6. INTRADAY PATTERNS IN RETURNS ON THE ROMANIAN AND BULGARIAN STOCK MARKETS

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Abstract

Intraday patterns in returns are well documented on the developed stock markets, but are less studied for the developing ones. Using a new tick-by-tick data sample, we provide evidence that intraday trading patterns are present on the Romanian and Bulgarian post-communist frontier markets. Similar to other capital markets, intraday returns follow a ω-pattern, although the magnitude is different. Some intraday effects are robust, while others have disappeared over time. The detected patterns can be associated with liquidity risk and market price manipulation, but cannot be used by investors to obtain systematic abnormal earnings.

Keywords: intraday patterns, returns, investor behavior, frontier markets, efficient market hypothesis, Romania, Bulgaria

JEL Classification: G10, G14

1. Introduction

Traditionally, practitioners and academics in portfolio management have been concerned to find if earning systematic abnormal returns is possible on stock markets (Fama, 1970; Malkiel, 2003). Additionally, Behavioural Finance has also studied the presence of anomalies in stock prices evolution by observing different trading patterns (*e.g.*, Thaler, 1987). Early studies were conducted using daily observations (*e.g.,* Fama, 1965), but, with the increase in the quantity and quality of available data, more studies have switched to intraday price patterns (Wood *et al*., 1985; Lockwood and Linn, 1990; Block *et al*., 2000). Most of these studies on intraday patterns are focused on the developed markets (Wood *et*

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al., 1985), while the emerging markets are significantly less analysed. However, some exceptions may be noticed (Bildik, 2001; Lee *et al*., 2001; Deev and Linnertová, 2013; Bedowska-Sójka, 2014). As far as we know, frontier markets have not been investigated until now.

Our study covers this gap in the literature by analyzing intraday trading patterns for companies listed on the Romanian Stock Exchange in Bucharest (hereafter, BVB, from “Bursa de Valori din București”) and on the Bulgarian Stock Exchange in Sofia (hereafter, BFBS, from “БългарскаФондова Борса–София”). These markets can be integrated in internationally managed portfolios alongside other more developed ones (D’Ecclesia and Constantini, 2006). Our study covers the period March 7, 2005 - December 11, 2015 for the Romanian capital market and the period October 9, 2006 - November 24, 2015 for the Bulgarian one. As far as we know, the intraday patterns for these markets have not been studied before, although some papers consider other aspects related to the intraday price evolution. For instance, Todea and Pleşoianu (2011) test the martingale hypothesis for the main market index in Romania using intraday data, while Anghel (2017) tests the random walk and the no economic profit hypothesis for 48 stocks listed on BVB.

Romania and Bulgaria are classified as frontier markets by MSCI and FTSE, which means they are smaller (and younger) than the markets studied previously. Specific characteristics also makes them an interesting choice in the context of this research topic. For example, both have implemented a mass privatization process in the 1990s opting for mandatory listings of the new private companies, which resulted in a large number of traded stocks. This determined a large number of shareholders: 19 million in Romania, representing approximately 85% of the total population, and 3 million in Bulgaria, representing about 35% of the total population (Miller and Petranov, 2000; Tchipev, 2003). However, given the very low financial literacy in the two countries, most share owners did not actively trade on the market, which resulted in a very low liquidity (Claessens *et al*., 2001). Among other reasons, this makes it possible to analyze the influence of (low) liquidity on the intraday patterns. An additional contribution of our study is that our methodology accounts for changes in the trading program. This is a common occurrence on BVB and BFBS, and presumably on other frontier markets.

Our results show that the patterns in returns are similar in shape, but differ in size, when compared to more developed markets. Specifically, returns follow a ω-pattern, being significantly positive in the first 30 minutes after the market opens and at the end of the day, while staying negative throughout the rest of the day. The magnitude of average returns is higher as compared to those observed on the developed US market (Wood *et al*., 1985), but lower as compared to those observed on the emerging Turkish market (Bildik, 2001). The results also show that only some of the patterns are persistent in time. Their appearance and behavior seem to be linked with specific market events (the financial crisis) or characteristics (market integration). This is an indication that changes in investors' structure and behavior might be responsible for the existence and magnitude of some of the detected intraday effects. We further find that intraday patterns significantly change on specific calendar days and vary in the cross-section of stocks when sorting by liquidity. This provides some indirect evidence that market price manipulation and liquidity risk play a role in determining the intraday patterns in returns.

One important research question in this context is whether the identified patterns can be exploited to obtain systematic abnormal earnings. We find that, although the intraday patterns in returns are statistically significant, they do not generate positive earnings for simple trading strategies. A direct implication of this result is that a passive portfolio management strategy is recommended. Also, from an academic perspective, our research reveals interesting features. For example, similar to how astrophysicists examine distant (early) regions of the universe in order to search for signs of its formation, the analysis of young and less developed stock markets can help academics better understand the reasons for the existence and formation of intraday price patterns. As both markets are classified as "frontier", we can presume that our results can offer some clues on the behavior of similar ones. However, we can expect some differences between the capital markets (Dragotă and Țilică, 2014).

The rest of the paper is structured as follows. Section II briefly reviews the related literature. Section III presents the data and the methodology. Section IV presents the main results, while Section V discusses them. Section VI concludes.

2. Related Studies

Several aspects related to the intraday market behavior can be studied, such as returns, calculated for different temporal lengths (1, 5 or 15 minutes; 1 hour), volatility, bid-ask spreads, liquidity (number of trades, trading volume), etc. Depending on the research question, the studies focus either on the identification of intraday patterns or on providing explanations for their occurrence. Papers in the first category usually find U-shape patterns in returns (Wood *et al*., 1985), volatility (Lockwood and Linn, 1990; Andersen *et al*., 2000; Hupperets and Menkveld, 2002), liquidity (Jain and Joh, 1988; Abhyankar *et al*., 1997; Ahn and Cheung, 1999), and trading costs (Chan *et al*., 1995; Brockman and Chung, 1998; Vo, 2007), but other shapes also arise in the form of the letters “J” (Lee *et al*., 2001), or “L” (Harju and Hussain, 2011). Papers in the second category are more recent and reveal interesting explanations for the occurrence of such patterns. For example, Hanousek *et al.* (2009) and Harju and Hussain (2011) associate their presence to the announcements of macroeconomic indicators. Other papers find a relationship between the activity of certain categories of investors (institutional, informed or uninformed) and the evolution of intraday quotes (*e.g*., Block *et al*., 2000; Lee *et al.,* 2001; Kalev and Pham, 2009). This suggests that private and asymmetric information play a part in the price formation process (Andersen *et al*., 2000). Also, intraday patterns might be explained by the level of integration between two markets (Hupperets and Menkveld, 2002), while market price manipulation has also been shown to influence them (Comerton-Forde and Putniņš, 2011).

Although many studies on intraday patterns exist, they tend to focus on large, developed markets, such as the ones from the United States, Japan, Hong Kong, Australia, or Western Europe. Emerging markets are significantly less studied, but some exceptions can be observed. Bildik (2001) focuses on the Turkish market and Lee *et al*. (2001), on the Taiwanese one. Concerning the European markets, Deev and Linnertová (2013) and Bedowska-Sójka (2014) analyze the case of the Czech and Polish stock markets, respectively. Their results show that intraday patterns in the emerging markets are similar to those in the more developed ones, but some differences exist. For example, Bildik (2001) finds that intraday returns follow a “W” pattern due to a pause in trading in the middle of the day. Similar findings show that characteristics unique to (or more accentuated in) emerging markets are influencing intraday patterns, this being very useful in comparative analyses that searches for better explanations for their occurrence.

As far as we know, intraday patterns in even smaller and less developed frontier markets have not been studied so far, although some papers consider other aspects related to intraday price evolution (Todea and Pleşoianu, 2011; Anghel, 2017). Among others, Dragotă and Țilică (2014) show that such markets behave differently in terms of daily returns, volatility and liquidity. Thus, the analysis of intraday patterns in the frontier markets can bring valuable contributions to the theoretical and empirical literature.

