6. INTRADAY MARKET EFFICIENCY FOR A TYPICAL CENTRAL AND EASTERN EUROPEAN STOCK MARKET: THE CASE OF ROMANIA

Dan Gabriel ANGHEL[*]

Abstract

Investors increasingly focus on high frequency data for fine-tuning portfolio management decisions in developed, emerging and frontier markets alike. However, the behavior of intraday price movements in the Central and Eastern European stock markets is insufficiently understood. We obtain a large sample of intraday prices in a typical Central and Eastern European stock market and we thoroughly investigate it for dependencies and economic profit opportunities. We determine that intraday price movements present important deviations from a random walk. Despite this, we find that investors are generally unable to use the dependencies imbedded in the price movements to gain economic profits when using trading strategies derived from three popular technical analysis indicators. Overall, we cannot reject the Efficient Market Hypothesis for intraday price movements in Romania. This implies that, because of the existing market frictions, trading on high frequency data is not feasible in the stock market of Romania, at least when using popular technical analysis indicators.

Keyword: Bootstrap, Central and Eastern Europe, Efficient Market Hypothesis, Hour of the Day Effect, Random Walk, Romanian Stock Market, Superior Predictive Ability, Technical Analysis

JEL Classification: G11, G14, G17

1. Introduction

Evaluating whether market prices aggregate information efficiently is a hot research topic in the international literature ever since Fama (1970) explicitly defined the Efficient Market Hypothesis. The topic is important because it influences investor portfolio selection and trading behavior. For example, choosing between passive and active portfolio management strategies is a question of market efficiency. Ultimately, informational efficiency has a profound impact on the way stock markets allocate resources in an economy and contributes to the wellbeing of entire nations.

[*] *Department of Money and Banking, Bucharest University of Economic Studies, E-mail: dan.anghel@fin.ase.ro.*

There is a large amount of work that investigates how efficient are stock price movements in Central and Eastern European (CEE) markets. Existing evidence shows that larger (more developed) markets – like Turkey or Poland – are more efficient than smaller (less developed) ones in this region (Smith, 2012; Todea and Plesoianu, 2013; Dragotă and Ţilică, 2014). Between the two extremes, the typical CEE stock market seems to present at least some deviations from efficiency, but the research is almost exclusively conducted on daily data. So, what about intraday price movements: do they also present deviations from efficiency and, if so, to what extent? As evidence regarding efficiency at the intraday level is scarce (especially due to insufficient data availability), we set out to fill in the gap in the literature and analyze the topic in more detail. We do this by investigating the specific case of Romania, which can be classified as a typical CEE market from the informational efficiency point of view, because it ranks in the middle in terms of efficiency in previous studies done for groups of countries in this region (Smith, 2012; Todea and Plesoianu, 2013). However, the fact that we obtain a long history of Romanian intraday trade data from a local brokerage firm significantly contributes to this choice.

Previous papers analyzing this topic in the CEE region show that daily stock prices exhibit some deviations from efficiency. This is also true when looking at the specific case of Romania (Dragotă and Oprea, 2014). Evidence is very thin when it comes to intraday price movements. Only a limited number of studies rely on intraday data in the region. For example, Deev and Linnertová (2013) reject the random walk hypothesis for intraday movements in returns on the stock market in the Czech Republic. They also find that model coefficients display significant time-variation. Bildik (2001) examines intraday "seasonality" in the stock market of Turkey and finds significant patterns in intraday returns, and also that a simple active trading strategy can earn excess returns over a passive strategy prior to transaction costs. These results reject the random walk hypothesis for intraday price movements on these markets, but cannot reject the no economic profit hypothesis. This is because market frictions (trading costs, trading restrictions, and other) can make excess returns unattainable to investors. In the case of the stock market in Romania, as far as we know, only two studies have previously examined the efficiency characteristics of the price movements on an intraday level. On the one hand, Cepoi and Radu (2014) do not reject the random walk hypothesis for intraday price movements of 4 blue chip stocks in the period January 2014 – February 2014. On the other hand, Todea and Plesoianu (2010) analyze the main market index (BET) over the period November 2009 – April 2010 using two tests of linear and nonlinear dependencies. Their results strongly reject the martingale hypothesis for intraday movements especially "due to the presence of nonlinear dependencies in the intraday data". These two papers "indicate the existence of a high potential of predictability", but their results cannot be generalized due to the limited data samples which they employ. As a result, there is a high potential for improvement and significant discoveries.

This paper contributes to the literature by thoroughly investigating informational efficiency of intraday price movements for the Romanian stock market, which is a typical one in the CEE region. The contribution is significant, because we evaluate both the random walk hypothesis as well as the no economic profit hypothesis, using a unique sample of tick-by-tick data spanning almost 11 years. We use a set of 4 econometrical tests (autocorrelation test, runs test, variance ratio test, and the hour of the day test) for investigating the random walk hypothesis, and trading simulation to evaluate if economic profit opportunities exist for investors trading using some popular technical analysis indicators. In the investigation on economic profits, we use the SPA test of Hansen (2005) to control for the data snooping bias, which, as far as we know, is a new approach for the literature on intraday price movements in the CEE region. Thus, this paper is important for scholars concerned with the topic on informational efficiency because it sheds some light on the behavior of intraday prices for a typical (fairly young, less developed and less liquid) market in the CEE region. It is also important for practitioners who invest or are planning to invest in the CEE stock markets, because it shows exactly how informative intraday price movements are and if intraday trading strategies can be considered to gain economic profits.

The paper is structured as follows. The second section presents the data and the econometric tests employed to evaluate market efficiency at an intraday level for Romania. The third section presents the results and comments on them. Finally, the fourth section summarizes and discusses the main conclusions and presents some main directions for future research.

2. Methodology and Data

2.1. Random Walk Hypothesis Tests

The Efficient Market Hypothesis is traditionally associated with the random walk model (Fama, 1965). Thus, the first step in evaluating market efficiency is validating if this model holds on our data by searching for linear and nonlinear dependencies in prices/returns. Previous papers that analyze market efficiency at an intraday level for Romania also evaluate this model (Todea and Plesoianu, 2010; Cepoi and Radu, 2014), but they do it in a limited specification (on a limited number of assets and on a restricted time interval). Besides the largely expanded data sample (this is detailed in subsection 2.3), we also make two important contributions from a methodological point of view. First, we do not restrict the analysis on only one data frequency. Instead, we investigate price dependencies on a wide variety of relevant intraday data frequencies. We use 1 minute, 5 minutes, 15 minutes, 30 minutes, 60 minutes, and 180 minutes as our chosen frequencies. For a comparative analysis, we also perform the tests on daily and monthly data as well. This enables us to gain additional insight about price behavior at different time horizons, and also about if and how the market converges towards market efficiency (Chordia *et al*., 2005). Second, we thoroughly examine the random walk property of stock returns by employing a broad set of econometric tests: the autocorrelation test, the runs test, the variance ratio test and the hour-of-the-day test. Using more than one test has the advantage of reducing model bias, thus providing more robust conclusions.

The autocorrelation test is designed to capture linear dependencies between successive returns. If we denote by $R_t = ln(P_t / P_{t-1})$ the geometric return computed at time *t* for a given price series, then we can estimate the linear autocorrelation coefficient for a given lag $k > 0$ using the regression:

$$R_t = \alpha + \beta R_{t-k} + \varepsilon_t$$

The existence of statistically significant autocorrelation coefficients would imply a violation of the random walk model. Note that we use the following set of lags when analyzing the autocorrelation patterns at all previously specified data frequencies $k = \{1, 2, 3, 4, 5, 6, 7, 8, 10, 12, 14, 16, 20, 24, 28, 32\}$.

The runs test (Wald and Wolfowitz, 1940) is a nonparametric test design to evaluate the null hypothesis that a series of price runs are independent and identically distributed. A run can be characterized as a sequence of similar sign price movements; thus, a positive run is a sequence of rising market prices, while a negative run is a sequence of declining or stagnating prices. If N_+ denotes the number of positive runs, N_- denotes the number of negative runs, and $N = N_+ + N_-$ denotes the total number of runs, then the expected number of runs (μ) and expected variance (σ^2) under the test null hypothesis should equal:

$$\mu = \frac{2N_+N_-}{N} + 1$$

$$\sigma^2 = \frac{(\mu - 1)(\mu - 2)}{N - 1}$$

When the actual number of runs is significantly different than expected, we can reject the null hypothesis and conclude that the price run series is not independent and identically distributed. This, in turn, would signal nonrandom price movement and would imply a violation of the random walk model.

