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June 2008

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Abstract.

This paper focuses on one of the heavily tested issue in the contemporary finance, i.e. efficient market hypothesis (EMH). However, we try to find the answers to some fundamental questions basing on the analysis of high frequency (HF) data from the Warsaw Stock Exchange (WSE). We estimate model on daily and 5-minute data for WIG20 index futures trying to verify daily and hourly effects. After implementing the base methodology for such testing, additionally we take into account the results of regression with weights, i.e. robust regression is used that assigns the higher weight the better behaved observations. Our results indicate that we observe the day of the week effect and hour of the day effect in polish data. What is more important is the existence of strong open jump effect for all days except Wednesday and positive day effect for Monday. Considering the hour of the day effect we observe positive, persistent and significant open jump effect and the end of session effect. Aforementioned results confirm our initial hypothesis that Polish stock market is not efficient in the information sense.

JEL Classification: G14, G15, C61, C22,

Keywords: high-frequency financial data, , robust analysis, pre-weighting, efficient market hypothesis, calendar effects, intra-day effects, the open jump effect, the end of session effect, emerging markets.

1. Introduction

The article investigates market inefficiencies on the Warsaw Stock Exchange, hereafter (WSE). We provide one of the first high frequency data analyses for European emerging market describing widely known phenomena of day of the week effect and hour of the day effect. The analysis is conducted using both high frequency data (5-minute returns for the period: 2003-2008) and daily data (for 10 years time span: 1998-2008) for WIG20 index futures[1]. We estimated separate models for 5-minute and daily log returns. To remove sudden price jumps that normally dominate the model, data filtering methods are used and provide result robustness. Financial return data are characterized by phenomena such as asymmetry, leptokurtosis and autocorrelation. This departure from normality has a significant influence on modelling strategy. We include regression with and without weights, additionally showing the results for each year separately (for analysis on HF data). To overcome existing problems we use pre-weighting and rely rather on the medians than the means to make our findings more robust in statistical sense.

The direct reason for our research was the need to answer some basic questions concerning EMH basing the research process on HF data. There exist extensive studies concerning EMH, however the analysis are performed on daily data mainly. Our aim is to bridge this gap and put the light on what happen during trading day. After analysis of financial literature, not only focusing on the issue of EMH, we hypothesized that Polish stock market should still reveal some patterns of inefficiency especially connected with daily volatility patterns (Slepaczuk and Zakrzewski, 2008), which clearly disclose strong differences between different parts of the stock market session. Basing on the presumptions built on these patterns we formulated the following hypothesis concerning Polish stock market:

- There exists intra-day effects, especially revealed in the open and final jump,

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[1] We use index futures data in order to stress increasing liquidity of this type of instrument and almost 10 times lower costs of transaction. It is of special importance when we consider practical implementation of EMH research's results.

- The existence of the day effect should die out in the consecutive years of the sample being tested, as a market gradually changes from emerging to developed,
- The robust methodology will enable us to reveal some patterns of distribution, which were not visible in the process of standard regression. Intra-day data are prone to fractional integration and quasi-outliers problems. By quasi-outliers we treat natural observations, that are a result of sudden change of market environment that would be treated as outlier in standard methodology

which were further tested in this research. Additionally, taking into account that Polish futures market (standardized products listed on the stock exchange) is the biggest within ten new member states, we assume that interpretation of our results could be extended to other emerging European markets.

The structure of our paper is as follows. After introduction in the first section, next one contains short description of the contemporary inefficiencies revealed in the process of research being conducted on the emerging market data. We focused only on the papers which introduced the concept of EMH in the early 60. and 70. (Fama, 1965, 1970, Samuelson 1965), defined well recognized inefficiencies (Rozeff and Kinney 1976, Lakonishok and Maberly 1990, etc.) and finally which recently tested the hypothesis on the emerging market data (Nath and Dalvi 2004, Das and Arora 2005). Next section contains the detailed description of the methodology and data with special attention to the empirical strategy used in the process of estimation. Our results, divided into daily and HF, and with and without weights, are presented in the fourth section. The summary of our research with short references to the future research is presented in the last section.

2. Market inefficiencies: Day and Intra-day effects

The Efficient market hypothesis is closely connected with Eugene Fama and his seminal paper in 1965, where he identified three forms of efficiency in the information sense (week, semi-strong and strong form). EMH simply states that, basing on which form of efficiency do we choose, specified set of information is included in the prices of listed assets and then we can not create any strategy beating the market. Historically, the first research which introduced the concept of efficient market hypothesis was dissertation of Luis Bachelier (1900) largely ignored until Samuelson (1965) who popularised Bachelier's work among economists.

The EMH started to gain acceptance between economists researching this subject from 60. and even until now it is one of the most heavily researched issue in contemporary finance. Through all this years researchers found many significant anomalies of capital market, no matter if we mean weak, semi-strong or strong form, which contradict the validation of initially defined hypothesis.