3. Data and Methodology

Besides their peculiarities, our choice for Romania and Bulgaria is also motivated by the availability of an extended data sample of tick-by-tick transaction data for all listed stocks. This is rarely obtained for such underdeveloped and opaque markets, which could explain the lack of papers on the topic. All data is provided by Tradeville, a stock market broker based in Romania. The data for Romania was also used in Anghel (2017). Each transaction is recorded using a timestamp (t), a ticker symbol (S), a price (P) and the traded quantity (Q). The data for the Romanian market starts on March 7, 2005 and ends on December 11, 2015, while the data for the Bulgarian market starts on October 9, 2006 and ends on November 24, 2015. We filter out stocks that average less than 10 trades per day, but we include stocks that have been listed after the start of the sample or have been delisted before the end of the sample, in order to avoid survivorship bias. These filters lead to a sample of 48 Romanian stocks and 19 Bulgarian stocks, which are detailed in Tables A1 and A2 in the Appendix.

Similar to other related papers (*e.g.*, Wood *et al.*, 1985; Bildik, 2001), we analyze patterns by estimating the multiple-day distribution of intraday returns on pre-determined time intervals. We focus on the average returns and evaluate their statistical significance using standard t-tests. Although this might seem rather simplistic, it is the best tool available for analyzing this research topic[4], especially given one important complication that we encounter. Specifically, the trading program in young markets, such as Romania and Bulgaria, changes frequently. In this case, the trading program at the start of the sample was between 10:15 and 14:15 on BVB and between 9:30 and 13:00 on BFBS. At the end of the sample, it was between 9:45 and 18:10 on BVB and between 10:10 and 17:00 on BFBS. In this period, it changed 8 times on BVB and 3 times on BFBS. As a result, the time difference from market open to market close varies, which biases the analysis of intraday patterns using linear models, GARCH models, or other time-series models with dummy variables, because the dummies would not consistently represent equivalent intervals throughout the entire sample.

To address this phenomenon, we depart from previous approaches by splitting the trading day in half and separately analyzing the two halves. Existing evidence shows that significant patterns predominately appear at the start and at the end of the trading day (Wood *et al.*, 1985; Bildik, 2001; Bedowska-Sójka, 2014) and our methodology accounts for this on BVB and BFBS. The procedure consists into three steps. First, we divide all days into distinct intervals. For this, we define a data sampling frequency (DF), expressed in minutes, and use it to split all days into intervals of equal length. In order to assure a balance between the level of detail and the fluency of exposure, we mainly consider a data frequency of 15

[4] For brevity, we leave the study of more complex intraday features to future research. For example, responses to macroeconomic news announcements or the long-memory of interdaily return/volatility dependencies can be investigated using ARIMA, GARCH, or other more advanced statistical models (e.g., Andersen et al., 2000).

minutes[5]. Second, we split the intervals into two equal groups and label them according to the market open (first half) or the market close (second half). When using a frequency of 15 minutes, the interval that contains the market open is labelled as "O+15", denoting that the trading activity is recorded 15 minutes after the market opens. The second interval is labelled as "O+30", the third interval is labelled as "O+45" and so on. Symmetrically, for the intervals in the second half of the day, the interval that contains the market close (the last trading interval of the day) is labelled as "C-0", denoting that the trading activity is recorded at the close. The second to last interval is labelled as "C-15", the one prior to that is "C-30" and so on. When the number of intervals in a trading day is an odd number, the interval exactly in the middle is labelled relative to the market close.

In the third step, for each standardized interval, we estimate the distribution of returns and report relevant statistics. Specifically, for all stocks, *"s"*, all days, *"d"*, and all standardized intervals, *"k"*, we consider the last price in the interval $C(I_{s,d,k})$. Some trading intervals have no activity and the inputs needed for the calculations are missing. In these cases, we considering the last price to be an effective price for the next period, as in Wood *et al*. (1985).

Returns are defined as the log difference between two consecutive prices, $r(I_{s,d,k}) = ln(C(I_{s,d,k})/C(I_{s,d,k-1}))$. The values computed for each interval are then aggregated at the market level (for all days and for all stocks). For example, the average return on each interval *"k"* ($\bar{R}_k$) is:

$$\bar{R}_k = \sum_{s=1}^{S} \frac{1}{S} \sum_{d=1}^{D_s} \frac{1}{D_s} r(I_{s,d,k})$$

where: *S* denotes the total number of stocks and D_s is the total number of trading days for stock "*s*". The statistical significance of the average is evaluated using the test statistic:

$$t_k = \frac{\bar{R}_k - 0}{\sigma/\sqrt{n}} \sim T(n-1)$$

where: n is the total number of observations and σ the standard deviation. Also, when discussing the results in Section V, we additionally use filters to split the distribution into independent parts and test the statistical difference between the average returns using the test statistic:

$$t_k = \frac{\bar{R}_k^1 - \bar{R}_k^2}{\sqrt{\frac{(n_1-1)\sigma_1^2+(n_2-1)\sigma_2^2}{n_1+n_2-1}}\sqrt{\frac{1}{n_1}+\frac{1}{n_2}}} \sim T(n_1+n_2-2)$$

4. Results

4.1. Intraday Patterns in Returns

The evolution of average intraday returns for the 15-minute data frequency is presented in Tables 1 and 2, as well as in Figure A1 in the Appendix. The results show the presence of an intraday pattern in both countries. The last two 15-minutes trading intervals show positive and statistically significant average returns, a pattern we call *the end-of-day effect.* Both

[5] We also analyse frequencies of 1 minute, 5 minutes, 30 minutes and 60 minutes, in order to detail or summarize the results as needed. The extended results are available upon request.

countries show similar values during this period: over 0.05% in the last interval (C-0) and around 0.01% in the previous one (C-15).

Table 1

First Four Moments of the Distribution of 15-minute Intraday Returns: Results for Romania

Time of Day	No. obs.	Mean	Standard Deviation	Skewness	Excess Kurtosis
O+15	105214	0,1226%***	2,3107%	-31,85	4252,73
O+30	105234	0,0156%***	1,1496%	-0,15	70,53
O+45	105235	-0,0027%	1,2130%	-2,04	382,04
O+60	105235	-0,0207%***	1,0111%	-0,83	95,22
O+75	105236	-0,0170%***	1,2238%	46,94	9172,02
O+90	105236	-0,0199%***	1,0059%	-1,41	357,40
O+105	105238	-0,0207%***	1,0814%	-3,24	925,58
O+120	89973	-0,0127%***	0,8817%	7,30	532,24
O+135	74670	-0,0175%***	0,7832%	-1,20	95,12
O+150	74670	-0,0113%***	0,7862%	1,12	256,77
O+165	74670	-0,0157%***	0,7562%	-1,85	101,94
O+180	74670	-0,0167%***	0,7365%	-1,26	121,97
O+195	43456	-0,0142%***	0,6352%	-1,80	102,42
O+210	19268	-0,0042%	0,5629%	-0,56	109,46
O+225	19268	-0,0076%*	0,5769%	0,89	110,13
O+240	15911	-0,0102%**	0,5184%	-1,71	84,74
O+255	3601	-0,0094%	0,5672%	-1,48	61,06
C-255	5362	0,0046%	0,5137%	1,14	86,73
C-240	19267	-0,0118%***	0,5753%	-2,71	162,44
C-225	19266	-0,0081%*	0,5983%	-6,92	341,47
C-210	19266	-0,0084%**	0,5363%	-1,16	74,36
C-195	74665	-0,0169%***	0,7209%	-1,32	107,30
C-180	74663	-0,0095%***	0,7488%	-2,28	184,22
C-165	74663	-0,0071%**	0,7368%	1,67	254,15
C-150	74662	-0,0057%**	0,7165%	-2,62	142,30
C-135	75902	-0,0071%***	0,6938%	0,14	92,71
C-120	105225	-0,0082%***	0,9480%	-3,24	1484,07
C-105	105226	-0,0071%**	0,8820%	11,22	977,30
C-90	105231	-0,0087%**	1,1395%	-85,56	17530,00
C-75	105235	-0,0033%	0,9530%	12,23	1437,55
C-60	105237	-0,0048%*	0,8380%	3,81	583,17
C-45	105236	-0,0093%***	0,9417%	5,14	1496,37
C-30	105231	-0,0023%	0,8089%	-1,36	144,65
C-15	105231	0,0101%***	0,9343%	0,64	627,38
C-0	105229	0,0598%***	1,3113%	2,70	460,49