The variance ratio test (Lo and MacKinlay, 1988) is a more recent test of the random walk model when compared with the previous two. It is based on the observation that the variance of a random walk return series should be linearly related to the sampling interval *q*. Thus, one can check if the price series is a random walk by defining the following variance ratio:

$$VR(q) = \frac{\tau_q^2}{q\tau^2}$$

In this specification, τ_q^2 represents the variance of a q-period return series, while τ^2 represents the variance of a 1-period return series. The random walk hypothesis will be rejected if the *VR(q)* statistic is significantly different from unity. Note that we conduct the variance ratio tests by assuming heteroskedasticity and by taking q from the following set of values *q = {2, 4, 8, 16}*.

Finally, *the hour-of-the-day (HoD) test* is designed to capture the "seasonality" of intraday price movements, similar to how the day-of-the-week test (Gibbons and Hess, 1981) or the month-of-the-year test (Rozeff and Kinney, 1976) deal with seasonality at daily and monthly intervals. We perform the *HoD* test using a simple linear specification, where we assign one dummy variables to price returns on each specific hour of the day:

$$R_t = \alpha + \sum \beta_h D_{h,t} + \varepsilon_t$$

In this specification, α is the intercept and $D_{h,t}$ represents the dummy variable associated with trading hour *h*. Because of its specification, the *HoD* test uses only data which is aggregated at 60 minutes. Intraday seasonality is identified using statistically significant dummy coefficients and imply a violation of the random walk hypothesis[1].

2.2. Trading Simulation Tests

The previous econometric tests enable us to evaluate if intraday stock prices on the Bucharest Stock Exchange are random walks. However, despite the classic definition of the Efficient Market Hypothesis, one might expect that this model does not adequately describe price behavior in real financial markets. The same is true for the martingale model, which is used as a reference following Fama (1970). The reason for this is the presence of market frictions (Grossman and Stiglitz, 1980). As a consequence, even if we reject the random walk model for a given stock, we cannot implicitly reject market efficiency. More recent

[1] *Using more advanced approaches to model intraday "seasonality" (such as a conditional variance approach-GARCH) could reveal some more insights into this aspect. However, a detailed analysis on the intraday patterns in stock prices is outside the scope of this paper, but can be addressed in future research.*

definitions of this concept are given by Jensen (1978) and Timmerman and Granger (2004). These connect market efficiency with the absence of economic profit opportunities. That is, in an efficient market, investors should not be able to gain statistically significant cost and risk adjusted returns over the market equilibrium return. Given this definition, a test which evaluates economic profit opportunities would be more relevant when trying to evaluate market efficiency. We perform such a test on our intraday data using the framework provided by Anghel (2015). The trading test employs a large number of practical prediction trading strategies from technical analysis indicators and searches for abnormal profit opportunities. Although Anghel (2015) uses 44 technical analysis indicators, here we only focus on three of the most popular ones: the Filter, the Moving Average Convergence-Divergence (MACD) and the Relative Strength Index (RSI). We do this because the test takes less time to compute and it should be representative for the bulk of the technical analysis indicator population. Another reason for selecting only these three is the need to assure comparability with other similar papers: the Filter, the RSI and the MACD indicators are widely employed in trading simulation tests at the international level (Park and Irwin, 2007).

Starting with Alexander (1961), the Filter rule has been widely used in market efficiency tests. The Filter can be defined in several ways, but it basically measures the relative price change when compared to previous local extremes. Here, we only focus on price troughs and define the filter as:

$$F_t(n) = \ln\left(\frac{C_t}{\min(L_t, L_{t-1}..L_{t-n+1})}\right)$$

In this specification, n represents the window length (i.e. the number of historical observations on which the filter searches for price troughs), C_t represents the market (close) price at time t and L_t represents the minimum (low) price at time t.

Moving averages constitute another very popular class of technical analysis indicators. The MACD indicator (Appel, 1979) is an extension of this class which is used to measure both momentum and price swings. The indicator is defined as the difference between two exponential moving averages computed over different window lengths:

$$MACD_t(n, m) = EMA_t(n) - EMA_t(m)$$

The first moving average is computed on short term, while the second is computed on medium or long term (this implies that $n < m$). On the other hand, the Exponential Moving Average can be defined as:

$$EMA_t(n) = \frac{2}{n+1} * C_t + \left(1 - \frac{2}{n+1}\right) * EMA_{t-1}(n)$$

Our final indicator is the Relative Strength Index (Wilder, 1978). It is the first indicator to be constructed especially for identifying overbought and oversold situations, although it can be viewed as a standardized momentum oscillator. It is defined as:

$$RSI_t(n) = 100 - \frac{100}{1 + RS_t(n)}$$

The term RS represents the ratio of two exponential moving averages: the first is computed using positive price increments and the second is computed using negative price increments. Both averages use the same n-period window length.

The trading simulation algorithm starts by using the previous described technical analysis indicators to construct trading rules and their corresponding trading strategy, which can be represented through a signal function (δ):

$$\delta_{t+1} = 1_{\{trading\ rule\}}$$

The signal actually represents the position that an investor is supposed to take in the market: 1 represents a long position and 0 represents that no position should be maintained. On the other hand, the trading rule is a logical proposition which is constructed using one of the previous mentioned indicators. For example, the trading rule *"MACD(12,26)>0"* is true when the difference between the 12-period and the 26-period exponential moving averages is positive (this represents a standard moving average crossover rule). Given that the moving average window lengths and the value to which the difference is compared to are parameters, we can construct other trading rules (trading strateies) by varying the parameters. We exactly follow Anghel (2015) and define multiple trading strategies for which we vary the parameters. Using the 3 indicators, this parameterization process produces a total of *m=15668* unique trading strategies in our case. All other aspects of the procedure are identical, including the transaction fee, which is set at 1% for a round trip, and the trading method, which simulates transactions at the least favorable prices.

Next, we conduct trading simulation using each individual trading strategy. The inherent data snooping bias is controlled by implementing Hansen's (2005) Superior Predictive Ability (SPA) test. This test uses the stationary bootstrap procedure of Politis and Romano (1994) to construct adequate confidence intervals for the test statistic. The statistic is based on the maximum average excess return evaluated over all individual trading strategies (*k = 1...m*) and it is designed to evaluate the null hypothesis that the best trading strategy in the rule universe has no predictive superiority over the benchmark buy and hold strategy. Using Hansen's (2005) original notations, below we provide the equations for the average excess return of each trading strategy *k* ($\bar{d}_k$), the adjusted (centered) average excess return ($\bar{d}_k^c$), the SPA test statistic (T_n^{SPA}) and the p-value that is used to evaluate the test null hypothesis ($\hat{p}_{SPA}$):

$$\bar{d}_k = \frac{1}{n}\sum_{t=2}^{n} \delta_{k,t-1}\zeta_t - \delta_{0,t-1}\zeta_t$$

$$\hat{d}_k^c = \bar{d}_k 1_{\left\{\frac{n^{1/2}\bar{d}_k}{\hat{\omega}_k} \leq -\sqrt{2\log\log n}\right\}}$$

$$T_n^{SPA} \equiv \max\left[\max_{k=1...m} \frac{n^{1/2}\hat{d}_k^c}{\widehat{\omega}_k}, 0\right]$$

$$\hat{p}_{SPA} \equiv \sum_{b=1}^{B} \frac{1_{\left\{T_{b,n}^{SPA*} > T_n^{SPA}\right\}}}{B}$$

where: ζ_t denotes the geometric return series of a given listed stock, *n* is the length of the return series, $\widehat{\omega}_k$ denotes the standard deviation of the excess return series, and $T_{b,n}^{SPA*}$ denotes the empirical distribution of the test statistic estimated using the bootstrap procedure with *b = 1...B* simulations (we use *B = 1000*). The SPA null hypothesis is rejected with 90% confidence when the estimated SPA p-value is lower than or equal to 10%. A SPA test null rejection means that at least one of the considered technical analysis trading strategies is capable of earning significant excess returns over the benchmark. Based on the intuition that no active trading strategies should be able to consistently outperform a passive strategy in an efficient market, we can reject market efficiency when the SPA test null is rejected.