Focusing on the EMH in the weak form stating that asset prices should incorporate the information contained in the historical time series we could define following market anomalies:

- The calendar effects: the month-of-the-year (the January effect – Rozeff and Kinney 1976, Haugen and Lakonishok 1988, the week-of-the-month Ariel 1987, Lakonishok and Smidt, 1988, the day-of-the-week (the Weekend effect – Cross 1973, Lakonishok and Maberly, 1990, the Holiday effect), and the hour-of-the-day (Smirlock and Starks 1986, Harris 1986, Wood, McInish and Ord 1985- the open and final jump effect).
- Correlation of rates of return in the short term – significant and positive relation (Campbell, Lo and MacKinlay 1997)
- Correlation of rates of return in the long term – significant and negative coefficients (Poterba and Summers 1988, Fama and French 1988),
- Contrarian Strategies – long and short term (Lehman 1990).
- Momentum strategies – mid term approach (Jegadesh and Titman 1993).

Evidently these are only the best documented anomalies but they gave the arguments for opponents of EMH and enabled its reconsideration on the ground of new results. Above mentioned anomalies were especially documented while testing emerging market data what contribute to the formulation of hypothesis that they are characteristics of the market which are not fully developed and should disappear in the later phase of development. However, searching the results of the emerging market researches we can not fully agree with this notion.

Latest researches on emerging market data as well as developed ones confirm the existence of day-of-the-week effect: Nath and Dalvi (2004), Lyroudi et al. (2002), Das and Arora (2005), Bhattacharya et al.

(2003), which most often result in significant Monday and Friday. When we consider hour-of-the-day effect we observe the open jump effect (Harvey and Huang 1991) and final jump effect (Guin 2005) which are closely connected with the daily patterns of volatility but there is much less evidence concerning this issue.

Taking into account researches on Polish data we have to admit that although we have four extensive works focusing on EMH in the information sense in all forms (Czekaj et al. 2001, Szyszka 2003, Jajuga 2000, Buczek 2005) the authors did not pay special attention to calendar effects. Only in Szyszka (2003) week-of-the-month effect and day-of-the-week are verified and some patterns of inefficiency are found: significant positive Monday and significant positive first week of the month. The papers mentioned above tested only the data on the daily level what naturally made impossible to reveal hour-of-the-day effects. That was one of the reasons why we conducted this research on HF Polish data trying to reveal the calendar effects widely identified in the literature, and compare them with overall notion that emerging markets most often reveal some patterns of inefficiency.

3. Research methodology and data description

Our empirical analysis is based on high-frequency financial data for WIG20 index futures. We based our study on the continuous time series for futures, where expiring futures contract was replaced by the next series, where the number of open positions achieves the higher value. It is one of the most common ways of creating continuous time series for futures. We do not have enough data for the longer period of time because of the short time to expiration of individual future contract, therefore we had to create continuous futures index.

WIG20 consists of 20 largest companies quoted on WSE and is computed as a weighted measure of the prices of its components. The daily data span is from 2nd February 1998[2] to 31st of March 2008. Unfortunately, the 5-minute data, which were supplied by Information Products Section from WSE, are available from 2nd June 2003 to 31st of March 2007. The number of 5-minute returns for a trading day depends on the trading hours for futures contracts but this have been changed once during our research period. The trading was from 9:00 to 16:00 for the time period from 2nd June 2003 until 30th September 2005 and from 9:00 until 16:30[3] for the next two years from 3rd October 2005 until 31st of March 31 2008. Thus, we had 84 or 90 five-minute returns for a day in the research period. All returns were computed as the first difference in the regularly time-spaced log prices of WIG20 index futures, with the overnight return included in the first intraday return. After correction for outliers (three on the basis of five-minute intervals) we get a total of 2547 trading days and a total of 92199 five-minute intervals.

Table 3.1. The descriptive statistics for log returns of analysed index futures returns for the period from 2nd June 2003 to 31st March 2008.

Statistics	Daily data	5-minute data
Mean	.0003047	.0008837
Standard Deviation	.0182882	.1601220
Variance	.0003345	.0256390
Skewness	.0922582	-.4723653
Kurthosis	5.283044	38.98765
N	2547	103122

Source: own computation based on WSE data

Table 3.1 summarizes the data descriptive statistics[4]. In the left column are daily data characteristics and in the right we have five-minute data. Five minutes average return are slightly higher than daily returns, however both numbers are not significantly different from zero. Analysing both returns series, we can evidently see higher than normal kurtosis and small skewness. The daily returns are slightly skewed.

[2] WIG20 was quoted from 20th January 1998, however there was a very few transactions. Continuous data are avaliable since February 1998.

[3] In practice, the continuous trading finished at 16:10, then the close price was settled between 16:10 and 16:20, and next investors could trade only on the basis of close price until 16:30. Therefore, we could even say that we have 86 instead of 90 intervals in the second period.

[4] Visual presentation of daily data in Appendix.