*Note: This table reports the number of observations and the first four moments of the distributions of intraday returns aggregated by standardized intervals at a 15-minute data frequency. "O+x" refers to the interval ending x minutes after the market open. "C-y" refers to the interval ending y minutes before the market close. We evaluate the significance of the mean using a standard two tailed t-test. ***, **, and * denote significance at the 99%, 95%, and 90% levels, respectively.*

Table 2

First Four Moments of the Distribution of 15-minute Intraday Returns: Results for Bulgaria

Time of Day	No. obs.	Mean	Standard Deviation	Skewness	Excess Kurtosis
O+15	45.373	0,0198%	3,1092%	-72,29	8790,63
O+30	45.376	0,0091%	1,2167%	-2,38	205,27
O+45	45.376	-0,0013%	1,1305%	0,27	599,67
O+60	45.377	-0,0089%	1,2400%	-7,59	1082,82
O+75	45.377	-0,0167%***	1,0715%	-7,45	598,61
O+90	45.378	-0,0062%	0,8122%	4,48	622,66
O+105	36.851	-0,0218%***	1,1139%	-2,77	276,30
O+120	36.852	-0,0250%***	1,1961%	-21,88	1703,76
O+135	14.930	-0,0208%**	1,1053%	-8,85	758,54
O+150	14.930	-0,0124%	1,1553%	-2,28	1159,29
O+165	14.929	-0,0212%**	0,9732%	-20,34	1484,40
O+180	14.928	-0,0045%	1,1898%	1,34	728,96
O+195	14.928	0,0009%	1,4161%	21,35	1680,77
C-195	14.928	-0,0068%	1,0354%	-13,96	971,77
C-180	14.928	-0,0047%	1,0129%	-24,91	1769,27
C-165	14.927	0,0033%	1,1204%	33,49	3298,87
C-150	14.926	-0,0073%	1,0328%	-9,34	954,28
C-135	18.279	-0,0102%	0,8546%	-3,78	320,33
C-120	36.846	-0,0200%***	1,0948%	-10,62	1855,75
C-105	45.374	-0,0163%***	0,8653%	-4,50	489,34
C-90	45.374	-0,0110%**	1,0725%	-12,93	2043,73
C-75	45.375	-0,0118%***	0,8220%	-0,09	376,60
C-60	45.376	-0,0059%	0,8904%	-12,73	1444,08
C-45	45.376	-0,0038%	1,0642%	34,48	4108,45
C-30	45.375	-0,0235%***	1,3071%	-48,43	4840,77
C-15	45.375	0,0124%*	1,2929%	49,03	5269,50
C-0	45.373	0,0541%***	1,4056%	5,46	285,50

*Note: This table reports the number of observations and the first four moments of the distributions of intraday returns aggregated by standardized intervals at a 15-minute data frequency. "O+x" refers to the interval ending x minutes after the market open. "C-y" refers to the interval ending y minutes before the market close. We evaluate the significance of the mean using a standard two tailed t-test. ***, **, and * denote significance at the 99%, 95%, and 90% levels, respectively.*

Additionally, positive average returns can also be observed at the start of the trading day in the first two 15-minutes intervals, an effect we call *the beginning-of-day effect.* However, its evolution is different as compared to the end-of-day effect. On the Romanian market, the returns, which are statistically significant, are around 0.12% in the first interval (more than double the value from the last trading interval) and around 0.01% in the second interval. On the Bulgarian market, the returns are borderline significant, but lower as compared to the ones in Romania (around 0.02% in the first interval with a t-stat of 1.35 and 0.01% in the second with a t-stat of 1.59).

The two effects found on the Romanian and Bulgarian stock markets are similar to the ones reported for other markets, both developed and emerging. For example, Wood *et al.* (1985) reported positive returns in the first and the last 30 minutes of the day for their sample of

NYSE stocks. Also, Bildik (2001), for the Turkish market, reported positive returns in the first 30 minutes after the market opened and in the last 15 minutes before the market closed. Thus, the existence of these effects on the smaller Romanian and Bulgarian markets can have similar explanations to the ones proposed for more developed markets, specifically information flow and the behavior of informed traders, liquidity risk, or inventory risk. However, the magnitude of the intraday patterns in returns in Romania and Bulgaria is higher as compared to the US market and is lower as compared to the Turkish market. Specifically, the average return coefficient for the first minute of the day in Romania is approximately 5½ times larger (the t-stat for the difference in means test is 10.22) than the one Wood *et al*. (1985) reported for the first minute of the day in the period 1971-1972 and 12 times larger (t-stat of 18.11) than the similar coefficient reported for trading days in 1982. Similarly, the end-of-day 1-minute returns are 5 to 10 times larger in Romania as compared to the US, with the differences being significant at the 1% level. However, when comparing the results with the ones reported by Bildik (2001), the average return coefficient in Romania is 2½ times lower (t-stat of -2.20) for the first 15 minutes of the day and 2½ times lower (t-stat of -2.20) for the last 15 minutes of the day. Explaining these differences is outside the scope of the present paper, but it might be a direction for future research. Possible causes for our findings include specific structural characteristics of the investigated markets, their level of market integration and/or the distribution of different investors' classes inside the market (large vs. small, institutional vs. individual, foreign vs. domestic) and their particular behaviors.

Furthermore, our results from Table 1 and 2 show that average returns throughout the rest of the day are usually significantly negative in both markets, which we call *the midday effect* in stock returns. They become negative from *O+45* and remain negative until *C-30*. This effect can be segmented into three relevant sub-periods: a period of significant negative returns that starts approximately 30 minutes after the open and lasts for 2½-3 hours (we call this the *midday1* effect), a period of statistically insignificant returns exactly in the middle of the day, and a period of significant negative returns that starts approximately 3 hours before the close and lasts for approximately 2½ hours (we call this the *midday2* effect). On the Romanian market, the average return on *O+60* is -0.0207% and is statistically significant at the 1% level with a t-stat of -6.63. Then, all returns up to *O+195* are negative and statistically significant at the 1% level with t-stats ranging between -3.94 and -6.20. In the middle of the day (between *O+210* and *C-225*), returns remain negative but tend to be insignificant. In the second part of the day, starting with *C-210*, the negative returns become significant again (*C-210* has an average return of -0.0084%, which is statistically significant at the 1% level with a t-stat of -2.16), although with lower absolute t-statistics as compared to the negative returns in the first part of the day. The same pattern can be observed in Bulgaria, although with minor differences regarding the timing and the magnitude. In this case, the midday returns are negative and usually statistically significant at a 1% level, but they have a smaller magnitude. Additionally, the period of insignificant returns from the middle of the day is longer: between *O+180* to *C-150*.

The midday effect is more intriguing than the beginning-of-day and the end-of-day effects, because it can be observed, as far as we know, only in some specific markets. In the study of the Turkish market, Bildik (2001) finds that after the initial positive returns (from the first 30 minutes of trading), the market shows negative returns for most of the trading day. The exception is observed in the 15-minutes interval around the closing of the market at noon, which appears to determine positive returns. Wood *et al*. (1985) also observe some negative 1-minute returns in the middle of the day, but their significance is weak and the authors do not investigate them further. Our results show that the negative returns in the middle of the day are far more significant in the case of Romania and Bulgaria. A possible explanation is that these returns correct the price overreactions from the beginning and/or the end of the day. We test this hypothesis in Section 5 and suggest a possible determinant of such price overreactions: market price manipulation.