2.3. Data

To the extent of our knowledge, the use of Hansen's (2005) test is a new approach to evaluating market efficiency on any data frequency in CEE stock markets. In this sense, it is an important aspect of our contribution, but the contribution that this paper makes also heavily depends on the unique data sample that it employs. Specifically, we use tick-by-tick data starting March 4, 2005 and ending December 11, 2015, this amounting to 10 years and 10 month of complete trading history for all stocks that are (were) listed on the Bucharest Stock Exchange in this period. The data is provided by Tradeville (*http://tradeville.eu/*), a local stock broker that specializes in retail services. Each observation consists of a timestamp, the stock symbol, the volume and the trade price. We include all companies that have been listed in the period, irrespective of their current status, as to not expose the analysis to survivorship bias. We filter out stocks that have less than 10 trades a day on average, because we also want to avoid complications derived from applying statistical tests to stocks which are virtually not traded. We are left with a sample of 5,597,057 individual tick observations for 48 stocks that are (were) traded on the Bucharest Stock Exchange in the interval[2]. Table 1 provides a summary of the data (the values in the final column represent the average number of trades per month, as a proxy for market liquidity).

Table 1

Data summary

Ticker symbol	No. of ticks	Date and time of first tick	Date and time of last tick	Avg. ticks/month
ALBZ	74,827	10.06.2005 10:34:38	11.12.2015 18:01:50	589
ALT	39,487	04.03.2005 12:29:55	10.12.2015 11:35:02	304
ALU	27,340	19.12.2006 14:52:08	09.12.2015 14:00:01	251
AMO	114,200	04.03.2005 12:31:57	05.06.2015 12:56:29	921
ARAX	102,905	07.03.2005 10:31:58	09.12.2015 17:06:03	792
ARCV	60,144	19.12.2006 11:48:21	11.12.2015 17:11:03	552
ARDF	14,561	07.06.2005 10:15:11	27.11.2009 10:20:47	270
ATB	73,348	07.03.2005 10:15:10	11.12.2015 17:24:46	564
AUCS	20,106	21.10.2005 08:44:46	12.01.2010 11:40:48	387
AZO	91,638	07.03.2005 10:15:30	21.08.2012 13:20:53	1,018
BCC	94,328	04.03.2005 12:30:19	11.12.2015 18:03:04	726
BIO	132,570	30.11.2005 10:16:11	10.12.2015 16:51:11	1,087
BRD	217,642	07.03.2005 10:15:22	11.12.2015 18:00:32	1,674
BRK	197,007	04.03.2005 12:56:31	11.12.2015 17:14:37	1,515
BVB	60,302	08.06.2010 10:00:08	11.12.2015 15:28:59	900
CEON	27,656	12.06.2006 11:44:59	10.12.2015 09:50:35	240
CMP	46,228	04.03.2005 12:24:04	11.12.2015 15:53:04	356
COFI	31,322	07.12.2005 09:08:29	14.03.2012 16:33:51	412

[2] *A comparison between stock level results and index level results could provide aditional insights. However, our data source (and even the Bucharest Stock Exchange) does not provide historical information on intraday index values, nor on the historical constituents of the main market indices and their weights. This does not enable us to perform such a comparison. However, we note that, although testing index data may provide some insight into market-level price behavior, this is less relevant to our analysis. Specifically, as market indices in Romania have not been traded untill recently, any evidence of index predictability and/or profitable trading opportunities on the index are not relevant for investors and for the discussion on market efficiency.*

Ticker symbol	No. of ticks	Date and time of first tick	Date and time of last tick	Avg. ticks/month
COMI	80,204	07.03.2005 13:58:37	20.07.2015 14:09:35	642
CRB	7,648	04.03.2005 12:58:32	05.04.2007 13:09:52	294
DAFR	134,635	22.03.2006 11:41:22	19.06.2015 12:32:59	1,202
EL	38,505	27.06.2014 18:19:08	11.12.2015 18:02:28	2,027
ELMA	51,263	04.03.2005 13:07:06	11.12.2015 14:56:42	394
FLA	20,924	18.07.2005 10:15:39	14.12.2009 11:33:08	387
FP	236,109	25.01.2011 10:00:18	11.12.2015 18:03:21	3,935
IMP	78,210	04.03.2005 12:35:44	11.12.2015 18:00:01	602
IPRU	41,424	04.03.2005 12:25:55	11.12.2015 15:44:13	319
OIL	40,939	04.03.2005 13:02:30	11.12.2015 18:00:00	315
OLT	85,810	07.03.2005 10:15:09	11.12.2015 16:42:10	660
PRSN	78,111	30.03.2006 12:36:29	11.12.2015 17:22:00	662
PTR	44,917	04.03.2005 12:53:11	09.12.2015 12:53:36	346
RRC	188,774	04.03.2005 12:24:19	11.12.2015 18:00:00	1,452
SCD	42,951	04.03.2005 12:36:45	11.12.2015 17:27:06	330
SIF1	288,413	14.03.2005 10:15:10	11.12.2015 18:00:00	2,219
SIF2	392,363	14.03.2005 10:15:30	11.12.2015 18:02:22	3,018
SIF3	456,638	14.03.2005 10:15:18	11.12.2015 18:08:26	3,513
SIF4	287,092	14.03.2005 10:15:16	11.12.2015 17:33:34	2,208
SIF5	445,301	14.03.2005 10:15:46	11.12.2015 18:00:01	3,425
SNG	64,467	06.11.2013 16:06:14	11.12.2015 18:05:47	2,480
SNN	43,896	26.09.2013 14:33:48	11.12.2015 18:09:25	1,568
SNP	335,526	07.03.2005 10:15:18	11.12.2015 18:09:58	2,581
SRT	28,765	04.03.2005 12:26:34	14.11.2014 17:02:01	246
TBM	61,252	07.03.2005 11:02:15	11.12.2015 18:04:24	471
TEL	143,854	29.08.2006 10:15:35	11.12.2015 18:00:00	1,273
TGN	112,123	11.12.2007 09:06:31	11.12.2015 18:05:20	1,156
TLV	299,722	07.03.2005 10:15:29	11.12.2015 18:00:25	2,306
VEGA	12,561	04.03.2005 13:08:43	15.12.2008 11:50:42	273
VNC	29,049	15.07.2005 10:15:49	11.12.2015 17:25:24	231

We should note that analyzing intraday price movements (based on tick-by-tick data) using the econometrical tests presented in subsection 2.1 can be biased by known microstructural phenomenon, such as nonsynchronous trading effects, the bid-ask bounce or low market resilience (Heston *et al.*, 2010; Anderson *et al.*, 2013).These effects are expected to be particularly important in less liquid stock markets such as the one that we analyze here. In order to control for spurious results, we conduct the econometrical tests in subsection 2.1 using both close-to-close returns, as well as open-to-close returns. Also, we perform an additional robustness check using a limited sample of returns computed from bid-ask midpoints. For the latter, we employ a sample of bid and ask quotes for 3 of the 48 analyzed companies (BRD, FP and SNP) in the period October 19, 2012 – May 3, 2013. All in all, using the three alternative return measurements should enable us to make more relevant inferences. On the other hand, this adjustment is not necessary for the trading simulation tests, because the procedure implicitly controls for spurious results by simulating trading at the least favorable prices during a specific time interval (Anghel, 2015).

3. Results

3.1. Full sample tests

In this section, we report and comment on the results obtained for the full sample between 2005 and 2015. Tables 2, 3 and 4 report the autocorrelation test results for each data frequency and lag. For the close to close returns, we observe a significant negative autocorrelation at the first lag, irrespective of the data frequency. Following the first lag, the negative autocorrelation persists for several more lags at higher data frequencies (1 minute to 30 minutes), but disappears at other data frequencies. In general, we find that intraday price movements display a short term negative linear dependence and a medium to long-term positive linear dependence. The negative autocorrelation at lower lags may be explained either by the bid-ask bounce effect or by low market resilience (see Heston *et al.*, 2010, pp.1381-1383, for details). The autocorrelation coefficients computed using the bid-ask midpoint returns helps us discern between the two. Table 4 shows that the negative autocorrelation remains persistent at the first lag, but the coefficients drop by a half in the case of 1 minute returns and by more than two thirds in the case of the other intraday frequencies. Also, the negative autocorrelations generally disappears at all other lags. This means that low market resilience is partially responsible for the observed short term negative autocorrelations, but the bid-ask bounce effect is more important in shaping intraday autocorrelation patterns. Also, the explanation power of low market resilience for the observed negative autocorrelation coefficients drops as we decrease the data frequency. Finally, when using open-to-close return series, the test reveals all around positive autocorrelation for all data frequencies and all lags. This highlights that, when eliminating the effects of the bid-ask bounce, the intraday returns are generally positively autocorrelated. All in all, the autocorrelation test results are consistent with international evidence regarding intraday autocorrelation patterns (Heston *et al.*, 2010). Thus, the results reject return independence and, in turn, reject the random walk hypothesis for intraday price movements on the stock market in Romania.