On the other hand, five-minute interval returns are left skewed. The distribution of the returns is leptokurtic, i.e. is almost symmetric and has fat tails and a substantial peak at mean value. Testing for normality, we get the same results for both data sets, i.e. the statistics reveal non-normality of the data sets tested[5]. Analyzing mean, standard deviation, kurtosis and skewness we observe some patterns of distribution (Table 3.2 and Figure 3.1 and 3.2).

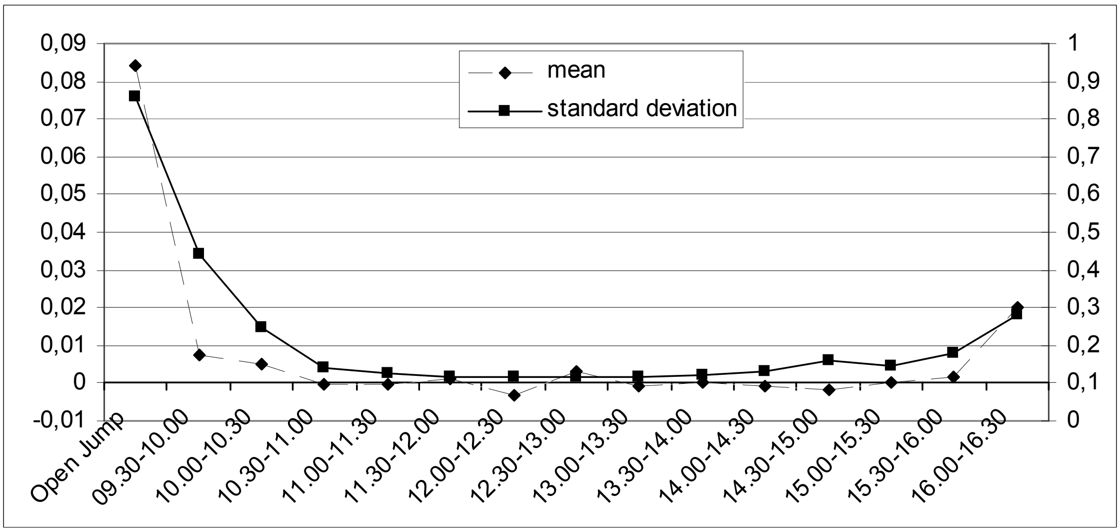
Table 3.2. The descriptive statistics calculated separately for each half an hour interval during the day.[a]

Period	Return	Std dev	Skewness	Kurtosis
Open Jump	0.0845649	0.7296813	-0.8220053	6.574713
09.00-09.30	0.0147039	0.3208124	-1.0734150	28.388360
09.30-10.00	-0.0031634	0.1418127	0.5770158	17.932900
10.00-10.30	-0.0023202	0.1642937	-0.1403808	7.934801
10.30-11.00	-0.0001690	0.1384769	0.1073290	7.559757
11.00-11.30	-0.0002199	0.1248630	-0.1761427	8.627885
11.30-12.00	0.0014125	0.1172726	0.1155043	8.827273
12.00-12.30	-0.0030406	0.1143765	0.2130371	11.481020
12.30-13.00	0.0029511	0.1149602	0.0132158	10.408220
13.00-13.30	-0.0007801	0.1148532	-0.1983475	8.339746
13.30-14.00	0.0004350	0.1208250	-0.0525039	12.341730
14.00-14.30	-0.0009016	0.1306344	0.6896316	31.747580
14.30-15.00	-0.0014733	0.1608028	-0.2442220	10.006480
15.00-15.30	0.0001727	0.1464368	-0.1424887	8.962907
15.30-16.00	0.0014616	0.1804251	0.2183429	9.870681
16.00-16.30	0.0201590	0.2812534	0.2936624	6.279024

[a] The descriptive statistics calculated for Wig20 index futures on the basis of 5-minute data in the analyzed period.
Source: own computation based on WSE data

J-shape of the fluctuations of std in Figure 3.1, presenting standard deviation and mean during the day and significant differences in kurtosis and skewness suggest us that some trading periods during the day could be more important than the others. We decided to check our presumption in the process of formal analysis described in the next sections.