4.2. Time Variation in Intraday Patterns

The following section investigates if the two markets show similar evolutions in the average 15-minutes returns throughout the whole analysis period or if their behavior has changed over time. For this, the evolution of the average returns is studied for each non-overlapping 3-month interval (quarter) of the analysis period and their statistical significance is tested. Our findings are presented in Table 3. We only report t-statistics evaluating the significance of the estimated averages (detailed results are available upon request).

Table 3

Time Variation in Intraday Patterns

	Romania				Bulgaria			
Quarter	Open	Mid1	Mid2	Close	Open	Mid1	Mid2	Close
2005Q1	-1.23	-2.94***	-1.95**	-1.55*				
2005Q2	-0.29	-0.34	-3.89***	2.72***				
2005Q3	3.46***	1.27	-1.21	3.99***				
2005Q4	2.74***	0.61	-0.81	1.10				
2006Q1	1.78**	1.17	-0.82	3.00***				
2006Q2	1.27	-2.45***	-0.39	0.50				
2006Q3	2.54***	2.28**	1.09	2.59***				
2006Q4	1.18	0.04	0.66	3.58***	1.38*	1.14	1.10	3.01***
2007Q1	-1.86**	-0.82	2.37***	2.87***	-0.21	2.13**	-0.50	1.49*
2007Q2	5.18***	3.08***	1.98**	1.22	2.77***	0.96	1.84**	1.09
2007Q3	4.85***	-1.21	-3.28***	0.12	6.47***	1.23	1.64**	1.16
2007Q4	3.17***	-4.32***	-2.86***	4.58***	1.38*	1.39*	-3.48***	-0.36
2008Q1	-1.24	-7.55***	-4.08***	2.04**	-0.99	-4.74***	-2.08**	1.96**
2008Q2	1.10	-2.99***	-4.67***	0.63	1.98**	-2.5***	-0.59	0.57
2008Q3	-3.70***	-6.55***	-2.08**	2.98***	-1.81**	-4.19***	-1.78**	1.71**
2008Q4	1.31*	-8.38***	-4.27***	-1.80**	-0.42	-2.69***	-5.34***	-2.11**
2009Q1	2.65***	-0.21	-2.81***	0.73	1.96**	-2.14**	-4.40***	0.34
2009Q2	13.18***	1.79**	-4.65***	-0.57	3.55***	0.78	-1.24	0.64
2009Q3	9.16***	0.85	-2.06**	1.91**	4.94***	0.04	0.15	2.49***
2009Q4	5.14***	-5.64***	-4.46***	3.71***	-0.12	-1.51*	-2.68***	2.05**
2010Q1	12.30***	1.47*	0.40	-1.87**	0.63	0.57	-2.59***	-0.09
2010Q2	1.71**	-4.88***	-4.37***	-1.97**	-0.20	-3.11***	-3.06***	1.64*
2010Q3	8.24***	-2.76***	-0.95	4.21***	1.95**	1.18	-3.03***	1.64*
2010Q4	3.24***	-2.46***	-3.42***	3.49***	-0.24	2.25**	-0.91	-0.58
2011Q1	5.28***	-2.26**	-1.69**	4.98***	2.49***	2.14**	0.03	1.01
2011Q2	5.84***	-4.36***	-3.19***	1.54*	0.94	-1.99**	-3.74***	1.21
2011Q3	1.06	-7.36***	-1.69**	2.65***	-3.05***	-0.59	-4.02***	2.39***
2011Q4	4.40***	-2.33**	-2.93***	1.60*	1.14	-2.58***	-2.13**	2.00**
2012Q1	6.09***	-3.12***	-1.96**	2.25**	0.31	-1.38*	-1.90**	1.24
2012Q2	2.71***	-4.84***	-4.99***	2.00**	-0.58	-1.60*	-1.46*	0.57
2012Q3	1.04	-0.46	-0.84	5.14***	1.38*	-1.65*	-0.93	1.95**

	Romania				Bulgaria			
Quarter	Open	Mid1	Mid2	Close	Open	Mid1	Mid2	Close
2012Q4	2.73***	-4.51***	-1.21	7.24***	0.57	-1.23	0.07	0.54
2013Q1	5.26***	-2.61***	-0.48	3.95***	0.71	-0.82	0.27	2.25**
2013Q2	0.21	-4.25***	-0.62	4.81***	3.13***	0.54	-1.59*	0.10
2013Q3	1.39*	-1.16	-0.03	5.98***	-1.06	-0.53	0.94	1.74**
2013Q4	4.78***	-3.38***	-0.65	7.04***	-0.13	-2.38***	-0.19	0.77
2014Q1	3.83***	-4.94***	-0.12	3.39***	2.60***	2.96***	-0.64	2.54***
2014Q2	3.38***	-1.02	0.26	4.41***	-0.46	-1.87**	-0.01	-0.09
2014Q3	3.34***	-2.65***	0.30	4.66***	0.07	-1.70**	-0.67	2.64***
2014Q4	4.30***	-6.23***	-0.63	4.46***	2.03**	-0.81	-0.72	1.37*
2015Q1	6.29***	-5.82***	0.47	4.70***	2.53***	-3.70***	-0.13	1.98**
2015Q2	-1.11	-2.84***	0.08	4.04***	-0.56	-3.49***	-1.94**	4.89***
2015Q3	-1.01	-1.24	1.11	2.29**	-0.23	-2.74***	-0.89	2.16**
2015Q4	4.00***	-4.18***	-0.21	2.94***	-1.55*	0.20	-0.04	1.39*

Our results show that the *end-of-day effect* is the most robust in both markets. In Romania, 39 out of 44 quarters have end-of-day positive returns, with 31 of them being statistically significant. In Bulgaria, 32 out of 37 quarters have positive returns, but only 15 of them are statistically significant. Additionally, only severe negative market events reverse the upward tendency in end-of-day returns, such as the Lehman Brothers collapse (2008Q4 presents statistically significant negative returns in both markets), or the European debt crises (end of day returns in the first half of 2010 were significantly negative in Romania, although Bulgaria was not affected).

The *beginning-of-day effect* is robust in Romania, 37 out of 44 quarters having positive returns in Romania, out of which 29 are statistically significant. In Bulgaria, the effect is less significant, with only 23 out of 37 quarters presenting positive beginning of the day returns, out of which only 12 are statistically significant.

The *midday1 effect* is also robust in Romania, with 35 out of 44 quarters presenting negative returns, out of which 27 are statistically significant. However, this effect seems to start at the beginning of the world financial crisis in 2007Q3, as 6 out of the 10 quarters prior to this moment present positive returns. In Bulgaria, we observe a similar variability in time, but a less significant effect. Before 2008, all quarters present positive returns, while after 2008Q1, 23 out of 32 quarters present negative returns, out of which 14 are statistically significant. Also, the average t-statistic for entire *midday1* interval after 2008Q1 is -4.45 in Romania as compared to only -2.84 in Bulgaria.

The *midday2 effect* is less robust in Romania than the *midday1 effect*, with 34 out of 44 quarters presenting negative returns, and only 20 of them being significant. It was very strong between 2007Q2 and 2012Q2, but outside of this period, the average returns tend to be insignificant or even positive. A similar pattern is observed in Bulgaria, but with a less significant magnitude. Specifically, 29 out of 37 quarters present negative returns, with only 14 statistically significant. The pattern is significant from 2007Q4 to 2012Q2 (the average t-statistic is -2.32 in Bulgaria as compared to -3.00 in Romania in the same period) and seems to disappear afterwards.

5. Discussion of Results

The results presented in Section IV show the presence of intraday patterns on the Romanian and Bulgarian markets. We find that prices in both countries increase in the first and last 30 minutes of the trading day. In between, they have a period of significant declines, with a pause in the middle of the day. This pattern is similar to the ones reported for other markets, but its magnitude is different. For example, the midday effect on both markets is significantly more pronounced, which suggests a different behavior as compared to the ones previously studied. We also study patterns in volatility and liquidity and find that they are similar to the ones in other markets, having U and inverted-U shapes, respectively. Because of this and also for brevity, we do not discuss them further, although we do report the results in Figure A2 in the Appendix.

