PRICE JUMPS IN VISEGRAD COUNTRY STOCK MARKETS: AN EMPIRICAL ANALYSIS

Jan Novotný

CERGE-EI

Charles University
Center for Economic Research and Graduate Education
Academy of Sciences of the Czech Republic
Economics Institute

WORKING PAPER SERIES (ISSN 1211-3298)
Electronic Version

412

Working Paper Series 412
(ISSN 1211-3298)

Price Jumps in Visegrad Country Stock Markets: An Empirical Analysis

Jan Novotný

CERGE-EI
Prague, August 2010

ISBN 978-80-7343-210-2 (Univerzita Karlova. Centrum pro ekonomický výzkum a doktorské studium)
ISBN 978-80-7344-200-2 (Národohospodářský ústav AV ČR, v.v.i.)

Price Jumps in Visegrad Country Stock Markets: An Empirical Analysis

Jan Novotny*

WP 412

Abstract

I empirically study price jumps using high frequency data comprising 5-, 10-, 15- and 30-minute market data on the main indices from the Prague, Warsaw, Budapest and Frankfurt Stock Exchanges for June 2003 to the end of 2008. I use two definitions of price jumps: the price jump index and normalized returns. First, I analyze the distribution of returns to support the presence of jumps. Second, I find that the distributions of the price jump indicators employed are significantly different for positive moves compared with negative moves in all the markets studied. In addition, the comparison of jump distributions across different frequencies and markets suggests a possible relationship with market micro-structure as well as with the composition of investors. In particular, at the Prague Stock Exchange, the lower the frequency, the lower the number of extreme jumps, but this is not so at the other markets. Last but not least, I show that the recent financial crisis caused an overall increase in volatility. However, this was not translated into an increase in the absolute number of jumps.

Abstrakt

V tomto článku studuji skoky na cenách za použití vysokofrekvenčních dat (5, 10, 15 a 30 minutová frekvence) pro hlavní akciové indexy z burz v Praze, Varšavě, Budapešti a Frankfurtu v období od června 2003 do konce roku 2008. Používám dvě definice skoků: index skoku cen a normalizované returny. Nejprve analyzuji distribuci returnů pro ukázání přítomnosti skoků. Poté ukazuji, že distribuce indikátorů jsou rozdílné pro pohyby nahoru a dolů pro všechna data. Porovnání distribuce skoků pro různé frekvence a trhy naznačuje možný vztah s mikrostrukturou trhu stejně jako se složením investorů. Jmenovitě, Pražská burza vykazuje vztah: čím menší frekvence, tím méně extrémních pohybů, což není na jiných trzích. Nakonec ukazuji, že současná finanční krize způsobila celkový růst volatility, ale ne růst počtu skoků.

Keywords: financial markets, Visegrad region, price jumps.
JEL Classification Codes: G15, P59.

* CERGE-EI, Center for Economic Research and Graduate Education - Economic Institute, a joint workplace of Charles University in Prague and the Academy of Science of the Czech Republic; Address: CERGE-EI, Politickych veznu 7, P.O. Box 882, 111 21 Prague, Czech Republic. Phone (+420) 224005187; e-mail: jan.novotny@cerge-ei.cz.

I am grateful to Jan Hanousek for his patient guidance and advice. This study is supported by GAČR grant (402/08/1376). The work was partially done during my stay as a Visitng Researcher at University of Pennsylvania, Philadelphia.

The work was supported by the grant SVV-2010-261 801.

1 Introduction

The volatility of financial markets—or, in other words, the uncertainty of the price process for various financial instruments—is a deeply studied phenomenon in the financial literature (see, e.g., Gatheral, 2006). However, most of the attention has been focused on the part of volatility known as regular noise, which can be described by a standard Gaussian distribution. The remaining component of volatility, known as price jumps, involves irregular but abrupt price changes. See Merton (1976) or the recent discussion of how to decompose volatility into two parts by Giot, Laurent and Petitjean (2010). Price jumps substantially differ from regular noise and are more difficult to explicitly define and handle mathematically (Broadie and Jain, 2008; Johannes, 2004; Nietert, 2001; Pan, 2002).