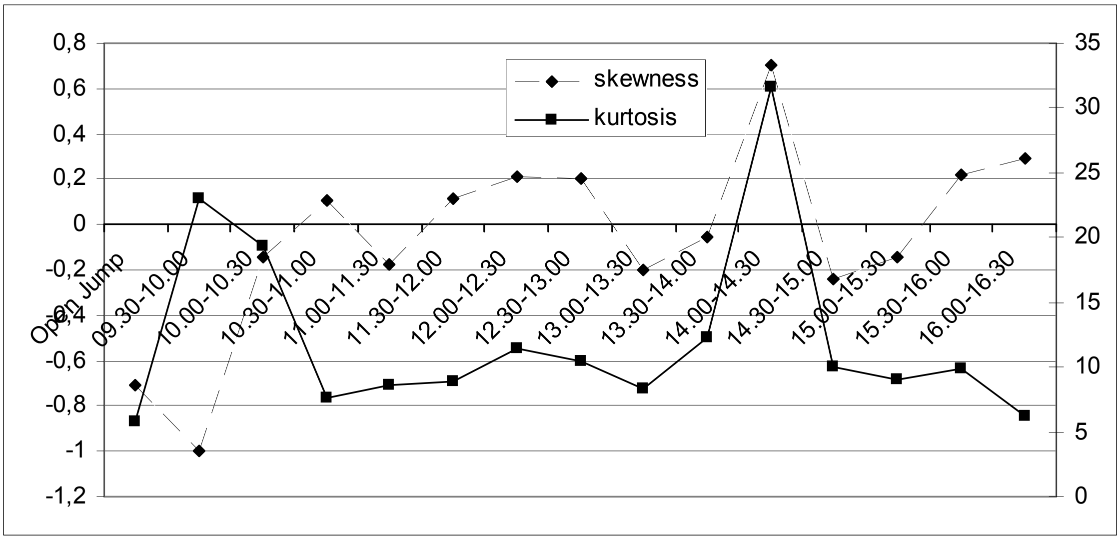
Figure 3.1. The fluctuations of mean and standard deviation during the stock market session. [a]



[a] The descriptive statistics calculated for WIG20 index futures on the basis of 5-minute data in the analyzed period
Source: own computation based on WSE data

[5] Normality tests are not presented to conserve space. They are available upon request.

Figure 3.2. The fluctuations of kurtosis and skewness during the stock market session. [a]



[a] The descriptive statistics calculated for WIG20 index futures on the basis of 5-minute data in the analyzed period.
Source: own computation based on WSE data.

Actual market data frequently contain a small fraction of unusual data points which are not consistent with Gaussian assumption. This problem is especially severe in a case of financial data, where, for instance, returns are well-known from being leptokurtic and fat-tailed. When normality of the error term cannot be assumed, OLS estimate will allow for unbiased estimation only for linear function of dependent variable. Moreover, for distribution with outliers, or heavy-tailed distribution statistical properties of estimators are problematic (Koenker, Portnoy 1987). In the literature some *ad-hoc* remedies are proposed such as removing or down-weighting questionable data. Chang and Lakonishok (1992) showed that robust estimation methods for returns data provide better estimates.

Robust statistical methods provide an attractive alternative and have recently attracted growing attention. Such estimators give less weight to "outlier" observations that poorly fits to the data. A M-estimation is a generalization of classical inference in econometrics. The M estimator is obtained by minimizing

$$\psi(t)F(t) \tag{1}$$

where $\psi(t)$ is a weighting function and F(t) is a distribution function.

Two popular weighting functions are used in applied researches: Huber psi, and Tukey bisquare. The former assigns median value for outlying observations. The latter yields more efficient estimator for heavy tailed distribution (Kleiner et al 1979).

$$\psi(t) = \begin{cases} t(1-t^2)^2 & |t| < c \\ 0 & |t| > c \end{cases} \tag{2}$$

Tukey bisquare function for *c=3* is similar to rule of a thumb that advocates to drop observations which are more than 3 standard deviations away from the centre of data. The actual value of *c* should be determined by size of empirical sample and distance from normality.

From the available information about value of the future contract, intervals on which market did not operate, were excluded (i.e. weekends and national holidays). As a result we have 2547 working days in the sample. In the further analysis we use log-returns instead of returns to remove the market expansion effect. Returns are calculated as a difference between successive log values of index:

$$r_t = \ln(P_t) - \ln(P_{t-1}) \tag{3}$$

for daily return, P_t is a FW20 close value at day *t*, and P_{t-1} is a FW20 close value at day *t-1*, respectively. For 5-minute return P_t is FW20 close value at the end of time interval *t*, and P_{t-1} is the same value one time period before. For the cases in which there was no data in previous time interval or information was not available or not reliable due to know market perturbations we used values form last available data period to calculate the adequate returns. Further in the analysis we have included OPEN dummy that captures the effect of market opening. Usually the close value of the index differs from opening value on the following day.

$$r_t = \sum_{1}^{q} \alpha r_{t-q} + \beta * D_j + \gamma OPEN_t + \varepsilon \tag{4}$$

t denotes current value of the variable and *t-q* value lagged for q periods. For daily data, lagged value is the value from previous trading day, for 5-minute data is the value for previous trading period. The lagged dependent variables are used for several reasons. Firstly, they capture persistency of return patterns on the market. Secondly, they are used to remove potential autocorrelation. It is widely known in the literature that high-frequency data are characterized by long correlation patterns, especially when an underlying variable is fractionally integrated. Proposed model has no constant term. Instead we use set of dummy variables. D_j are dummies for day or half-hours, and OPEN is a dummy that captures the difference between close value of the index on previous day and the opening value. Its role is to capture changes that happen during closure of the market.

