is not the case for five return series from DAX and two return series from WIG20. There is no autocorrelation (at the 5% level) in nine series of absolute returns and four returns of volumes from WIG20. In most of the remaining cases of absolute series, we observe a well-known pattern in the autocorrelation function. In Figure 1, we present the autocorrelation function of Austrian company VOE, German company DAI, and Polish PZU (all figures are available from the authors upon request). Further examination is performed for these companies, with an observed autocorrelation in absolute returns series at a 1% significance level. Polish companies excluded from the analysis are KGHM, PGE, EUROCASCH, TAURON, ASSECOPOL, JSW, HANDLOWY, SYNTHOS, and KERNEL.

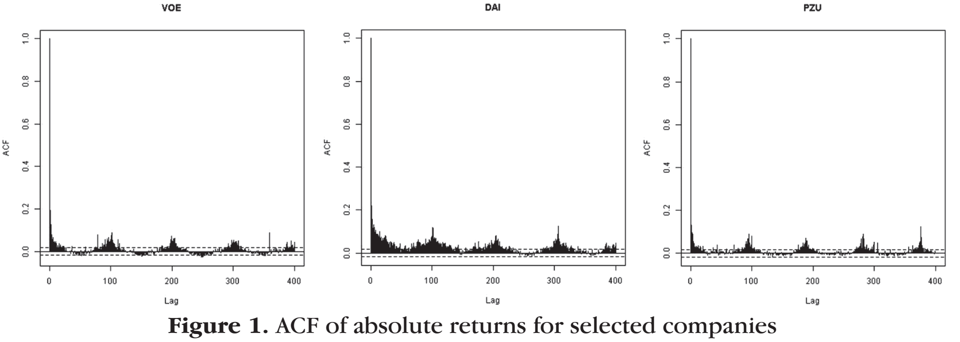

Figure 1. ACF of absolute returns for selected companies

Source: own elaboration

We conduct a similar analysis for trading volumes. Some companies from WIG20 present a lack of autocorrelation due to the Ljung-Box test with 15 lags; however, this is indeed not the case if the number of lags increases. These companies are PKOBP, PKNORLEN, BZWBK, BRE, and SYNTHOS.

In Figure 2 below, we present some examples of autocorrelation function plots (Austrian RBI, German CBK, and Polish ASSECOPOL). For all DAX companies, a clear pattern of seasonality is observed. This is the case only for Austrian companies ANDR, EBS, OMV, RBI, TKA, and VOE, and only in the case of Polish companies KGHM, KERNEL, and PGE. In most cases (ASSECOPOL, BRE, BZWBK, HANDLOWY, PEKAO, PKNORLEN, SYNTHOS, and TPSA), we observe high seasonal peaks at the end of trading hours.

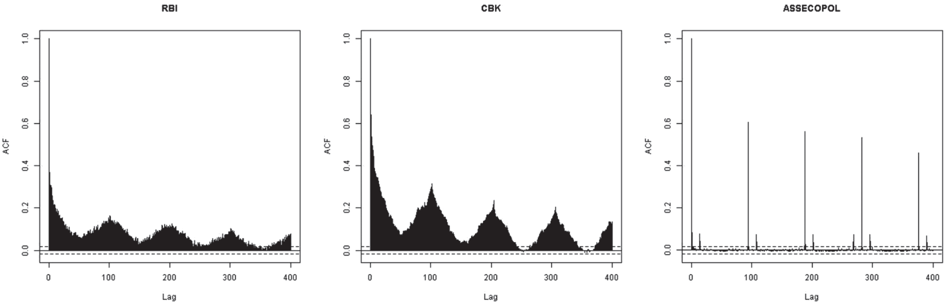

Figure 2. ACF of five-minute returns for selected companies
Source: own elaboration

Intraday volatility pattern

To investigate intraday patterns in volatility, we compute the mean of absolute returns (with each five-minute period). We observe some differences in the shapes. In Figure 3, we present the typical shapes of intraday patterns.

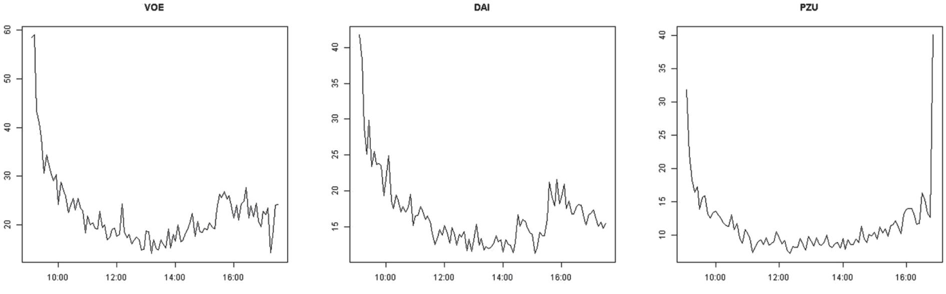

Figure 3. Intraday volatility pattern of selected companies
Source: own elaboration

The intraday patterns of ATX companies are, in most cases, L-shaped or reverse-J-shaped (clear exceptions are CWI, LNZ, RHI, SBO, TKA, UQA, and VER) with a very high peak at the beginning of the trading day. A similar conclusion can be drawn with respect to the DAX companies. The averages of absolute returns are the highest at the opening and decay during the rest of the day. In many cases, one can note an increase at 16 CET. This can be viewed as the impact of announcements regarding US macroeconomic indicators. In the case of Polish companies, a clear shape of the letter U can be recognized, with the highest peak near the closing hour.