Table 2

Average autocorrelation coefficients (close-to-close returns)

Lag	Frequencies							
	1m	5m	15m	30m	60m	180m	D	M
1	-0.2962	-0.2728	-0.2549	-0.2349	-0.2105	-0.1515	-0.0033	0.0130
2	-0.0037	-0.0122	-0.0087	-0.0123	0.0040	0.0424	0.0062	0.0000
3	-0.0122	-0.0111	-0.0104	-0.0006	0.0065	0.0246	0.0028	0.0123
4	-0.0009	-0.0049	-0.0017	0.0040	0.0177	-0.0077	0.0042	-0.0010
5	-0.0040	-0.0006	0.0020	0.0081	0.0182	-0.0035	0.0077	0.0013
6	-0.0018	-0.0016	0.0035	0.0069	0.0081	0.0163	-0.0066	0.0506
7	0.0002	0.0011	0.0014	0.0087	0.0053	-0.0087	0.0035	0.0094
8	-0.0009	0.0001	0.0039	0.0092	0.0010	0.0030	0.0078	-0.0366
10	0.0003	0.0005	0.0026	0.0053	0.0020	-0.0044	0.0000	-0.0229
12	-0.0006	0.0000	0.0054	0.0031	-0.0055	0.0116	-0.0022	0.0344
14	0.0003	0.0030	0.0059	0.0052	-0.0005	0.0025	0.0165	-0.0352
16	0.0009	0.0021	0.0015	-0.0029	-0.0033	-0.0012	0.0149	-0.0233
20	0.0008	0.0035	0.0025	-0.0009	0.0007	0.0015	-0.0121	0.0128
24	0.0014	0.0021	0.0014	-0.0040	-0.0003	0.0162	-0.0127	-0.0312
28	0.0000	0.0003	0.0010	0.0000	0.0031	0.0027	-0.0029	-0.0369
32	0.0008	-0.0005	-0.0016	0.0017	-0.0027	0.0020	-0.0045	-0.0265

Table 3

Average autocorrelation coefficients (bid-ask midpoint returns)

Lag	Frequencies						
	1m	5m	15m	30m	60m	180m	D
1	-0.1445	-0.0926	-0.0765	-0.0461	-0.0128	0.0152	0.0583
2	0.0136	0.0150	-0.0003	0.0015	0.0248	0.0124	0.0803
3	-0.0220	-0.0202	0.0109	0.0268	0.0042	0.0851	0.1443
4	0.0060	0.0088	-0.0133	0.0053	0.0123	-0.0714	-0.0103
5	0.0186	0.0000	0.0200	0.0009	0.0089	0.0108	-0.0074
6	-0.0040	0.0007	0.0052	0.0098	0.0039	0.0096	0.0625
7	0.0149	-0.0145	0.0277	0.0049	0.0614	0.0823	0.0733
8	-0.0130	0.0200	-0.0138	0.0195	-0.0114	0.0161	0.0252
10	0.0165	0.0170	0.0069	-0.0085	-0.0370	0.0319	0.0909
12	-0.0005	0.0090	0.0008	0.0464	-0.0144	0.0459	-0.0685
14	-0.0025	0.0147	-0.0022	0.0163	-0.0077	-0.0069	-0.0350
16	0.0093	0.0151	0.0212	-0.0217	0.0352	-0.0071	-0.0437
20	0.0024	-0.0023	0.0170	-0.0246	0.0068	-0.0267	-0.1258
24	-0.0077	0.0051	-0.0301	0.0145	-0.0011	-0.0349	-0.0505
28	-0.0009	-0.0066	0.0190	-0.0123	0.0393	-0.0006	-0.1197
32	0.0009	0.0037	-0.0238	0.0245	-0.0339	0.0607	-0.0832

Table 4

Average autocorrelation coefficients (open-to-close returns)

Lag	Frequencies							
	1m	5m	15m	30m	60m	180m	D	M
1	0.0290	0.0324	0.0189	0.0141	0.0071	0.0267	0.0783	0.0979
2	0.0222	0.0145	0.0136	0.0080	0.0206	0.0502	0.0441	0.0057
3	0.0242	0.0127	0.0108	0.0157	0.0187	0.0250	0.0432	0.0685
4	0.0127	0.0115	0.0077	0.0108	0.0225	0.0150	0.0296	0.0626
5	0.0109	0.0092	0.0106	0.0141	0.0195	0.0221	0.0367	-0.0207
6	0.0092	0.0043	0.0103	0.0181	0.0201	0.0280	0.0184	-0.0356
7	0.0080	0.0082	0.0081	0.0130	0.0091	0.0089	0.0404	0.0022
8	0.0076	0.0109	0.0124	0.0117	0.0045	0.0236	0.0404	-0.0291
10	0.0072	0.0064	0.0069	0.0053	0.0090	0.0134	0.0278	-0.0357
12	0.0058	0.0076	0.0109	0.0099	0.0057	0.0162	0.0326	0.0172
14	0.0046	0.0080	0.0055	0.0034	0.0083	0.0104	0.0275	-0.0656
16	0.0068	0.0054	0.0059	0.0060	0.0065	0.0036	0.0330	-0.0414
20	0.0037	0.0039	0.0052	0.0062	0.0089	0.0142	0.0213	-0.0312
24	0.0037	0.0050	0.0047	0.0086	0.0081	0.0209	0.0239	-0.0769
28	0.0035	0.0059	0.0034	0.0060	0.0085	0.0137	0.0150	-0.0371
32	0.0029	0.0048	0.0049	0.0053	0.0083	0.0159	0.0281	-0.0160

Table 5 reports the results for the runs test. For each type of return series, the first column reports the null rejection rate (number of tests that identified nonrandom runs, divided by the total number of tests), the second column reports the average z-statistic, while the third column reports the average ratio between the total number of runs and the expected number of runs.

Table 5

Runs tests summary results

Frequency	Close-to-close returns			Bid-ask midpoint returns			Open-to-close returns		
	Null rejection rate	Avg. z-stat	Avg. runs / E[runs]	Null rejection rate	Avg. z-stat	Avg. runs / E[runs]	Null rejection rate	Avg. z-stat	Avg. runs / E[runs]
1 minute	91%	243.2	1.05	33%	-2.93	0.97	100%	-71.15	0.91
5 minutes	100%	56.74	1.06	33%	-1.29	0.98	100%	-30.80	0.91
15 minutes	100%	11.59	1.07	33%	-1.03	0.98	100%	-11.65	0.91
30 minutes	100%	10.87	1.09	0%	0.65	1.01	100%	-8.28	0.93
60 minutes	100%	9.15	1.09	33%	0.65	1.02	97%	-5.98	0.93
180 minutes	87%	6.42	1.09	0%	0.91	1.04	87%	-3.64	0.94
Daily	50%	0.54	1.01	66%	-0.08	0.99	91%	-3.62	0.91
Monthly	27%	-0.50	0.96	0%	-0.26	0.93	16%	-0.61	0.94

Using close-to-close returns, we observe that price runs at the intraday levels are much more frequent than what we might expect from random prices. This denotes a mean-reverting behavior. On the other hand, using open-to-close returns, we observe that intraday price series display momentum, with the number of actual runs being significantly lower than the expected number of runs. Finally, when using return series computed using bid-ask midpoints, which should be the most relevant in this analysis, we observe a combination of the previous two results: the returns display mean-reverting properties at the highest frequencies (1 minute, 5 minutes and 15 minutes) and momentum properties at lower frequencies (30 minutes, 60 minutes and 180 minutes). In this aspect, the runs tests are in accordance with the results obtained for the autocorrelation tests. The high number of runs corresponds to negative autocorrelation patterns – price reversals – at lower frequencies, while the low number of runs corresponds to positive autocorrelation patterns–price momentum–at other frequencies. Thus, the runs test reinforces the rejection of the random walk hypothesis for intraday price movements in Romania.