When analyzing higher frequencies, the conclusions remain the same. We observe that the beginning-of-day and the end-of-day effects in stock returns span approximately 30 minutes in both markets and get stronger as we approach the market open or close. In the case of Romania, for a data frequency of 1 minute, half of the first 30 average returns are positive and significant at least at the 10% level, with 12 of them being in the first 15 minutes. Also, 15 of the last 30 average returns are positive and significant at least at the 10% level, with 9 of them being in the last 15 minutes. Furthermore, the returns in the first and last minute of a trading day are significant and explain between 55% and 60% of the effects' magnitude of the15-minute returns. We observe the same pattern in Bulgaria, with the beginning of the day effect being significant for returns computed at a frequency lower than 15 minutes.

A more in-depth analysis shows that intraday patterns in returns vary over time, considering both their magnitude and their level of significance. Their signs are usually stable, but occasional sign reversals occur. The end-of-day effect is the most robust in both markets. However, while the beginning-of-day effect is robust in Romania, it is not significant in Bulgaria. The financial crisis which started in 2007 had a significant effect on the patterns, some of them (like the midday patterns) seemingly appearing while the crisis was unfolding. In Romania, the *midday1* effect remains robust until the end of our sample, while the *midday2* effect disappears in the second half of 2012. The two midday effects are less significant in Bulgaria, but have a similar behavior in time as compared to Romania. Finally, as compared to Bulgaria, we notice that the intraday patterns in returns are more robust in the larger, more liquid and more integrated market of Romania.

A natural extension to our investigation is to analyze the reasons behind the behavior of intraday returns in Romania and Bulgaria. The following sub-sections provide possible explanations which can be linked to these intraday patterns.

5.1. Market Price Manipulation

A possible phenomenon which could explain the observed behavior of these markets is price manipulation. While it has no generally accepted definition (Putniņš, 2012), it refers to a set of practices that distort market prices with the intent of gaining some direct or indirect monetary advantages. We search for indirect evidence on the possibility of such practices influencing the intraday patterns in Romania and Bulgaria.

We investigate signs of the “marking the close” strategy specific to window dressing by fund managers and contract base manipulation by testing whether the patterns for some relevant days present significant deviations from the patterns in all other days. If manipulation is an explanation, we would expect to find significantly higher end-of-day returns in these specific days. The days (periods) considered for studying the "marking the close" strategy are the end of the month (*EOM*) and the end of the quarter days (*EOQ*).The contract base manipulation includes the derivative contracts expiry days (*DEX*), the last trading day for derivative contracts (*LTDD*), and the last two weeks prior to the expiry of a derivative contract (*DEX_2w*). We investigate contract-based manipulation only for the case of a few Romanian stocks because we can find corresponding (and reasonably liquid) derivatives contracts listed on the Sibiu Stock Exchange (Sibex), the primary market for derivatives in Romania. We focus on futures contracts and we do not consider options contracts, which are largely not traded. Data is obtained from Sibex (contract expiry dates) and Tradeville (trading data on derivatives). We also investigate beginning of the month (*BOM*) days and beginning of the quarter (*BOQ*) days to search for signs for subsequent price reversals. Table A3 in the Appendix reports the t-statistics for the test of the difference in average intraday returns on these relevant days, except EOM and BOM days, which are completely explained by the results on EOQ and BOQ days[6].

In the case of Romania, we observe higher average returns on days close to derivative contract expiry (DEX), but they are insignificant. However, the results show significantly higher returns throughout *EOQ* days. We find significant positive deviations in the first part of the day and in the last hour before the close. Although they only constitute indirect evidence, the results point towards window dressing by fund managers as partially explaining intraday patterns in returns in Romania. One intriguing aspect is that prices on subsequent *BOQ* days do not seem to reverse. Rather, the returns on *BOQ* days also present positive deviations, which are significant in the first part of the day. This implies that the effects of window dressing determine a persistent positive shift in prices. For Bulgaria, the evidence is not conclusive. We observe some signs for positive deviations on *EOQ* and some signs of negative deviations on *BOQ* days, but the results are not statistically significant most of the time.

5.2. Liquidity Risk

Another aspect of price manipulation is that stocks with low and mid-level liquidity are more likely to be manipulated as compared to high liquidity stocks (Comerton-Forde and Putniņš, 2014). Alternatively, Bildik (2001) points out that overnight inventory management and the associated liquidity risk may partially explain the end-of-day behavior of prices. To investigate these implications, we split the stocks from each market into quartiles based on liquidity and we test for significant differences in intraday return patterns between the resulting portfolios. The liquidity is estimated using the trading frequency (*i.e*. the average number of trades per month). Table A4 in the Appendix reports the results of the difference in mean t-test for the second, third and fourth portfolios ranked by liquidity, using as a benchmark the average returns for the portfolio consisting of the most liquid stocks.

For Romania, the results show that the end-of-day effect is significantly stronger for less liquid portfolios. The hypothesis of equal average returns for *C-0* is rejected for all portfolios at the 1% level with increasing t-statistics: 2.21 for the second, 4.07 for the third, and 11.62 for the fourth portfolio, respectively. We also observe signs that the midday effect is more pronounced in less liquid portfolios, although the differences tend to be insignificant. Overall, intraday return patterns in Romania vary with liquidity: the less liquid a stock is, the more pronounced the patterns get. This constitutes indirect evidence that price manipulation and/or liquidity risk are factors that influences intraday patterns in Romania.

[6]The results are available upon request.

We also observe some evidence of a link between liquidity and the end-of-day effect in Bulgaria in the case of the two most illiquid portfolios, but the results are not as conclusive as in the case of Romania. Considering our previous results, in the case of Bulgaria, we do not have sufficient evidence that point towards price manipulation or liquidity risk as a factor that influences intraday patterns in returns.

Table 4

Trading Simulation Results

Panel A: Romania				
Trading strategy		Buy and hold	Long only	Short only
Average return		-10.23%	46.35%	56.58%
Standard deviation		21.74%	16.26%	14.40%
Skewness		-2.28	-4.78	1.03
Kurtosis		198.58	589.17	82.62
Sharpe Ratio†		-0.52	2.66	2.18
Information Ratio†			3.93	2.02
Jensen's alpha (t-stat)			49.24%*** (15.00)	42.69%*** (13.01)
Break-even transaction cost			0.00000165%	0.00000195%
Panel B: Bulgaria				
Trading strategy		Buy and hold	Long only	Short only
Average return		-25.69%	29.44%	55.13%
Standard deviation		26.58%	16.02%	21.19%
Skewness		-7.56	-2.01	14.04
Kurtosis		483.25	828.99	926.94
Sharpe Ratio†		-0.91	1.57	1.77
Information Ratio†			2.60	1.78
Jensen's alpha (t-stat)			35.62%*** (8.43)	30.72%*** (7.27)
Break-even transaction cost			0.00000232%	0.00000340%

*NOTE. This table presents the first four moments of the return distribution and some relevant excess return measures for a trading strategy that takes a long position 30 minutes before the market closes and a short position 30 minutes after the market opens. We also report results for the benchmark buy-and-hold strategy. The trading simulation is conducted on a 15-minute data frequency and both strategies trade on the equal-weighted index constructed using all stocks in our sample. ***, **, and * denote statistical significance at the 99%, 95%, and 90% levels, respectively.*

†For annualizing Sharpe Ratios and Information Ratios we use the robust estimator of Lo (2002) to correct for the bias caused by the autocorrelation in returns. We use the autocorrelation coefficients for the first 125 lags (given the 15-minute data frequency, they correspond to about 5 days of trading activity) and we consider the coefficients at all other lags as insignificant.