To estimate model (4) we apply a robust estimator from a class of M-estimators and rely completely on robust methodology. For selection of threshold values of *c*, that detects deviant observations we use robust analogy of 99,5% confidence interval[6]. We decided to use quite wide interval due to having lot of observations. However, we are aware that it is hard to distinguish outliers from the values that occur with low probability in large samples. As a result, we excluded from our sample only extremely deviant observations by setting their weights to zero. For the remaining observations, we used scaled residuals, i.e. residuals divided by mean absolute deviation, as input for weighting function and then calculated weights. Application of ψ -function is analogous to weighted estimation. The primary role is to eliminate the influence of outliers on the estimate. This procedure assigns higher weights to those observations with relatively small residuals, and lower weights for those with large ones.

The next section contains the results of our estimations separately for the model on daily and 5-minute data.

4. Results for daily and HF data

The analysis on daily data is not an aim of the research. The investigation is performed for benchmark purpose only but the main attention will be paid to the results on HF data presented further in this section.

Model on daily data

The dependent variable in the analysis is a daily log-return from future contract. As explanatory variables are used lagged by 1 and 2 periods log-return of future contract to control for market fluctuations and set of day-dummies to capture daily effects.

[6] The robust counterpart for 99.5% confidence interval is $MED\,(y) \pm 5.2(1+\frac{4}{n})MAD\,(y)$. Where MED(y) is a median of variable, MAD(y) stands for mean absolute deviation form the median, and *n* is a sample size.

Table 4.1. Models on daily data.

Variable	Standard		Robust	
Lagged 1 period return	-.0050546		-.0217709	
Lagged 2 period return	.048647	**		
Monday	-.000158		-.0003544	
Tuesday	-.0005757		-.0009403	*
Wednesday	-.0006993		-.0007059	
Thursday	.0011882		.0012453	**
Friday	.001518	*	.0011537	**

*** 1%; ** 5%; * 10%. Significance level
Source: own computation based on WSE data

Second lag of dependency is enough to remove correlation of the error term. We tried to include additional lags to check robustness of model specification and it seems that is correct as long as lagged values of the dependent variable were not significant. Results in Table 4.1 indicate that there exists weak evidence in the data for abnormal positive returns at Fridays.

Model (4) was also estimated by robust method with weights and robust standard errors. In this model special attention is paid to observations with small errors, and those with large ones are omitted. In that model 2nd lag of dependent variable turns out to be not significant, also first lag is on the edge of 10% significance level. It seems that on the market exist negative Tuesday effect (at 10% level) and positive Thursday and Friday (both at 2.5%). This suggests that polish stock market in the analysed period was not fully efficient and our result confirm the ones obtained in the literature (Lyroudi et al, 2002, Agrawal and Tandon, 1994), especially when we consider positive and significant Friday effect.

<u>Model on 5-minute data</u>

Daily effects

In the main scope of the research are HF data based analyses. We divided our HF analysis on daily and hourly effects, additionally presenting results for two separate periods. In the table 4.2 estimations of equation (4) on five-minute data are reported. We omit coefficient values for six lags of dependent variable. These lags were included to alleviate eventual autocorrelation problem. In addition, the analysis for each yearly period, starting from June to May the following year were performed. Starting point for the analysis is data driven.

Table 4.2. Daily effects based on five-minute data models for all analyzed period and two separate periods.

Variable	Standard		Robust		Robust period 0		Robust period 1	
Monday	.0017307		.0022584	***	.0036817	***	.0008559	
Tuesday	-.0004684		.0002019		.0012556	*	-.0008087	
Wednesday	-0005551		-.0004234		-.0014654	**	.0006545	
Thursday	-.0016883		-.0006338		.0006225		-.0018425	**
Friday	-.0003390		.0008401		.0028375	***	-.0001823	
Open Monday	.0319049	***	.0436897	**	.0794787	***	.0030769	
Open Tuesday	1006387	***	.1151625	***	.1594882	***	.0797756	**
Open Wednesday	.0338937		.0650980	***	.108494	***	.0195413	
Open Thursday	.1799356	***	.1831279	***	.0994264	***	.2645347	***
Open Friday	.0814471	***	.0927011	***	.1307886	***	.066525	***

*** 1%; ** 5%; * 10%. Significance level
Source: own computation based on WSE data

Table 4.3. Robust daily effects based on five-minute data models - model with weights and robust standard errors.

Variable	01.06.2003-31.05.2004		01.06.2004-31.05.2005		01.06.2005-31.05.2006		01.06.2006-31.05.2007		01.06.2007-31.03.2008	
Monday	.0056	***	.0003		.0059	***	.0012		-.0018	
Tuesday	-.0017		.0017	*	.0028		-.0008		.0006	
Wednesday	-.0031	*	-.0007		.0028	**	-.0003		-.0014	
Thursday	.0013		-.0009		.0025	**	-.0014		-.0058	***
Friday	.0038	***	.0022	**	.0023	**	-.0012		-.0009	
Open Monday	.1146	***	.0655	***	.0953	***	.2027	***	-.2627	***
Open Tuesday	.2768	***	.0828	***	.0925	***	.0575		.1306	***
Open Wednesday	.1213	***	.0899	***	-.0397		.1828	***	-.0682	
Open Thursday	.0825	**	.0992	***	.1728	***	.3146	***	.2316	***
Open Friday	.1845	***	.0628	***	.1515	***	.0805	***	.0058	