Price jumps, i.e., irregular and extreme price movements, are associated with various interesting market phenomena. Price jumps can be connected to important issues in market micro-structure (see the survey in Madhavan, 2000), such as the efficiency of price formation or the provision of liquidity among market players. Traders are also interested in price jumps since they are a part of volatility. The proper description of volatility is closely connected with the performance of various financial instruments (Gatheral, 2006). Thus, understanding price jumps helps to avoid big losses, improve portfolio performance and better hedge positions. Finally, a knowledge of price jumps is needed by financial regulators; see Becketti and Roberts (1990) or Tinic (1995). Price jumps can be also used as a proxy to study market inefficiency, to model information spread across markets—including the spread of information-driven trading—and to better understand market panic. Therefore, the empirical stylized facts about price jumps, which are the main goal of this paper, can shed more light on a broad class of market phenomena and significantly extend the existing knowledge.

One of the major problems associated with price jumps is the lack of evidence of their origins. The literature follows two main streams: the first stream in the literature claims that price jumps primarily originate in news announcements. This stream is represented by Lee and Mykland (2008) or Lahaye, Laurent and Neely (2009), where the authors claim that the main source of price jumps are corporate statements or macro-economic news announcements, for example. In addition, many authors, e.g., Hanousek, Kocenda and Kutan (2008), claim that news announcements cannot be perceived absolutely, but rather only relatively with respect to market expectations. The second stream, on the other hand, states that the main source of price jumps is the lack of liquidity on either the bid or the ask side. Joulin, Lefevre, Grunberg and Bouchaud (2008) and Bouchaud, Kockelkoren and Potters (2004), two representative works, study the so-called excess liquidity and its impact on the formation of price jumps. In addition, this stream opposes the explanation that the primary source of price jumps is revealed news. The lack of a theoretical explanation of price jumps calls fora sound empirical analysis as a prerequisite for building a price jumps theory.

In addition to the two main streams of literature, trading reality provides several different explanations. Sudden price movements could be how markets respond to changes in market mood. When the market mood changes, events are perceived differently (Andersen, Bollerslev, Diebold and Vega, 2007), producing price jumps. For example, when a market bottoms out, it is not affected by negative news, and even less-negative-than-usual news can cause an upswing. Such an upswing could be further fueled by herd behavior. Market mood is also closely connected with a phenomenon known from international finance: in bad times markets are more correlated with each other than in good times (Erb, Harvey and Viskanta, 1994; Ribiero and Veronesi, 2002; Knif, Kolari and Pyronnen, 2005). Therefore, a change in market mood can affect the way markets are correlated with the underlying economic fundamentals, supporting the strong relation between price jumps and market mood.

Price jumps can also be a useful tool to study information spillover in financial markets. The spread of price jumps across markets can be perceived as the spread of important information. An especially interesting case is the connection between price jumps and the revelation of insider information. Insider trading was studied by Cornell and Sirri (1992) or Kennedy, Sivakamur and Vetzal (2006), and causes problems for policy makers and other market participants. Price jumps can be perceived as a signal indicating potential insider-trading problems. Price jumps can also reflect the inefficiency of financial markets. Efficient financial markets, as Fama (1970) puts it, should reflect all the available information. A market with more price jumps should be less efficient.

To my knowledge, this is the first study of price jumps for small emerging markets from the Visegrad region that includes economic and financial inference. In this study, I empirically estimate a broad range of price jump properties in a discrete-time framework, which is suitable for markets with a low and irregular frequency of trades. I use high frequency data for the main stock indices[1] from the countries of the Visegrad region. These countries are small emerging markets. Comparing the results of this study with the existing results from mature or big emerging markets can provide more insight into market micro-structure effects. The markets included in this study are the Prague Stock Exchange (PSE), the Budapest Stock Exchange (BSE) and the Warsaw Stock Exchange (WSE), and one index from a geographically close mature market, the Frankfurt Stock Exchange (FSE). The data are for June 2003 to the end of 2008. Most of the studies to date use data from before the recent financial crisis, so this study extends the knowledge of price jumps by including data from the beginning of the crisis. For the robustness of our findings, I employ two statistical definitions of price jumps, which are not common in the literature. Overall I find several similarities with the other studies conducted on developed markets. In contrast with existing studies I did not find intuitive asymmetry, favoring negative

[1] In contrast to existing studies, the indices included in this work are not directly traded, which can have consequences for the properties of their price processes, namely, serial auto-correlation can have a slower decay.

returns. The different behavior of the Prague Stock Exchange could indicate possible connections to market micro-structure and the population of investors. In addition, the financial crisis has had a rather weak effect on price jump behavior.