5.3. Economic Significance

The intraday pattern previously observed on the Romanian and Bulgarian stock markets can be interpreted as anomalies in the context of the Efficient Market Hypothesis. To test if this is indeed the case, we investigate if traders are able to exploit these patterns to earn abnormal profits. For this, we define a trading strategy which includes these patterns and test if it is capable to outperform the benchmark buy-and-hold strategy. The strategy trades as follows: it takes a long position in the market portfolio 30 minutes before the close and a short position 30 minutes after the market opens the next day. Although short trades are not operational in the two markets, we also examine them in order to test if this feature has an influence on (*i.e*. causes an asymmetry in) intraday patterns. We employ a 15-minute data frequency for this test and we use the equal weighted portfolio of all the stocks in our sample as a proxy for the market. The performance measures are annualized and split by trade type.

The results are reported in Table 4 and show that, prior to transaction costs, our trading strategy can earn abnormal returns (alphas) in excess of 40% per year in Romania and 30% per year in Bulgaria for both trade directions. However, break even transaction costs are small, being well below the actual costs in the two markets, which range in the period from 0.2% to upwards of 1% per trade, depending on the type of investor and the value of their portfolio (*e.g*., see Appendix 3 from Ţilică, 2018). Incorporating the minimum 0.2% cost–and without taking into account other costs, such as the bid-ask spread–turn all excess returns negative. This means that although the intraday patterns in returns are statistically significant, they cannot generate positive abnormal returns for simple trading strategies.

Also, the results show that an asymmetry exists between long and short trades. Specifically, short trades are on average more profitable (they earn 10% more in Romania and 25% more in Bulgaria), but more volatile (see the alphas of the two strategies, which is lower for short trades in both markets). This implies that (1) the presence or absence of short trading has an influence on intraday patterns in returns, and (2) the beginning and end of the day effects are more stable as compared to the price declines in the middle of the day.

6. Conclusions

This paper analyses intraday patterns in returns in the frontier stock markets of Romania and Bulgaria using a methodology that accounts for changes in the trading program, which can be rather common in such markets. We use an extensive data sample of tick-by-tick prices for 48 Romanian stocks and 19 Bulgarian stocks in the period 2005-2015.

We find that the patterns in returns are similar in shape with the ones identified in other markets, but they differ in shape. Specifically, returns follow a ω-pattern: they are significantly positive in the first 30 minutes after the market opens and at the end of the day, and stay negative throughout the rest of the day, with the exception of the middle of the day. The magnitude of average returns is higher as compared to those observed on the US market (Wood *et al*., 1985), but is lower as compared to those observed on the Turkish market (Bildik, 2001). Also, as compared to the Turkish market, where trading stops in the middle of the day, the results for Bulgaria and Romania are qualitatively different, as they appear even when trading is continuous.

Moreover, we check the robustness of the patterns in returns and find that the end of the day effect is the most stable over time. This suggests a general feature of the two stock markets. However, the other effects are less robust and seem to be influenced by significant market events, by specific characteristics of the investigated markets or by shifts in investor behavior. For example, one interesting finding is that the beginning of the day and the *midday1* effect in returns in Romania have appeared after the financial crisis, starting approximately 2008Q2, while in Bulgaria those effects have been rather insignificant. These patterns coincide with shifts in the correlation coefficients between the returns of the two markets with the one in the United States. This indicates that market integration plays a role in determining the appearance of some of the intraday patterns in returns in the less developed markets. One implication is that shifts in market integration can lead to changes in the structure of investors (large vs. small, institutional vs. individual, foreign vs. domestic) and in their behaviors, which in turn alters intraday patterns.

Additionally, we investigate if market price manipulation is another factor behind these intraday patterns. We find that the magnitude of the different patterns differs significantly in some specific calendar days - related to the end of reporting periods or to the expiry of derivatives contracts - and for portfolios of stocks ranked by liquidity in Romania, but not in Bulgaria. This provides some indirect evidence that market price manipulation plays a part in determining the intraday patterns in returns for Romanian stocks. Also, end-of-day returns are significantly higher for lower liquidity portfolios, which additionally points towards price manipulation and/or liquidity risk as possible explanations for the observed patterns. Finally, we find that a simple strategy that trades the observed patterns is able to generate substantial profits in a no-cost environment, but is unprofitable when considering transaction costs. However, because results differ between long and short trades, it indicates that limitations on short selling trades have an influence on intraday price patterns in these frontier markets.

From a theoretical perspective, our results show that intraday patterns in returns also exist in these frontier markets and are significantly influenced by both general and specific market characteristics. From a practical perspective, our results show that investors cannot generally earn excess profits from trading the observed patterns. However, the existence of such patterns implies that they can choose favorable moments of the day for executing specific trades.

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Appendix

Table A1

List and Details of Companies Listed on the Romanian Stock Market

			Number of observations per data frequency					
Symbol	First day	Last day	Tick-by-tick	1 minute	5 minutes	15 minutes	30 minutes	60 minutes
ALBZ	06/10/2005	12/11/2015	74,827	49,947	34,818	23,448	17,227	11,682
ALT	03/04/2005	12/10/2015	39,487	25,128	18,89	14,073	11,132	8,232
ALU	12/19/2006	12/09/2015	27,34	18,408	14,156	10,975	8,856	6,71
AMO	03/04/2005	06/05/2015	114,2	68,398	43,382	27,337	19,112	12,161
ARAX	03/07/2005	12/09/2015	102,905	64,238	38,827	23,333	16,015	10,192
ARCV	12/19/2006	12/11/2015	60,144	38,322	26,157	17,6	13,12	9,09
ARDF	06/07/2005	11/27/2009	14,561	9,44	6,885	4,95	3,845	2,755
ATB	03/07/2005	12/11/2015	73,348	55,629	40,94	27,499	19,877	13,082
AUCS	10/21/2005	01/12/2010	20,106	12,274	7,684	4,814	3,418	2,582
AZO	03/07/2005	08/21/2012	91,638	55,461	34,626	21,473	14,891	9,271
BCC	03/04/2005	12/11/2015	94,328	65,041	46,29	31,241	22,367	14,486
BIO	11/30/2005	12/10/2015	132,57	91,78	56,295	32,263	21,335	13,211
BRD	03/07/2005	12/11/2015	217,642	143,987	83,674	46,553	29,331	16,861
BRK	03/04/2005	12/11/2015	197,007	128,956	75,891	42,775	27,53	16,239
BVB	06/08/2010	12/11/2015	60,302	37,962	27,104	18,613	13,166	8,427
CEON	06/12/2006	12/10/2015	27,656	17,413	13,251	10,239	8,377	6,465
CMP	03/04/2005	12/11/2015	46,228	33,418	25,502	18,622	14,377	10,215
COFI	12/07/2005	03/14/2012	31,322	19,924	13,128	8,723	6,254	4,485
COMI	03/07/2005	07/20/2015	80,204	53,119	36,455	24,631	17,895	11,932
CRB	03/04/2005	04/05/2007	7,648	4,96	3,673	2,6	2,041	1,485
DAFR	03/22/2006	06/19/2015	134,635	85,7	53,152	32,256	21,582	13,134
EL	06/27/2014	12/11/2015	38,505	25,449	15,887	9,039	5,555	3,208
ELMA	03/04/2005	12/11/2015	51,263	33,457	24,903	18,244	14,045	9,971
FLA	07/18/2005	12/14/2009	20,924	14,367	10,713	7,625	5,84	4,042
FP	01/25/2011	12/11/2015	236,109	136,255	69,081	33,2	18,196	9,587
IMP	03/04/2005	12/11/2015	78,21	52,564	35,143	22,301	15,824	10,458
IPRU	03/04/2005	12/11/2015	41,424	28,778	20,601	14,406	11,045	7,971
OIL	03/04/2005	12/11/2015	40,939	27,503	21,167	16,078	12,768	9,441
OLT	03/07/2005	12/11/2015	85,81	52,048	34,666	22,608	15,864	10,065
PRSN	03/30/2006	12/11/2015	78,111	50,802	34,498	22,976	16,533	10,861
PTR	03/04/2005	12/09/2015	44,917	32,275	23,825	16,685	12,545	8,769
RRC	03/04/2005	12/11/2015	188,774	105,948	55,082	28,563	18,553	11,597
SCD	03/04/2005	12/11/2015	42,951	31,357	23,643	17,413	13,44	9,469
SIF1	03/14/2005	12/11/2015	288,413	192,78	106,152	54,25	32,323	17,663
SIF2	03/14/2005	12/11/2015	392,363	237,13	115,808	55,836	32,624	17,733
SIF3	03/14/2005	12/11/2015	456,638	272,952	133,853	61,363	34,162	17,99
SIF4	03/14/2005	12/11/2015	287,092	188,18	100,637	51,382	31,136	17,344
SIF5	03/14/2005	12/11/2015	445,301	258,165	120,638	56,719	32,842	17,752
SNG	11/06/2013	12/11/2015	64,467	40,243	24,304	13,445	8,034	4,524
SNN	09/26/2013	12/11/2015	43,896	30,044	19,197	11,385	7,25	4,307
SNP	03/07/2005	12/11/2015	335,526	206,675	110,75	55,812	32,82	17,84
SRT	03/04/2005	11/14/2014	28,765	19,663	15,41	11,499	9,172	6,717
TBM	03/07/2005	12/11/2015	61,252	40,389	29,166	20,54	15,525	10,983
TEL	08/29/2006	12/11/2015	143,854	96,287	62,452	37,92	24,771	14,71
TGN	12/11/2007	12/11/2015	112,123	74,8	51,209	32,817	21,975	13,198
TLV	03/07/2005	12/11/2015	299,722	197,292	104,417	52,485	31,174	17,18
VEGA	03/04/2005	12/15/2008	12,561	8,79	7,023	5,334	4,28	3,126
VNC	07/15/2005	12/11/2015	29,049	20,782	16,815	12,951	10,495	7,923