Tables 6 and 7 report the summary results for the variance ratio tests. Here, we omit the results for open-to-close returns because they are less relevant and because the other two converge in terms of a similar conclusion. In general, most variance ratios are significantly different than unity.

Table 6

Average variance ratios (close-to-close returns)

Lag	Frequencies							
	1m	5m	15m	30m	60m	180m	D	M
2	0.7574	0.7853	0.8058	0.8308	0.8491	0.9055	1.0131	1.0111
4	0.6226	0.6639	0.7048	0.7448	0.7938	0.9060	1.0361	1.0615
8	0.5584	0.6071	0.6662	0.7300	0.8046	0.9194	1.0329	1.1524
16	0.5312	0.5897	0.6700	0.7425	0.8157	0.9192	1.0301	1.2132

Table 7

Average variance ratios (bid-ask midpoint returns)

Lag	Frequencies							
	1m	5m	15m	30m	60m	180m	D	M
2	0.8552	0.9083	0.9271	0.9565	0.9867	1.0154	1.0680	
4	0.7870	0.8690	0.8962	0.9489	1.0092	1.0831	1.2636	
8	0.7652	0.8495	0.9020	0.9737	1.0624	1.1237	1.5319	
16	0.7647	0.8724	0.9445	1.0473	1.0899	1.3449	1.9980	

Specifically, 81.94% (40.27%) of all variance ratio tests performed on all intraday data frequencies for the close-to-close (bid-ask midpoint) returns reject the null hypothesis at the 5% confidence level. The null rejection rate reaches 76.28% (31.94%) for the 1% confidence level. These results provide additional evidence to reject the random walk hypothesis for intraday price movements. Besides the general conclusion, we also note that the variance ratios increase as we decrease the data frequency, or as we decrease the lag. This is also in line with the runs and autocorrelation test results as they point out to the same conclusion: intraday returns are mean-reverting at higher intraday frequencies and display momentum at lower intraday frequencies, with the mean-reversion being explained by the bid-ask bounce effect and by imperfect market resilience.

We finally evaluate the random walk hypothesis by looking at intraday "seasonality". We mainly analyze close-to-close returns (Table 8) because they should not be affected by the microstructural noise in this test. We also compute and report the results for bid-ask midpoint returns (Table 9), as to provide a robustness check. Columns 2, 3 and 4 report the results for all estimated hourly coefficients, while columns 5, 6, 7 and 8 report the results for statistically significant coefficients only (we use a threshold significance level of 10%). Overall, almost 40% of the estimated dummy coefficients (for all stocks and for all trading hours) are statistically significant.

Table 8

Hour of the day tests summary results (close-to-close returns)

Hour of the Day	Avg. coefficient	Avg. t-stat	Avg. p-value	Percent Significant coefficients	Avg. significant coefficient	Avg. t-stat*	Avg. p-value*
Open	0.62%	1.63	0.2259	48.78%	1.34%	3.46	0.0163
11	0.06%	2.48	0.1664	72.34%	0.09%	3.28	0.0120
12	-0.11%	-2.05	0.1544	51.06%	-0.15%	-3.18	0.0054
13	-0.08%	-1.51	0.2468	51.06%	-0.13%	-2.30	0.0380
14	-0.05%	-0.97	0.3543	34.04%	-0.11%	-1.86	0.0497
15	0.04%	-0.21	0.3850	17.02%	0.24%	-0.59	0.0443
16	-0.03%	-0.95	0.4170	19.15%	-0.17%	-2.59	0.0197
17	0.08%	1.16	0.3052	37.78%	0.23%	2.48	0.0247
18	0.21%	1.30	0.3549	41.46%	0.44%	2.76	0.0187
Close	0.23%	0.40	0.4018	10.81%	1.50%	2.48	0.0300

Table 9

Hour of the day tests summary results (bid-ask midpoint returns)

Hour of the Day	Avg. coefficient	Avg. t-stat	Avg. p-value	Pct. Significant coefficients	Avg. significant coefficient	Avg. t-stat*	Avg. p-value*
Open	0.23%	1.80	0.2568	59.52%	0.33%	2.76	0.0225
11	0.11%	2.80	0.1979	66.67%	0.14%	3.96	0.0096
12	0.01%	-0.32	0.3795	27.08%	0.02%	-0.98	0.0428
13	0.01%	-0.15	0.4951	14.58%	0.13%	0.72	0.0559
14	0.03%	0.15	0.4564	12.50%	0.15%	0.69	0.0500
15	0.06%	0.87	0.3373	37.50%	0.08%	1.71	0.0452
16	0.07%	0.15	0.4404	18.75%	0.10%	0.73	0.0383
17	0.09%	2.12	0.2187	58.70%	0.12%	3.13	0.0235
18	0.21%	2.16	0.2840	54.76%	0.34%	3.52	0.0221
Close	0.08%	0.42	0.5464	8.11%	0.31%	0.95	0.0533

This implies that significant intraday return patterns exist for the stocks which are listed on the Bucharest Exchange, these further contradicting the random walk hypothesis for intraday price movements. When we analyze the average coefficients, we see that intraday returns present a U-shape pattern: significant positive returns during the first couple of trading hours (near market opening hours), are followed by significant mid-day negative returns and by significant positive returns near market closing hours. The market-open and market-close return behavior is consistent with international evidence on intraday return seasonality (an early example is Wood *et al*., 1985), and can be explained using informed and liquidity trading (Webb *et al*., 2016). However, because the effect seems to be more pronounced for Romania when compared to more developed markets, and because significant negative mid-day negative returns also appear, it points out that other economic factors may be responsible for generating the abnormal intraday seasonality. One possible explanation is price manipulation, as pronounced positive end-of-day returns followed by significant price reversals the next day are consistent with existing theoretical and empirical evidence in this direction (Putniņš, 2012). But a detailed analysis on the intraday "seasonality" of prices in Romania is outside the scope of this paper and we do not investigate the topic further. Instead, this should constitute a very interesting direction for future research.

Thus far, the results reported for all tests clearly reject the random walk hypothesis in the case on intraday price movements on the Romanian stock market. This results extend the conclusions of Todea and Plesoianu (2010) to the whole Romanian market and to a significant time interval. It is also in accordance with previous findings for other markets in the Central and Eastern European region (Bildik, 2001; Deev and Linnertová, 2013) in showing that intraday stock prices significantly deviate from random walks. In addition, we also observe that the dependencies are lager on the intraday level compared to other commonly analyzed data frequencies (daily, weekly and monthly). Further, we note that the speed of convergence towards efficiency seems to be lower in Romania when compared to more developed stock markets (Chordia *et al*., 2005). Specifically, the estimated coefficients decay slower when decreasing the frequency and even remain significant for the daily and monthly data. However, as we discussed in subsection 2.2, the modern interpretation of efficiency can only be evaluated in terms of economic profit opportunities. This is done using the trading simulation test.

We present a selection of results for this test in Tables 10 and 11. Table 10 summarizes the average results and also the most favorable results in terms of rejecting market efficiency (the maximum excess return and the minimum p-value for the SPA test). To complement these summary statistics, we report the most favorable individual results in terms of rejecting market efficiency for each analyzed data frequency in Table 11. We see that only two tests reject the SPA null hypothesis, this being the case of the SNN stock prices when aggregated at 15 and 30 minute intervals. Despite of this, the rest of the tests show that the excess returns of the best trading strategies are not statistically significant when adjusting for market frictions and data snooping. This is a very interesting finding, as it shows that the previously discovered intraday price dependencies – which reject the random walk hypothesis – do not generally give rise to economic profit opportunities when considering some very popular technical analysis indicators. The apparent contradiction in results can be explained trough market frictions: although significant price dependencies exist, these cannot be converted into economic profits due to significant transaction cost and trading limitations. As trading strategies are able to earn excess returns prior to the consideration of market frictions, this result is similar to what Bildik (2001) reported for the Turkish market. But our tests enable us to further reject the statistical and economic relevance of these returns on a large universe of trading strategies derived from technical analysis. Because of this, we cannot reject the

Efficient Market Hypothesis for intraday price movements of Romanian stocks. This conclusion stands at least when employing active intraday investment strategies using three popular technical analysis indicators (Filter, RSI and MACD).