*** 1%; ** 5%; * 10%. Significance level
Source: own computation based on WSE data

First of all, we have to reveal that until July 2007 there was a significant upward trend on WSE and other emerging and developed stock market, which were finished by US subprime mortgage crisis spreading through financial institutions all other the world. Secondly, as one can easily notice in table 4.3 there exists persistent open effect on Mondays, strong and positive open effect on Thursdays, and weakling, but positive effect on Fridays. Thirdly, considering the day-of-the-week effect we can not distinguish any effect which is persistence through consecutive years of our research.

Our last observation is in contradiction to the results on daily data where we identified positive and significant Friday effect. On the other hand, we can simply explain this phenomenon stating that the open jump effect is responsible for all day effect.

Hour effects

Table 4.4. Intra-daily effects based on five-minute data models for all analyzed period and two separate periods.

Variable	Standard		Robust		Robust period 0		Robust period 1	
Open Monday	.0332887	***	.0431633	***	.0796399	***	-.0002165	
Open Tuesday	.0999710	***	.1126434	***	.1580862	***	.0761237	***
Open Wednesday	.0329045	***	.0624706	***	.1035983	***	.0194294	
Open Thursday	.1775156	***	.1804894	***	.0968423	***	.2615018	***
Open Friday	.1810202	***	.0910487	***	.1299158	***	.0635320	***
09.00-09.30	.0005691		.0025103	***	.0035837	***	.0015835	
09.30-10.00	-.0034541		-.0023248	***	-.0019931	*	-.0033376	**
10.00-10.30	-.0020015		.0005255		.0006654		.0005543	
10.30-11.00	-.0000939		.0004464		.0000624		.0009186	
11.00-11.30	-.0006329		.0002647		.0035878	***	-.0028283	**
11.30-12.00	.0016751		.0009119		.0012987		.0006247	
12.00-12.30	-.0031015	*	-.0020990	***	-.0022407	*	-.0021691	*
12.30-13.00	.0031205	*	.0028138	***	.0049659	***	.0008446	
13.00-13.30	-.0009271		.0004872		.0037989	***	-.0028142	**
13.30-14.00	.0004559		.0004078		.0015297		-.0008244	
14.00-14.30	-.0009303		.0006573		.0007367		.0006148	
14.30-15.00	-.0014699		-.0008185		.0005208		-.0021163	
15.00-15.30	.0002428		.0021025	**	.0021027	*	.0021978	*
15.30-16.00	-.0014326		-.0017034		-.0007450		-.0027457	*
16.00-16.30	.0169178	***	.0152226	***	.0162160	***	.0150186	***

*** 1%; ** 5%; * 10%. Significance level
Source: own computation based on WSE data

Open jump is significant and positive on all days but Monday and Wednesday in the second period (Period 1). Moreover, the end of session effect is significant and positive, despite period analysed or chosen method of estimation. The significant value for 15:00-15:30 and 15:30-16:00 intervals may be linked with an effect of the anticipation of and reaction for NYSE opening but these effects are not persistent when we conduct our analysis separately on two time periods.

Mid–session significant results are only statistically different from zero for the first period, i.e. for the period when the future market was young and emerging. The existence of these effects we can explain on the basis of Macro data announcement which were revealed by the Main Statistical Office in may different hours of the day (10:00, 11:00, 13:00, !4:00, etc).

Table 4.5. Intra-daily effects based on five-minute data models (Newey-West regressions)

Variable	Robust		Robust period 0		Robust period 1	
Open Jump	.0899028	***	.1075805	***	.0719269	*
09.30-10.00	-.0068127				-.0036315	
10.00-10.30	-.0017638		-.003567		-.0032355	
10.30-11.00	-.0002819		-.0022015		.0015484	
11.00-11.30	-.0003506		.0044112	**	-.0048052	**
11.30-12.00	.0013597		.001302		.0016386	
12.00-12.30	-.0033257	**	-.0040781	**	-.0023849	
12.30-13.00	.0030934	**	.0051013	***	.0008165	
13.00-13.30	-.0008091		.0025709		-.0040103	**
13.30-14.00	.0004011		.0004852		.0001893	
14.00-14.30	-.0008872		-.0023798		.0004827	
14.30-15.00	-.0016025		-.0015225		-.001535	
15.00-15.30	.0002379		-.0007748		.00113	
15.30-16.00	-.0014896		-.001043		-.0025331	
16.00-16.30	.0171273	***	.021536	**	.0158256	**

*** 1%; ** 5%; * 10%. Significance level
Source: own computation based on WSE data

When autocorrelation is controlled by Newey-West standard errors with 36 lags, beside open jump and end of session effect, two returns on mid-session periods are statistically significant but not persistent. Therefore, after controlling of possible autocorrelation of order 36 we found similar results to the previous ones.