We apply the methodology described in the previous section to discover if there is a significant difference in volatility across the days of the week at the company level. In the regression (2), we use dummies for the day-of-the-week effect. For this purpose, we estimate the regression models twice: first without dummy variables (restricted model) and second with dummy variables (unrestricted). Then, we test if there is a day-of-the-week effect. Formally, the null hypothesis is given as H_0: $\gamma_1 = \gamma_2 = \gamma_3 = \gamma_4 = \gamma_5 = 0$. The testing is performed with an F-test. The number of trigonometric functions is based on the Bayesian Information Criterion and does not exceed eight. In all companies under study, we reject the null at a 1% significance level. This confirms the day-of-the-week effect observed in high-frequency data. In Figure 4, we present the periodic intraday pattern of German company ADS. We observe differences in shapes (some are rather U-shaped) and different ranges.

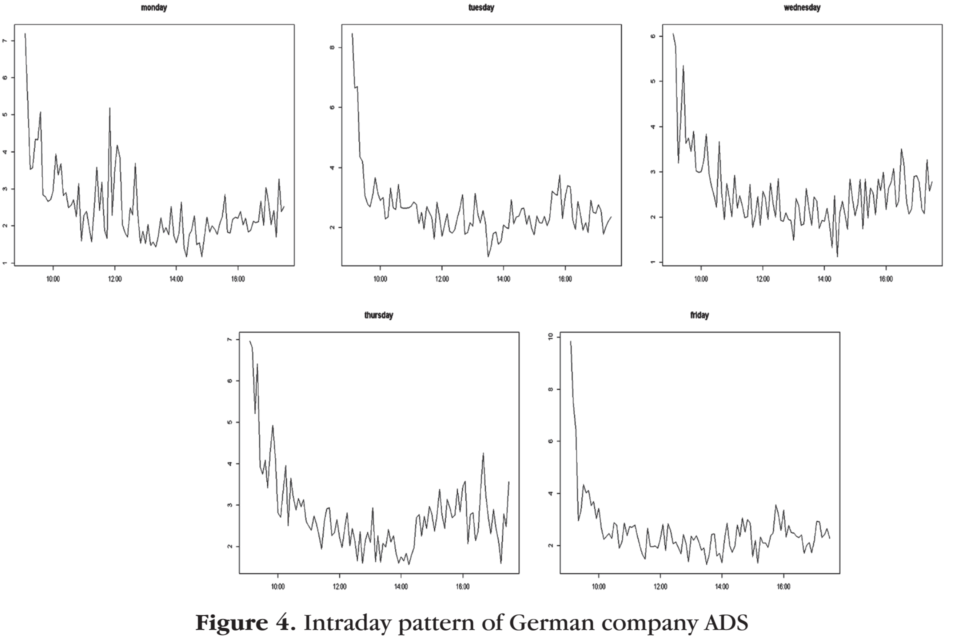

Figure 4. Intraday pattern of German company ADS

Source: own elaboration

Intraday volume pattern

The intraday patterns of volume are the most-regular only for DAX companies. We observe a shape of the letter U, with two peaks at 11:55 (in most cases). These peaks can be related to the industrial production announcement at 12:00 in Germany and/or other announcements in the US and possible leakage of this information (the second peak could be identified at 13:10). The patterns of ATX companies are very messy. We can specify that companies ANDR, EBS, IIA, OMV, VOE, and WIE have a similar and evident peak at around 12 CET. The volume patterns of the Polish stock mentioned above are in line with the autocorrelation function (in such cases, we notice reversed L-shaped patterns). The patterns of companies JBW, KERNEL, KGHM, PGE, PGNIG, PKOBP, and PZU are all of the form of a U, whereas BOGDANKA and GTC are not of typical shapes. In Figure 5, we present the typical shape of intraday pattern for selected companies (Austrian ANDR, German BAYN, and Polish BRE).