2 Literature review

The volatility of financial instruments can generally be decomposed into two parts: regular noise and the remainder. Regular noise is characterized by an underlying Gaussian distribution that was first identified by Bachelier (1900) and since then it has been extensively discussed in the literature. The remainder, known as price jumps, includes irregular but extreme price movements, and has not been deeply studied in the economic literature. It is believed that these extreme price movements follow a Levy distribution (Fama, 1965), which, in principle, can have infinite moments; see Levy (1925). This is in stark contrast to the Gaussian distribution where all moments are finite. Despite the fact that there exist models of price movements taking into account this non-Gaussian component (e.g., Merton, 1976), a deeper theoretical understanding of price jumps is still missing.

In the literature, there is still not full agreement on what source of price jumps dominates.[2] Joulin et al. (2008) advocate that jumps are mainly caused by a local lack of liquidity on the market. They also claim that news announcements, such as company profits or scheduled macroeconomic news, have a negligible effect and are not a primary source of price jumps. On the contrary, Lee and Mykland (2008) and Lahaye, Laurent and Neely (2009) consider news announcements a significant source of price jumps and show a connection between macroeconomic announcements and price jumps on developed markets.

Finally, the liquidity issue was studied by Lillo and Farmer (2004), where the authors establish a quantitative model that focuses on the role of liquidity in price changes. They performed a series of simulations where they aimed to show that

[2] In reality, even the term "price jump" is defined quite vaguely.

a gap in liquidity significantly contributes to price movement. They defined the so-called relative liquidity, the difference in liquidity between sellers and buyers, and showed that sudden changes in this quantity significantly contributed to price movements. The size of this effect, however, depends on the particular stock and one cannot conclude that this is the only or major effect contributing to sudden price changes. Finally, the authors of the above-mentioned paper also hypothesize that market makers have incentives to manipulate liquidity to avoid big losses from holding positions opposite to their clients. In a competitive market, however, such an approach would have a positive impact only in colluding strategies.

Similar quantitative studies were done by Bouchaud, Kockelkoren and Potters (2004) and Joulin et al. (2008). They also focus mainly on liquidity issues and claim that liquidity has a big impact on prices; however, the effect is rather temporary. Consequently, liquidity providers actually produce what they call "liquidity molasses," which dampens price fluctuations and thus reduces market volatility. In addition, they claim that news does not have a big impact on the formation of prices.

Generally, it is believed that the most extreme events are downward, connected with panic and market crashes. For example, Plerou et al. (1999) used normalized returns for the stock prices of individual companies and estimated the tail behavior for positive and negative normalized returns separately. They found that extreme negative normalized returns happen more often than extreme positive cases.

Mathematically, price jumps can be defined in two different frameworks: continuous-time and discrete-time. The continuous-time framework assumes that the underlying process governing the evolution of price is continuous. Then, the price process is described by a stochastic differential equation (like in Black and Scholes, 1973). Price jumps are modeled by adding a Poisson-like differential process into the stochastic equation, e.g., Merton (1976). The continuous-time framework is feasible for huge liquid markets. As a perfect example, one can consider FOREX (see Melvin and Taylor, 2009), which is a huge, global and highly liquid market with global currencies. The discrete-time framework, on the other hand, assumes that time flows discontinuously in given, often equidistant, steps. In the vast majority of applications, the discrete-time approach clearly dominates and therefore in our empirical analysis I will primarily use a discrete-time framework.

Price jumps—or, in other words, the tail properties of the return distributions—for homogeneously spaced data were studied for example in Stanley and Mategna (2000), where the authors summarize the to-date knowledge about extreme returns. Their work is based on an empirical study of returns in a discrete-time framework. Price jumps are studied either by the inspection of the returns themselves, as was done in Stanley and Mategna (2000), or by introducing an indicator for price jumps.

Joulin, Lefevre, Grunberg and Bouchaud (2008) introduce an indicator known as the price jump index, defined as the ratio of absolute returns to the recent market realized volatility, which is taken as the moving average of absolute returns. The authors used the price jump index and one-minute data for US stocks to conclude that the tail distribution of individual stocks follows an inverse cubic distribution.