When we take a closer look at results of robust estimation of daily effects we can easily discover that there is a shift from day effects to open effects. As a market grows it is supposed to become more similar to his developed counterparts, revealing their characteristics as well. However, strong open effects on all days but Wednesday, and at the end of session effect remain persistent.

Table 4.6. Intra-daily effects based on five-minute data models (Newey-West regression)

Variable	Standard		Robust	
Open Monday	.0658942	***	.0807635	***
Open Tuesday	.0591933	***	.0664849	***
Open Wednesday	-.011504		-.0025753	
Open Thursday	.1760493	***	.1809812	***
Open Friday	.1604134	***	.1734226	***
09.30-10.00	-.0065774	**	-.0010692	
10.00-10.30	-.0015168		.0012462	
10.30-11.00	-.0003997		.0005782	
11.00-11.30	-.0004671		.0004218	
11.30-12.00	.0012664		.0009079	
12.00-12.30	-.0032964		-.0022638	***
12.30-13.00	.0031173		.0027322	***
13.00-13.30	-.0008653		.0006154	
13.30-14.00	.000392		.0004083	
14.00-14.30	-.0008671		.0007486	
14.30-15.00	-.0015678		-.0009256	
15.00-15.30	.0002608		.0021406	**
15.30-16.00	-.0013289		-.0016553	
16.00-16.30	.0167264	***	.0150899	***

*** 1%; ** 5%; * 10%. Significance level
Source: own computation based on WSE data

Our last table (4.7) presenting results of intra-daily analysis informs us that intra-day mid-session effects are not stable when we analyse subsets of data. It is hard to judge if this instability comes from a smaller database or differences between periods (i.e. strong and significant upward trend in the first phase of our research or strong downward movement in the second phase). On the other hand, next time we observe significant and positive end of session effect and open effect, which is persistent for Monday, Thursday and Friday.

Table 4.7. Intra-daily robust effects based on five-minute data models

Variable	01.06.2003-31.05.2004		01.06.2004-31.05.2005		01.06.2005-31.05.2006		01.06.2006-31.05.2007		01.06.2007-31.03.2008	
Open Monday	.2359	***	.0623	**	.1850	***	.1519	***	-.2629	***
Open Tuesday	.1684	***	.0040		.0570	**	.0052		.0616	
Open Wednesday	.0326		-.0210		-.1453	***	.1381	***	-.1456	***
Open Thursday	.0441		.1692	***	.1357	***	.3570	***	.2419	***
Open Friday	.3345	***	.1617	***	.1338	***	.1677	***	.0513	*
09.30-10.00	-.0002		.0013		.0059	*	-.0018		-.0023	
10.00-10.30	.0001		.0021		.0028		-.0035	*	.0025	
10.30-11.00	-.0013		-.0006		.0015		.0034	*	-.0009	
11.00-11.30	.0082	***	-.0001		.0033	*	.0002		-.0086	***
11.30-12.00	.0013		.0009		.0006		.0023		-.0008	
12.00-12.30	-.0056	***	-.0014		-.0002		.0011		-.0063	***
12.30-13.00	.0026		.0050	***	.0065	***	-.0006		-.0015	
13.00-13.30	.0047	**	.0040	**	.0027		-.0027		-.0079	***
13.30-14.00	.0034	*	-.0029	*	.0063	***	-.0030		-.0025	
14.00-14.30	-.0012		.0002		.0005		.0022		.0025	
14.30-15.00	.0016		-.0013		.0005		-.0050	**	.0002	
15.00-15.30	-.0010		.0050	***	.0047	**	.0016		-.0011	
15.30-16.00	-.0003		-.0023		.0029		-.0032		-.0080	***
16.00-16.30	.0378	***	.0058		.0087	**	.0121	***	.0236	***

*** 1%; ** 5%; * 10%. Significance level
Source: own computation based on WSE data

5. Summary and questions for future research

Taking into account all the results presented above we can formulate the following conclusions:. Firstly, there exists strong hour of the day effect revealed in two effects connected with the start and end of the stock session:

- the open jump effect, which is persistent for Monday, Thursday and Friday.
- the end of session effect, which is additionally persistent

Secondly, the results confirmed our initial supposition about significant open jump and end of day effect closely connected with substantial fluctuations of volatility at the same time (Figure 3.2).

Our next conclusion concerns the shift from day-effect into open jump effect, i.e. the day-of-the-week effect is restricted only to open jump effect or on the other hand the uncertainty between the close and open on the following day is revealed just after the market open. Such an explanation presenting the example of market inefficiency, on the other hand, informs us about much faster incorporation of the new information into the traded prices in comparison to the daily effect.

When we focus on the methodology applied in our research we can additionally notice that the results are resistant, because we eliminated an influence of potential outlying observations which usually dominate the data. Additionally, we employed robust estimators for variance-covariance matrix in order to obtain more reliable estimators of variance what enabled us to reveal presented effects more precisely.