Table A2

List and Details of Companies Listed on the Bulgarian Stock Market

			Number of observations per data frequency					
Symbol	First day	Last day	Tick-by-tick	1 minute	5 minutes	15 minutes	30 minutes	60 minutes
ATERA	10/19/2006	11/24/2015	44,929	13,640	11,726	9,891	8,337	6,541
BREF	10/26/2006	11/24/2015	27,606	8,272	7,230	6,306	5,529	4,648
CCB	10/09/2006	11/24/2015	120,043	31,531	22,885	16,486	12,295	8,630
CENHL	03/22/2007	11/24/2015	26,403	10,697	8,991	7,333	6,133	4,930
CHIM	11/03/2006	11/24/2015	144,954	46,937	31,999	21,138	14,854	9,895
DOVUHL	10/09/2006	11/20/2015	26,084	14,838	11,696	8,656	6,607	4,931
ENM	01/23/2008	11/23/2015	35,118	12,753	10,148	8,165	6,769	5,459
EUBG	03/02/2007	11/24/2015	67,161	24,701	17,516	12,160	8,941	6,327
FIB	06/25/2007	11/24/2015	69,045	24,026	17,756	12,693	9,478	6,790
HDPAT	09/11/2007	04/24/2015	40,960	15,319	11,280	8,202	6,193	4,534
IHLBL	10/09/2006	11/23/2015	35,118	15,406	12,304	9,459	7,439	5,552
KAO	05/22/2007	11/15/2013	27,344	12,062	9,370	7,024	5,504	4,170
MONBAT	01/04/2007	11/24/2015	49,002	21,432	15,933	11,544	8,770	6,454
OTZK	10/09/2006	04/25/2014	27,874	13,528	9,670	6,801	5,181	3,863
PET	10/09/2006	11/24/2015	25,642	8,187	6,498	5,276	4,398	3,548
PETHL	10/09/2006	11/20/2015	31,893	16,261	12,934	9,608	7,343	5,466
SFARM	10/09/2006	11/24/2015	67,799	24,611	19,211	14,524	11,249	8,242
TRACE	12/15/2007	11/24/2015	43,974	15,761	11,943	9,138	7,299	5,615
ZHBG	12/17/2007	11/24/2015	56,808	18,621	14,441	11,001	8,601	6,379

Figure A1

Average Pattern in 15-minute Intraday Returns

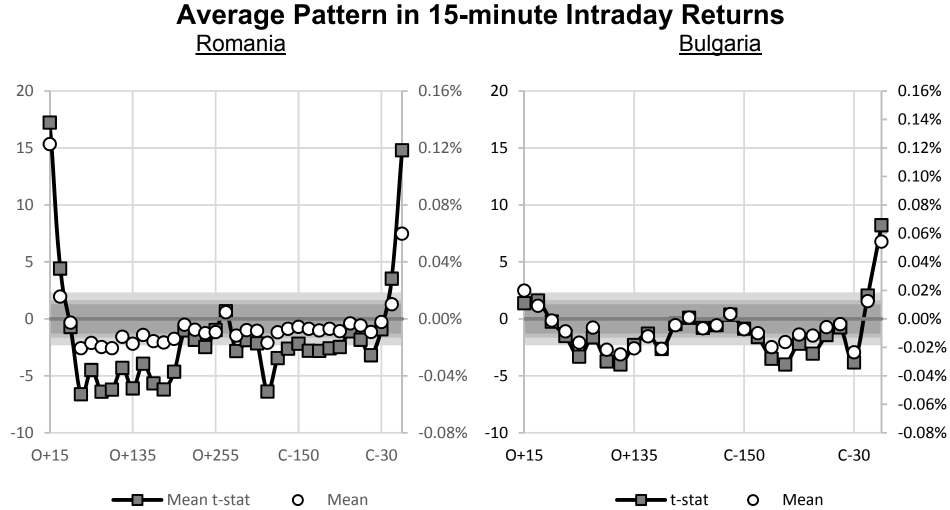


Table A3

Results of t-test for the Difference in Average Returns for Specific Days of the Year

Time of Day	Romania					Bulgaria	
	EOQ	BOQ	DEX	LTDD	DEX_2w	EOQ	BOQ
O+15	-1.70*	1.39	1.16	0.68	1.04	0.44	-2.70***
O+30	1.80*	3.31***	-0.67	1.07	0.29	0.77	0.72
O+45	2.98***	2.02**	-0.69	0.21	-1.17	-0.88	-0.70
O+60	3.22***	-0.99	-1.61	0.28	-0.54	-5.50***	-1.27
O+75	0.23	0.85	0.27	-0.50	-2.43**	-0.49	0.03
O+90	2.09**	3.49**	-1.02	-0.49	-2.35**	-0.46	-0.98
O+105	-0.07	2.59***	-0.82	0.34	1.12	-0.41	-1.50
O+120	-0.30	0.40	-0.08	3.69***	0.98	0.42	-1.04
O+135	0.68	0.46	0.08	-0.75	-0.23	0.37	-0.30
O+150	2.04**	2.48**	1.49	0.97	0.72	1.12	0.77
O+165	2.98***	-2.26**	-0.04	1.47	1.84*	0.23	-2.45**
O+180	0.89	-0.71	0.49	-0.50	0.51	0.56	-0.26
O+195	-0.49	0.19	0.61	-0.20	0.34	1.59	-0.14
O+210	-0.44	-1.71*	-0.89	0.10	0.30		
O+225	0.03	1.65*	0.11	-0.32	0.20		
O+240	1.76*	-0.96	0.20	-0.13	0.24		
O+255	-1.74*	0.72			-0.42		
C-255	-1.46	0.09			-0.33		
C-240	0.80	2.20**	-0.12	0.25	-0.29		
C-225	-0.12	-0.98	0.17	0.74	-0.61		
C-210	0.97	0.36	0.13	0.02	0.62		
C-195	2.57***	0.81	0.93	1.63	1.55	0.98	-0.86
C-180	-0.34	-0.98	1.00	-0.34	0.92	0.80	1.02
C-165	-0.34	0.86	-0.42	-0.02	-0.40	5.76***	0.23
C-150	0.23	0.43	0.17	1.07	0.92	1.49	-0.83
C-135	-0.92	0.27	-0.39	-0.24	0.34	0.57	0.48
C-120	-0.34	1.55	0.62	0.16	0.05	0.87	-1.07
C-105	0.64	1.36	1.27	-0.31	0.69	-1.84*	0.09
C-90	-0.13	1.15	-0.14	-0.21	-0.30	1.03	-0.67
C-75	1.58	0.24	0.08	0.47	-0.96	0.71	2.10**
C-60	-0.97	-1.00	1.05	-0.67	-0.18	-0.13	-0.22
C-45	2.39**	1.39	0.60	-0.74	0.62	0.46	-0.28
C-30	1.50	-0.06	1.11	0.55	0.79	0.72	-1.61
C-15	2.75***	2.04**	0.34	0.60	1.96**	1.74	0.73
C-0	3.71***	0.21	-0.61	-1.96**	-2.15**	-0.38	-0.52
All day	4.63***	4.73***	0.73	1.11	0.15	1.08	-2.96***