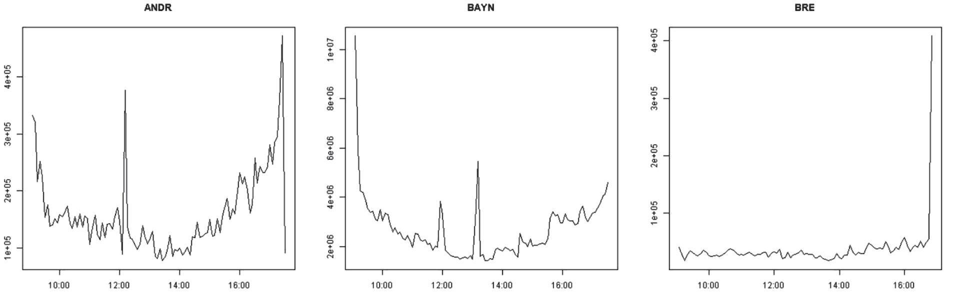

Figure 5. Intraday pattern of volumes for selected companies

Source: own elaboration

To investigate deeper trading activity, we use the trading volumes for each day of the week separately. In the case of DAX companies, the peaks at 11:55 and 13:10 (mentioned previously) are observed only on Friday. These peaks may reflect the impact of the information content of macroeconomic announcements both in the USA and Germany. For all other days, U and reversed-J shapes are typical. In Figure 6, the intraday pattern of BAYN is presented for each day of the week.

The same observation can be made with respect to the ATX companies mentioned above. The high peaks are observed only on Friday. For all other days, a disturbed U-shape is observed most often, with the largest value occurring at the beginning of the trading day. For Polish companies, a reversed-L shape and disturbed-U shape are observed most frequently, but there are days where none of the typical shapes can be recognized.

We test the day-of-the-week effect with the method used above (regression), but we now apply it to trading volumes. The conclusions are the same as for volatilities. The day-of-the-week effect is confirmed in all cases under study.

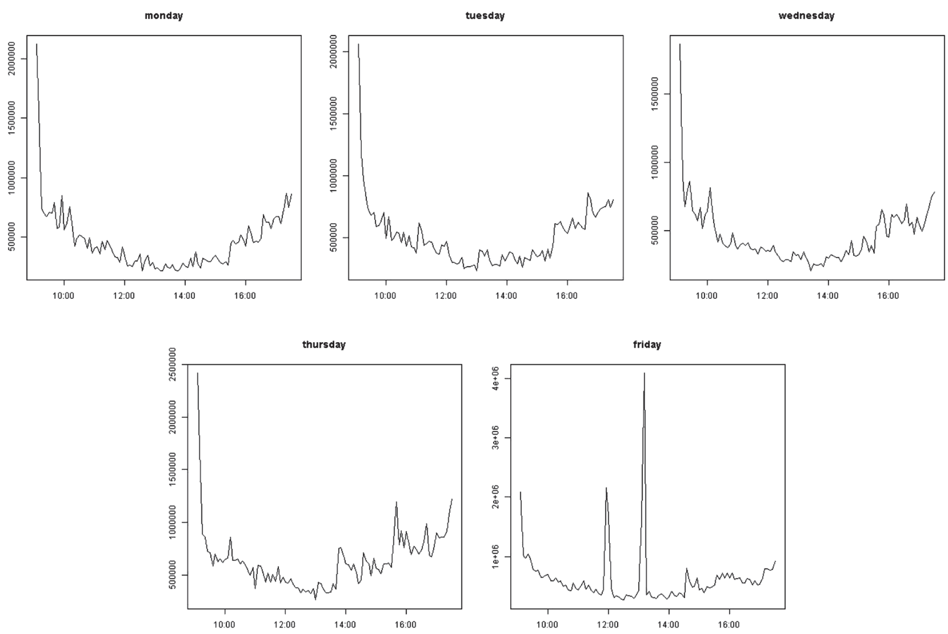

Figure 6. Intraday volume pattern of BAYN

Source: own elaboration

5. Conclusions

The aim of this paper was to show the differences in intraday patterns of volatilities and volumes across markets at the company level. In addition, the paper shows the practical usefulness of Flexible Fourier Form regression as a method of modeling periodicity in an intraday data. Moreover, the use of dummy variables in regression allows us to show the existence of the day-of-the-week effect in intraday data. We conclude that the regularity of autocorrelation and intraday patterns depend on the maturity level of the market under study. In the case of DAX companies, we observe the most-regular patterns of seasonality in autocorrelation functions, either for volatilities or volumes. A similar conclusion can be made for intraday patterns. For the ATX and DAX companies, a shape of the letter L or a reversed J is observed (which is in line with previous research) with an increase before 16 CET. The situation is different for Polish companies, which are U-shaped (this is the case if clear pattern can be recognized). The analysis of intraday patterns of volumes leads to similar conclusions. We noticed U-shaped or reversed-J patterns for almost all DAX companies and for a few Austrian and Polish companies (here, the reversed-L shape is observed frequently).

To investigate the trading activity deeper, we use the volatilities and trading volumes for each day of the week separately. Either volatilities or volumes patterns are characterized by the day-of-the-week effect. In the case of ATX and DAX companies, the peaks in volumes are observed only on Friday, probably due to the high concentration of different kinds of announcements on Friday (both in Germany and the US). For all other days, the U and reversed-J shapes are typical. The same conclusion can be drawn for all companies under study.

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