Another approach in the literature is to study normalized returns, which are simply centered returns normalized by their standard deviation. Plerou, Gopikrishnan, Nunes Amaral, Meyer and Stanley (1999) and Gopikrishnan, Plerou, Nunes Amaral, Meyer and Stanley (1999) employ normalized returns and study price jumps for US stocks and the S&P 500 index using high-frequency data. Among other results, they confirm that the tail distribution of normalized returns for US stocks follows a distribution close to the inverse of the cubic one, i.e., they do not behave either as a pure Gaussian or as a Levy-like distribution with infinite variance. Eryigit, Cukur and Eryigit (2009) study price jumps for a broad range of stock market indices with the help of normalized returns. In addition, they test the different functional forms of the tail distribution.

The big Chinese emerging market is studied by Jiang et al. (2009). The authors employ normalized returns and show that power-law behavior is valid only for long-term moving averages, i.e., when returns are compared to a long history of data. On the other hand, for a short-term history, the tail behavior behaves in a more exponential-like manner.

Clearly from this review, small emerging markets with regional importance are relatively under-researched in terms of price jumps, and at the same time a more general theoretical basis for price jumps is also absent from the literature.

3 Methodology

In this study, I employ two statistical indicators for measuring price jumps for homogeneously spaced time series data: The first indicator is called the price jump index. The second indicator is based on normalized returns. Both indicators work with log-returns r_t, defined in a standard way as $r_t = \log(R_t/R_{t-1})$ with R_t being the price of an asset at time step t. The philosophies of both indicators are very similar: they compare in some way the current return with the immediate history of the preceding returns, thus enabling us to judge the rate and size of price jumps over a given period.

3.1 The Price Jump Index

The price jump index $j_T(t)$ at time t using a history of length T (employed by Joulin et al., 2008) is defined as

$$j_T(t) = \frac{|r(t)|}{< |r(t)| >_T}, \tag{1}$$

where $< |r(t)| >_T$ denotes the equally weighted moving average of T values of absolute returns, including the current value, i.e.,

$$< |r(t)| >_T = \frac{1}{N_T} \sum_{i=0}^{T-1} |r(t-i)| \ . \tag{2}$$

Here N_T stands for the actual number of observations in the time window to control for missing observations.

In addition, Joulin et al. (2008) showed that the tail part of the price jump index distribution should follow a tail behavior $\propto s^{-\alpha_T^{(f)}}$ for a broad class of financial assets, i.e.,

$$P(j_T > s) \sim s^{-\alpha_T^{(f)}} \ , \tag{3}$$

where this relation says that the probability of observing a price movement with the price jump index j_T above some threshold s is proportional to the power-law behavior. The crucial parameter of this power-law distribution is $\alpha_T^{(f)}$, usually denoted as a characteristic coefficient. The characteristic coefficient governs the rate of price jumps occurrence. The high values of the characteristic coefficient mean that the probability of observing a price jump is more suppressed compared to the cases with low values of the characteristic coefficient. It is clear that the following rule holds: the lower the α is, the more likely extreme price jumps will be observed. In addition, the value of $\alpha \leq 3$ indicates a Levy-like behavior with infinite volatility, see Kleinert (2009). An economic explanation of the characteristic coefficient is not so straightforward. A plausible explanation would require detailed knowledge of the market micro-structure, the economic environment as well as a knowledge of the legal issues, which is beyond the scope of this empirical paper.

The characteristic coefficient depends both on the frequency of the data and on the length of the time window T. In the following formulas and expressions, I will omit the frequency index. The index for the time window T will be kept explicitly in all expressions. Joulin et al. (2008) found a stylized fact that holds for a large set of US stocks: the characteristic coefficient α tends to be around

4. Such a value of the characteristic coefficient corresponds to the inverse cubic distribution. This importance of the power-law tail distribution and the range of the characteristic coefficient–values corresponding to the inverse cubic distribution– were also confirmed by Plerou et al. (1999) and Gopikrishnan et al. (1999). On the other hand, the value of $\alpha \leq 3$ indicates a Levy-like behavior with infinite volatility, see Kleinert (2009).

3.2 Normalized returns

Normalized returns, as used by Plerou et al. (1999) or Jiang et al. (2009), are defined as

$$r_T^n(t) = \frac{r(t) - < r(t) >_T}{\sigma_T(t)}, \tag{4}$$

where $< r(t) >_T$ is defined in a similar way as in equation (2), and $\sigma_T(t)$ is the standard deviation calculated from the same set of T returns. Therefore, returns are first centered around the mean and then normalized by their deviation.