We finally note that average excess returns (p-values) tend to rise (fall) as we decrease the data frequency (Table 10). Specifically, the considered technical analysis trading strategy universe tends to obtain the best average results on daily data, and the worst average results on 1 minute data. This result may indicate that prices become less informative and noisier as we increase the intraday data frequency. It may also point out that the earlier detected microstructural phenomenon (specifically the bid-ask bounce) disrupt the performance characteristics of active investment strategies, making them unusable in high frequency trading.

Table 10

Trading simulation summary statistics

Statistic		Frequencies						
		1m	5m	15m	30m	60m	180m	D
Number of null rejections		0	0	1	1	0	0	0
Excess return (annualized)	Maximum	364.12%	359.23%	603.00%	665.68%	293.78%	710.78%	1153.51 %
	Average	19.00%	19.74%	32.09%	34.10%	30.14%	52.60%	95.56%
	St. Dev.	62.39%	59.70%	98.24%	104.83%	57.59%	123.45%	223.43%
SPA p-value	Minimum	0.1690	0.2310	0.0690	0.0970	0.1700	0.2080	0.1940
	Average	0.8358	0.7836	0.7639	0.7303	0.7377	0.7104	0.6613
	St. Dev.	0.1734	0.1751	0.1887	0.1906	0.1987	0.1784	0.2057

Table 11

Best trading simulation results (p-value criteria)

Frequency	Stock symbol	Best trading strategy	Excess return (annualized)	SPA p-value
1 minute	IMP	RSI(35) |↗ 10 || RSI(35) > 95	242.61%	0.1690
5 minutes	ARAX	RSI(32) |↗ 15 || RSI(32) > 90	213.06%	0.2310
15 minutes	SNN	RSI(29) |↗ 5 || RSI(29) > 90	12.77%	0.0690
30 minutes	SNN	RSI(17) |↗ 5 || RSI(17) > 95	12.83%	0.0970
60 minutes	ARAX	RSI(14) |↗ 5 || RSI(14) > 95	142.17%	0.1700
180 minutes	BRK	RSI(23) |↗ 15 || RSI(23) |↘ 20	710.78%	0.2080
Daily	BRK	RSI(20) |↗ 20 || RSI(20) |↘ 25	535.46%	0.1940

Note. This table presents the best results obtained in the trading simulation tests for each data frequency, using the minimum SPA p-value criteria (column 5). The SPA test evaluates the null hypothesis that the best trading strategy in the universe has no predictive superiority over the buy and hold benchmark. A small p-value corresponds to a higher ability for the trading strategy to anticipate future prices and earn statistically significant excess returns (column 4). The first two columns present the data frequency and the stock symbol on which the best result was obtained. The third column presents the trading strategy that obtained the best result. Each strategy consists out of two trading rules that are divided using the "||" symbol: an entry/buy rule (on the left) and an exit/sell rule (on the right). The values in parenthesis represent look-back windows for calculating the indicators. The operators ">" and "<" signify "larger than" and "smaller than" respectively. The operators "|↗" and "|↘" signify "falls below and then rises above" and "rises above and then falls below" respectively. For example, the best result for the 1 minute data frequency was obtained for IMPACT Developer & Contractor SA (IMP). The strategy that obtained the best result is "RSI(35) |↗ 10 || RSI(35) > 95". It instructs the investor to buy the asset when the 35-observation Relative Strength Index (RSI) falls below and then rises above 10, and then to sell the asset when the same indicator rises above 95. However, when adjusting for data snooping, the reported 242.61% annualized excess return is not statistically significant at the 10% level (p-value is 0.1690), which means that the strategy's performance is statistically indistinguishable from the buy and hold benchmark.

3.2. Subsample tests

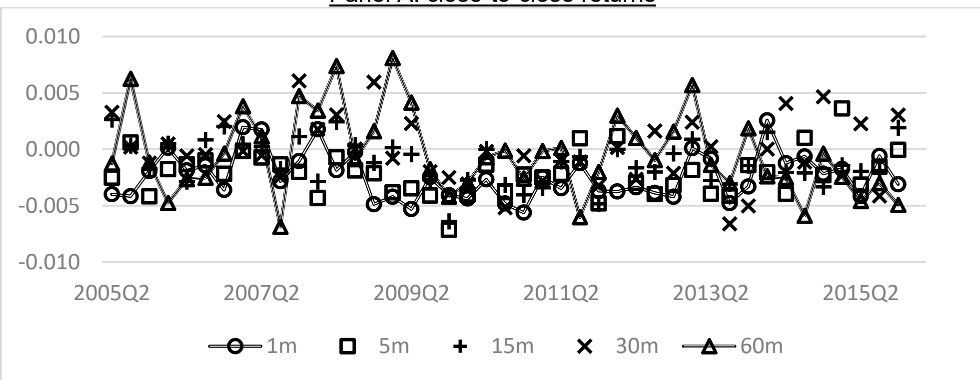
We further investigate the robustness of our results by searching for structural breaks that may occur in our sample due to significant market events such as the recent financial crisis. The investigation is performed by splitting the data into subsamples consisting of three months of trading data and performing the tests on each subsample. We obtain 44 distinct subsamples spanning 2005Q1 to 2015Q4 on which we perform the tests in section 2. Where applicable, we test for statistically significant differences between the estimated parameters using adequate t-tests (for differences in means) and F-tests (for differences in variances). In order to avoid complications arising from small samples, we only use data frequencies of up to 60 minutes and we eliminate all subsamples containing less than 30 observations. For brevity, we summarize and report only some relevant results concerning autocorrelation coefficients and variance ratios. We also report only a selection of relevant results from the trading simulation tests. A complete set of test results can be provided on request by the corresponding author. However, we note that the conclusions that can be drawn from the unreported results converge with the ones that are stated in the following paragraphs.

Figure 1 reports average autocorrelation coefficients for all considered data frequencies.