*NOTE. This table reports the t-statistics of a t-test that evaluates the difference between average returns on specific standardized intervals of specific days in the year, compared to the similar standardized interval in the rest of the days in the sample. "O+x" refers to the interval ending x minutes after the market open. "C-y" refers to the interval ending y minutes before the market close. ***, **, and * denote significance at the 99%, 95%, and 90% levels, respectively. EOQ-end of quarter days, BOQ-beginning of the quarter days, DEX-associated derivative expiry days, LTDD-last trading day of associated derivative contracts, DEX_2w-last 2 weeks prior to associated derivative expiry day.*

Table A4

Results of t-test for the Difference in Average Returns between Liquidity Portfolios and the Portfolio Formed Using the Most Liquid Stocks

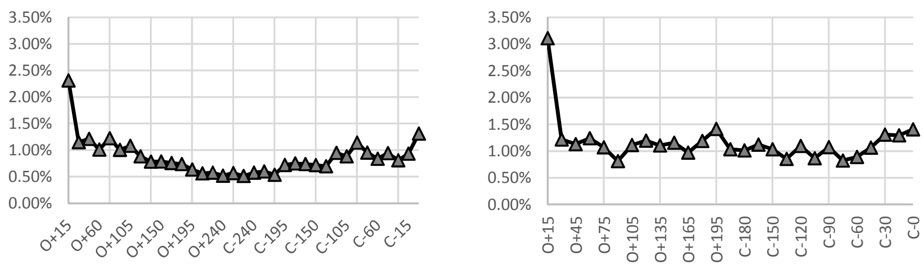
	Romania			Bulgaria		
Time of Day	Portfolio 2	Portfolio 3	Portfolio 4	Portfolio 2	Portfolio 3	Portfolio 4
O+15	3.42***	0.34	-3.48***	-2.22**	0.03	-4.43***
O+30	-2.06**	-0.73	-1.82*	-0.40	-1.59	-1.91*
O+45	-0.45	1.78*	0.68	1.14	-0.24	1.16
O+60	-3.97***	0.67	-1.88*	-0.01	-0.57	1.85*
O+75	-0.73	0.17	-1.01	-1.41	-1.60	2.32**
O+90	1.38	1.01	1.64	-1.01	2.31**	0.29
O+105	-2.02**	-0.59	-1.72*	0.58	1.31	1.22
O+120	-1.91*	-1.34	-1.05	-0.97	-1.04	-0.32
O+135	-0.25	-0.21	-1.24	1.38	-0.10	-1.52
O+150	-0.21	-0.73	-1.79*	1.38	-0.79	-1.64
O+165	-0.44	-2.57***	-2.76***	0,06	-1,63	0,79
O+180	-1,50	-1,67*	-0,90	0,93	0,61	1,62
O+195	-1,68*	-1,25	-2,07**	1,28	0,23	-0,15
O+210	-1,80*	-0,49	-1,03			
O+225	0,23	-2,13**	-0,07			
O+240	-0,57	0,06	-0,94			
O+255	-0,24	-0,66	-1,81*			
C-255	-0,24	0,27	0,54			
C-240	-0,53	-1,09	-0,94			
C-225	0,18	1,36	-0,57			
C-210	0,92	-1,18	-0,69			
C-195	-1,98**	-1,75*	-2,33**	2,01**	-1,70*	-0,02
C-180	-2,32**	-1,32	-1,08	-0,18	-0,63	0,24
C-165	0,15	0,82	-1,97**	-0,44	1,39	-0,79
C-150	-1,62	-1,07	-2,52**	1,66*	0,46	-0,22
C-135	-0,39	-3,69***	-0,09	0,92	-0,92	1,34
C-120	-0,27	0,52	-0,88	-0,07	0,31	2,42**
C-105	-1,31	-0,84	-1,00	-0,57	-0,53	0,54
C-90	1.12	-1.06	-0.33	-0.40	0.65	1.55
C-75	0.99	0.23	0.95	0.64	0.61	0.00
C-60	-1.14	-0.63	-1.08	-0.05	-0.83	1.48
C-45	-0.35	0.17	0.41	1.25	-1.40	2.11
C-30	-1.07	0.22	0.43	-0.45	-2.66***	-0.90
C-15	-4.08***	-2.33**	-0.76	-1.06	-0.05	2.71***
C-0	2.21**	4.07***	11.62***	-1.98**	2.44**	-1.84*
ALL	-1.63	-0.93	-1.20	-1.51	-0.89	0.71

*NOTE. This table reports the t-statistics of the tests that evaluate the difference between average returns on specific standardized intervals for three liquidity portfolios, compared to the similar standardized interval for the most liquid portfolio (first quartile of stocks when grouped by liquidity). "O+x" refers to the interval ending x minutes after the market open. "C-y" refers to the interval ending y minutes before the market close. ***, **, and * denote significance at the 99%, 95%, and 90% levels, respectively. Portfolio x designates the equal-weighted portfolio formed using stocks in the x-th quartile when sorted by liquidity.*

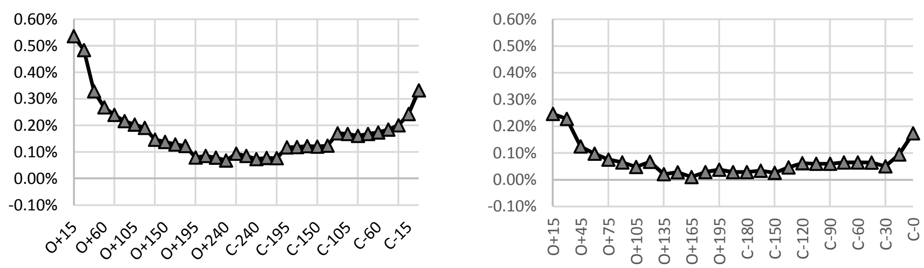
Figure A2

Intraday Patterns in Volatility and Liquidity on BVB (Left) and BFBS (Right)

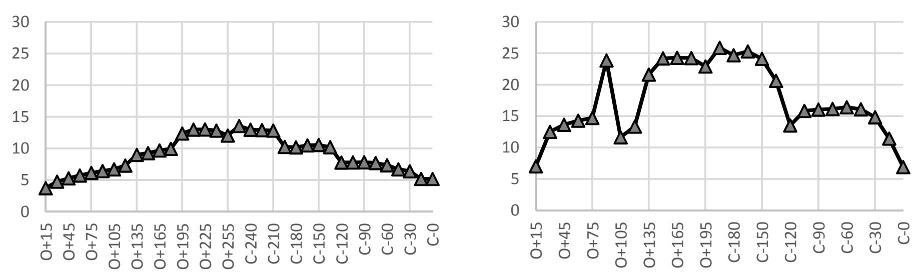
Panel A: Standard Deviation of Returns



Panel B: Average Trading Range (relative difference between High price and Low price)



Panel C: Average Time Between Trades (minutes)



Panel D: Average Turnover (EUR equivalent)