Revealed patterns do not necessary be persistent. We are aware of the fact that inefficiencies found in the data will diminish while the market become less emerging market and more developed but we have to stress that it is still not the case of WSE.

At the end we would like to describe some paths for future research into this subject which could enable finding the answer for the degree of emerging market efficiency and the stability of our results. In the future researches more emphasis should be put to the analysis of higher frequencies (tick data). Such analysis could identify the causes of open and final jumps, additionally, explaining inefficiency on the ground of market microstructure. Finally, more evidence concerning the intra-day effects should be revealed while analysing the volatility on the base of high frequency data what will be the subject of our next research.

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Appendix

Figure 3.3. Daily log-returns

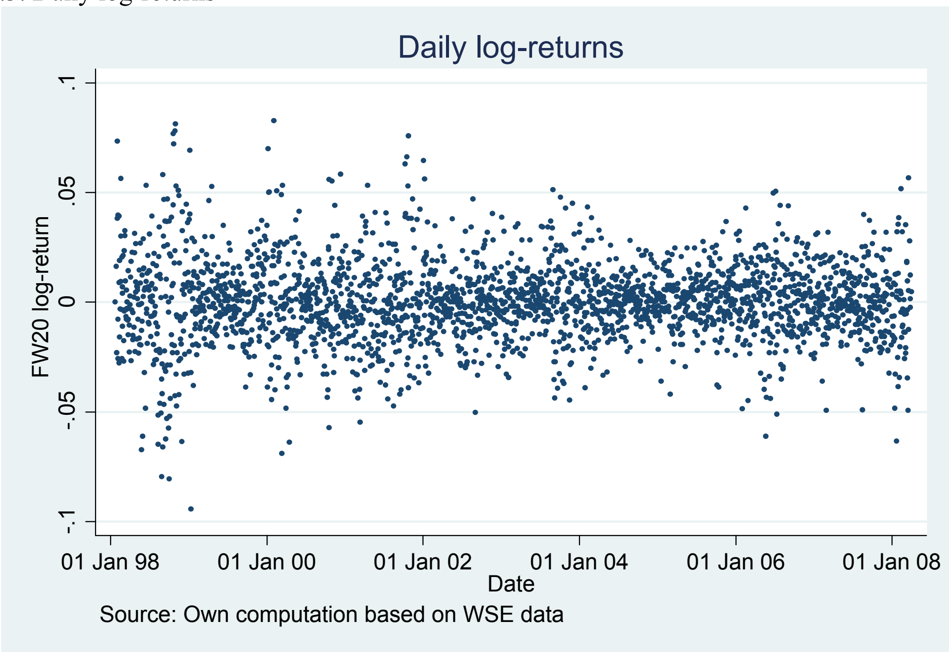

Figure 3.3. Daily log-returns squared

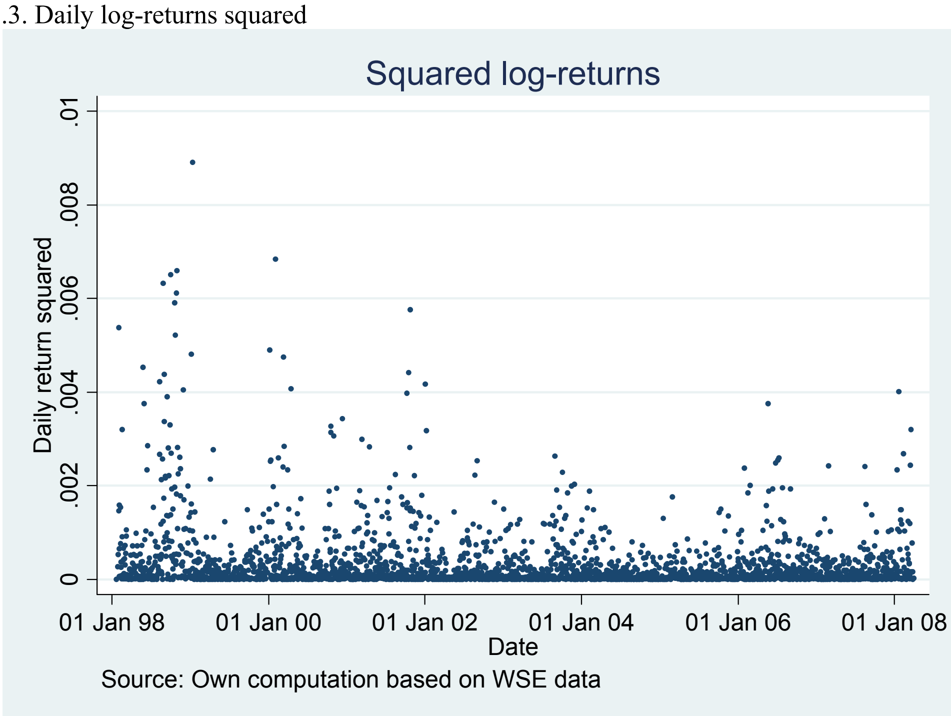

Figure 3.5 Histogram of daily log-returns