Figure 1

Average autocorrelation coefficients

Panel A: close-to-close returns



Panel B: open-to-close returns

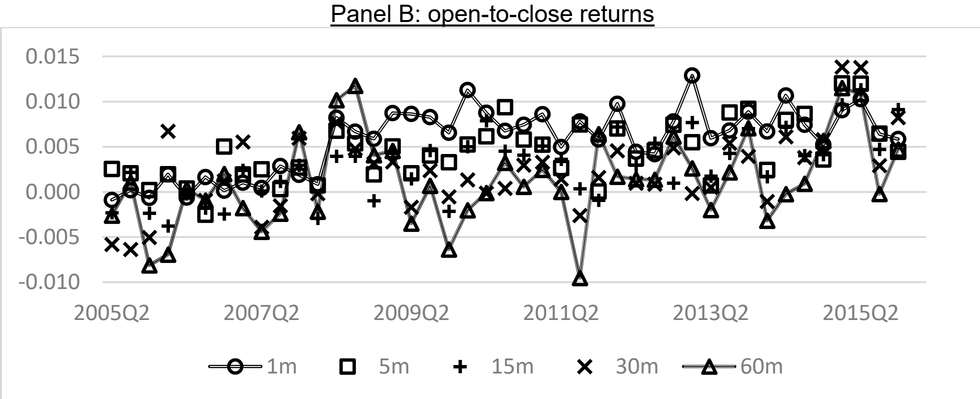


Figure 2

Average variance ratios for a lag of 4 observations

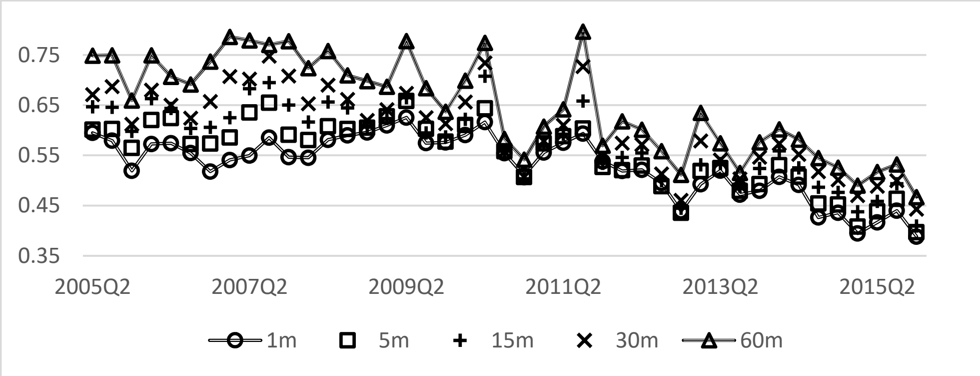
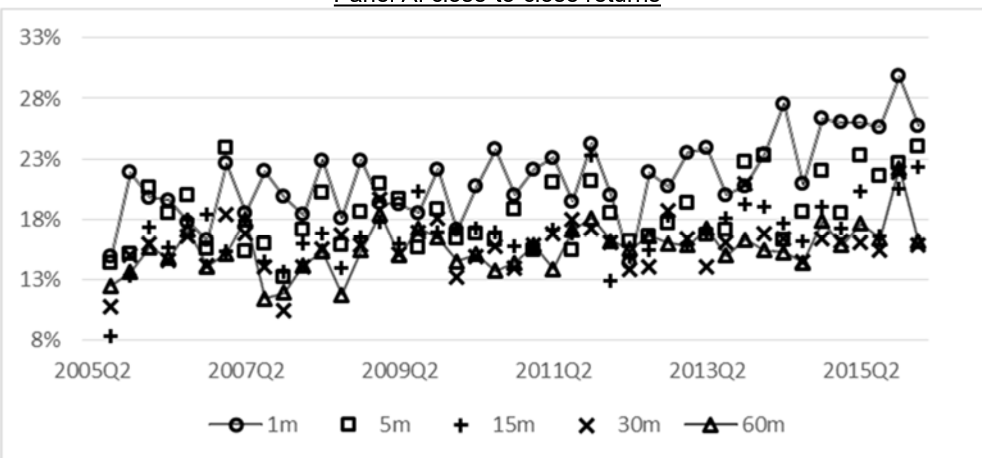


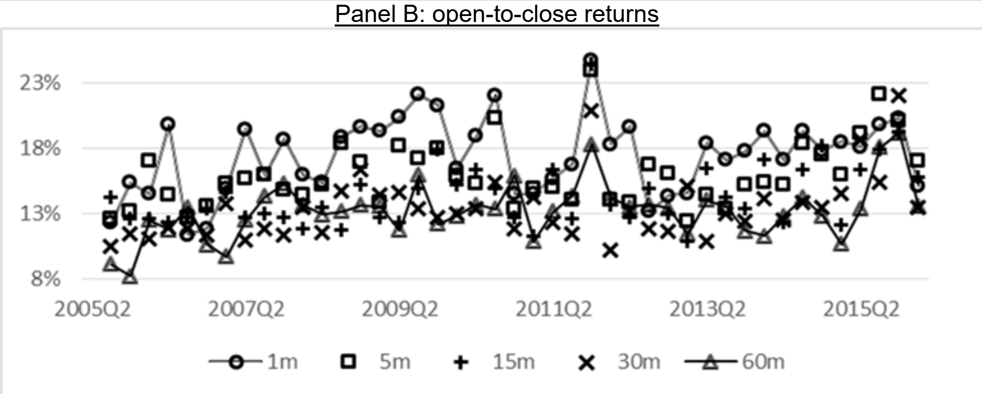
Figure 3

Relative number of test rejections in autocorrelation tests

Panel A: close-to-close returns



Panel B: open-to-close returns



The averages for each data frequency is calculated using all results, irrespective of the lag, because this should provide a general overview on the time-behavior of autocorrelation patterns. We note that the behavior of average autocorrelation coefficients for individual lags closely follow the reported averages. Figure 2 reports the average variance ratios computed for all data frequencies at a lag of 4 observations. The results for all other lags display a similar behavior in time and differ only in their level (as can be observed in the full sample results, variance ratios computed at lower lags are higher than the ones computed at higher lags). Figure 3 reports the number of autocorrelation tests that reject the null hypothesis (using corresponding t-tests) relative to the total number of tests.

The results show that intraday price dependence varies trough time on the Romanian stock market. The main findings can be summarized as follows. In general, the number of random walk rejections are fairly consistent in all subsamples. Specifically, depending on the choice of lag, data frequency and type of return, between 10% and 25% of autocorrelation tests reject the null hypothesis. We notice an increase in null rejection rates during and after the crisis period starting in 2008. When analyzing average autocorrelation coefficients, we observe that they increase in absolute value in the second part of the sample, especially after 2008Q3 (this can be linked with the Lehman Brother collapse). In terms of variance ratios, we observe increasing deviations from a random walk also following 2008Q3. Specifically, ratios increasingly diverge from unity and absolute z-statistics get larger at all intraday data frequencies and at all lags. Further, following 2010Q3, average variance ratios settle at a level approximately 0.15 lower compared to their pre-crisis values.

Overall, the results reject the random walk hypothesis on the subsample level. Also, we observe that price predictability increases during and after the crisis, possibly signaling decreasing efficiency and increasing possibilities of economic profits. This implies that the crisis itself has caused a permanent shift in the intraday behavior of stock prices. Possible causes for these results include a drop in market liquidity caused by the flight to quality phenomena, changes in investor attitude towards risk, or behavioral biases (loss aversion, panic, herding). Investing the causes for this shift is outside the scope of this paper, but this may constitute yet another very interesting topic for future research. Instead, we focus our attention to the trading simulation results, in order to analyze if increased price predictability in certain time intervals can lead to economic profit opportunities and the rejection of market efficiency.

In the trading simulation tests, we also observe significant variations in the results from one subsample to the next. Table 12 reports all null rejections for the performed tests, while Figure 4 plots the average excess returns obtained by the trading strategies, together with the rate of null rejections for each subsample. Both are based on the results obtained using a 15m data frequency, but the results for all other investigated frequencies are qualitatively similar. The results are interesting in several aspects. First, we notice that average excess returns obtained by technical analysis indicators vary trough time. Similar to the results obtained for the autocorrelation and variance ratio tests, the crisis has a positive impact on excess returns. As a consequence, compared to the full sample results, we notice that economic profit opportunities do exist from time to time on intraday prices in Romania. Profitable trading opportunities are largely concentrated in 2008, the climax year of the recent financial crisis. An interesting aspect is that in most of these cases, the best trading rule is based on the RSI indicator that trades on oversold prices. This implies that the profitable trading strategies arise in profound negative trends. Given this finding and also that null rejections for the SPA test imply inefficient price movements, a possible explanation for these results can be investor behavior, such as panic, loss aversion or herding.

Table 12

Null Rejections for Trading Simulation Tests - 15m Frequency

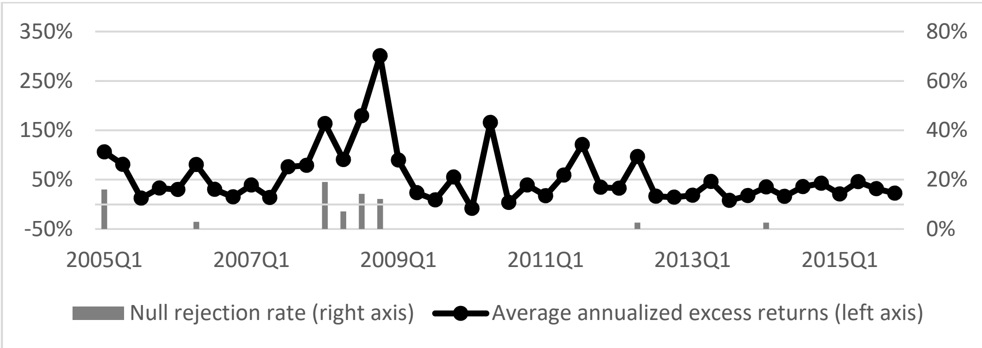
Trimester	Stock symbol	Best prediction model	Excess return (annualized)	SPA p-value
2005Q1	IMP	RSI(14) |↗ 18 || RSI(14) > 72	119.90%	0.0690
2005Q1	SIF3	Filter(4)	156.38%	0.0560
2005Q1	SIF5	RSI(14) |↗ 6 || RSI(14) > 80	96.52%	0.0940
2005Q1	SRT	RSI(14) |↗ 14 || RSI(14) > 74	169.91%	0.0830
2006Q2	CMP	RSI(14) |↗ 6 || RSI(14) > 74	181.09%	0.0710
2008Q1	ATB	RSI(14) |↗ 14 || RSI(14) > 88	161.18%	0.0720
2008Q1	BCC	RSI(14) |↗ 10 || RSI(14) > 80	186.41%	0.0870
2008Q1	BIO	RSI(14) |↗ 4 || RSI(14) > 90	292.19%	0.0190
2008Q1	COFI	RSI(14) |↗ 12 || RSI(14) > 60	668.76%	0.0880
2008Q1	IMP	RSI(14) |↗ 6 || RSI(14) > 84	276.45%	0.0120
2008Q1	SCD	RSI(14) |↗ 24 || RSI(14) > 28	269.89%	0.0450
2008Q1	SIF1	RSI(14) |↗ 4 || RSI(14) > 96	114.95%	0.0550
2008Q1	TBM	RSI(14) |↗ 16 || RSI(14) > 66	192.78%	0.0920
2008Q2	ARCV	RSI(14) |↗ 6 ||RSI(14) > 84	282.75%	0.0520
2008Q2	SIF1	RSI(14) |↗ 12 || RSI(14) > 94	106.60%	0.0410
2008Q2	TLV	RSI(14) |↗ 8 || RSI(14) > 92	87.18%	0.0870
2008Q3	ARDF	RSI(14) |↗ 14 || RSI(14) > 80	260.13%	0.0570
2008Q3	BIO	RSI(14) |↗ 12 || RSI(14) > 82	290.58%	0.0530
2008Q3	BRK	Filter(12)	395.54%	0.0130
2008Q3	IMP	RSI(14) |↗ 14 || RSI(14) > 76	342.95%	0.0800
2008Q3	SIF5	Filter(5)	304.77%	0.0350
2008Q3	TBM	Filter(9)	382.59%	0.0670
2008Q4	ALU	RSI(14) |↗ 58 || RSI(14) > 84	560.09%	0.0210
2008Q4	ARCV	RSI(14) |↗ 16 || RSI(14) > 74	592.14%	0.0820
2008Q4	AZO	MACD(12,26) > 0	611.57%	0.0560
2008Q4	IMP	Filter(14)	558.36%	0.0420
2008Q4	OIL	RSI(14) |↗ 14) || RSI(14) > 72	380.30%	0.0890
2012Q2	IMP	RSI(14) |↗ 4 || RSI(14) > 96	338.12%	0.0120
2014Q1	SNN	RSI(14) |↗ 8 || RSI(14) > 96	76.73%	0.0250

Note. This table presents the SPA test null rejections at the 10% significance level in subsample tests. The SPA test evaluates the null hypothesis that the best trading strategy in the universe has no predictive superiority over the buy and hold benchmark. A null rejection corresponds to a statistically significant ability for trading strategies to anticipate future prices and earn excess returns (column 4). The first two columns present the subsample and the stock symbol on which the result was obtained. The third column presents the trading strategy that obtained the result. Each strategy consists out of two trading rules that are divided using the "||" symbol: an entry/buy rule (on the left) and an exit/sell rule (on the right). When an exit rule is not specified, it means that it is the opposite of the entry rule. The values in parenthesis represent look-back windows for calculating the indicators. The operators ">" and "<" signify "larger than" and "smaller than" respectively. The operators "|↗" and "|↘" signify "falls below and then rises above" and "rises above and then falls below" respectively. For example, the strategy "RSI(14) |↗ 18 || RSI(14) > 72" earned an annualized excess return of 119.9% over the buy and hold benchmark in 2005Q1 when used for IMPACT Developer & Contractor SA (IMP). This strategy instructs the investor to buy the asset when the 14-observation Relative Strength Index (RSI) falls below and then rises above 18, and then to sell the asset when the same indicator rises above 72.

Other possible explanations exist, besides investor behavior. One of the most relevant alternative hypothesis is a varying level in market risk. While the first hypothesis contradicts the Efficient Market Hypothesis, the second one does not (Fama, 1991). In the context of our tests, a clear distinctions between the two hypotheses cannot be made. However, we do note that null rejection rates are small compared to the total number of tests. Also, they are linked to extraordinary market conditions, which do not seem to be frequent in time and have a fairly random nature. This means that additional evidence is unlikely to reject the Efficient Market Hypothesis. This is because, even if markets do not incorporate information efficiently in such periods and allow for profitable trading opportunities from time to time it would be difficult for investors to anticipate such periods and trade on them, given their random nature. Overall, the evidence casts some doubt on market efficiency, but it is not sufficient to reject the Efficient Market Hypothesis for intraday price movements of stocks that are listed on the stock market in Romania. This implies that reliying on high frequency data for portfolio decisions is not feasible in the stock market of Romania, at least in the context of trading strategies derived from technical analysis indicators.

Figure 4

Average excess returns and null rejection rates in trading simulation test



4. Conclusions

This paper makes a detailed analysis of intraday efficiency in the typical Central and Eastern European stock market of Romania. The contribution is supported by a detailed sample of tick-by-tick data starting March 4, 2005 and ending December 11, 2015. After filtering stocks that are virtually not traded, we analyze the intraday price movements for 48 different companies, this amounting to almost 5.6 million individual tick observations. But the methodological contributions are also important. Specifically, we do not restrict the analysis to only one data frequency, instead investigating six different ones. Also, when testing efficiency, we look at both the random walk hypothesis – which represents the classic definition of market efficiency (Fama, 1965) –, as well as the no economic profit hypothesis – which is incorporated in latter definitions (Jensen, 1978; Timmerman and Granger, 2004). For the first, we employ a broad set of econometrical tests: the runs test, the autocorrelation test, the variance ratio test and the hour-of-the-day test. For the second, we conduct trading simulation using three of the most popular technical analysis indicators (Filter, RSI and MACD), while properly controlling for data snooping using the SPA test of Hansen (2005).

We find that returns are mean-reverting at short intraday intervals and display momentum at long intervals. When adjusting for known microstructural phenomenon, the return series display significant positive autocorrelation. Also, we find that the convergence rate to market efficiency is slower when compared to more developed markets (Chordia *et al*., 2005), ultimately leading to non-random price movements even at the daily level. The hour-of-the-day test reveals that a significant U-shape pattern exists in intraday returns. Overall, all test results converge to reject the random walk hypothesis for intraday price movements on the Bucharest Stock Exchange, both on the full sample, as well as on subsamples consisting of three months of trading data. Despite the random walk rejection, the trading simulation test provides no significant evidence in favour of rejecting the Efficient Market Hypothesis (as formulated by Jensen, 1978, or Timmermann and Granger, 2004) for the intraday price movements of Romanian stocks. Specifically, full sample results present only two situations in which trading strategies based on technical analysis indicators are capable of earning significant excess returns (at 10% level). Also, 29 null hypothesis are rejected in the SPA tests performed on subsample data, most of them occurring in 2008. Regardless of the cause of these rejections, the relative low number of deviations from efficiency and their seemingly random nature makes it unlikely that investors anticipate such periods and profit from them. As a consequence, trading on intraday data doesn't seem feasible in the Romanian stock market, at least when using popular technical analysis indicators.

Our results have important theoretical and practical implications. First, we find that the stock market of Romania, a typical tone in Central and Eastern Europe (CEE), presents large intraday price dependencies, thus providing additional evidence to the limited literature that focuses on this topic. Second, the existing market frictions (low liquidity, large trading costs, and trading restrictions) are large enough to eliminate the possibility of economic profits on the intraday level. Specifically, we find that these dependencies generally cannot be used by investors to earn economic profits, thus providing novel evidence to support the Efficient Market Hypothesis for a typical CEE market at the intraday level. For professionals, this is an important conclusion, as it implies that using high frequency data for fine-tuning portfolio management decisions in such a market should be treated with care. At least when using trading methods derived from technical analysis, active trading strategies doesn't seem to outperform passive strategies at intraday level.

Our results also encourage some directions for future research. First, there is the matter of providing some detailed explanations for some of our findings. Specifically, how do price dependencies (patterns in autocorrelation coefficients, variance ratios and runs) compare to other markets in magnitude and time-behavior? And what factors explain these differences? Also, how does the intraday "seasonality" in returns, volatility and liquidity looks like in detail, and what factors explain it? Further, what is the cause for SPA test null rejections in specific time intervals, such as 2008? Is investor behavior involved, or can the results be explained by a time-varying risk premium? Second, there is the matter of expanding the analysis in other directions. For example, subject to data availability, one should analyze intraday behavior of stock prices in other markets in the CEE region. Also, one could consider testing market indexes where they are traded. Further, regardless of the data sample involved, one might consider employing other testing frameworks that would provide more insight into the intraday behavior of stock prices. Finally, one might consider testing some other (maybe a more complex) class of high frequency trading strategies to confirm our findings or reject market efficiency at the intraday level.

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