3.3 Filtering Properties of the Two Indicators

Both definitions of the price jump indicator, i.e., the price jumps index and normalized returns, operate with history. The history is characterized by the number of preceding returns for which the realized volatility is calculated. The length of the time window defines the filtering property of the price jump indicator, i.e., it is related to the frequency of processes that will be captured by the indicator. Generally, the longer the moving average, the more sensitive the indicator would be with respect to low frequency processes (cycles), and the more insensitive the indicator would be to high frequency events. On the other hand, a very short time window does not take into account slowly varying processes and considers only fast abrupt changes.

4 Data and Descriptive Statistics

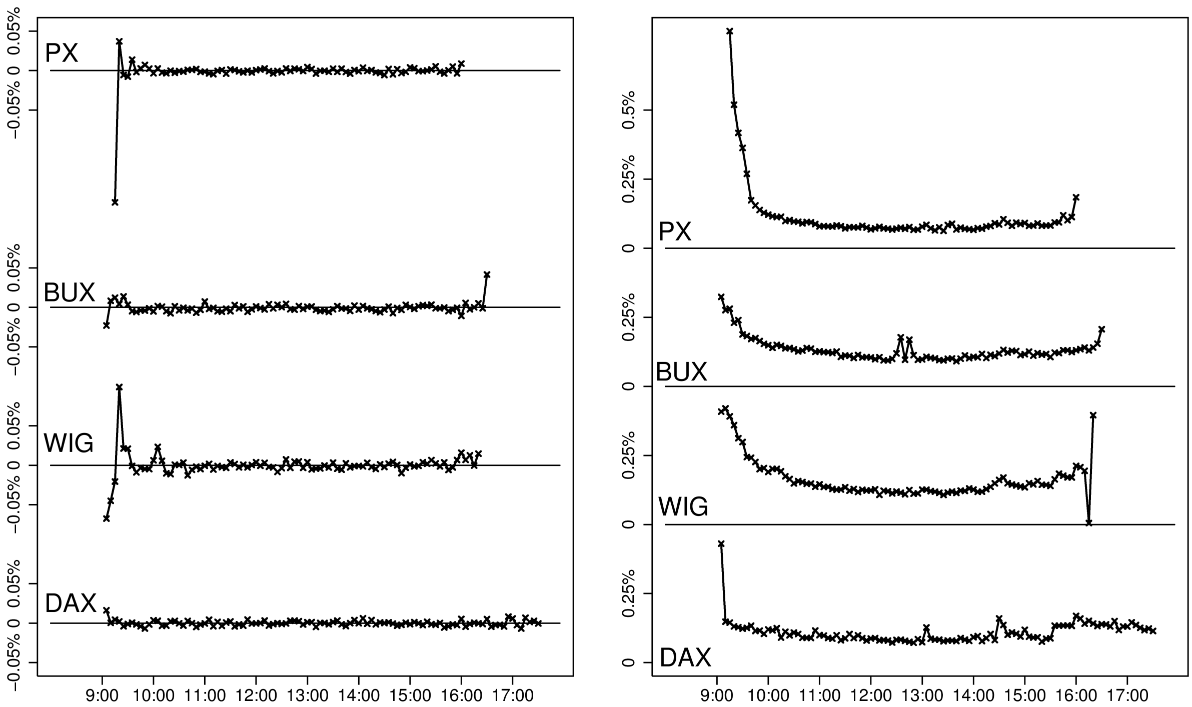
I use data with 5-minute frequency for the main stock market indices from the Prague Stock Exchange (PSE, the PX index), the Budapest Stock Exchange (BSE, the BUX index), the Warsaw Stock Exchange (WSE, the WIG20 index) and the Frankfurt Stock Exchange (FSE, the DAX index); the data spans from June 2003 to December 2008. When there is no value in the data-set, I treat it as a missing value. I have derived three lower frequencies from the original data set: 10, 15 and 30 minutes. Since the main purpose of this research is to study markets with respect to the phenomena present due to market dynamics, I have cut off the very beginning and the very end of each trading day.

The cut-off at the beginning of the trading day is performed due to the different dividend structures of the indices. Generally, an index can be dividend-included or dividend-excluded. Dividends and other similar events are included in dividend-included indices, and these events are not considered when the value of the index is determined for dividend-excluded indices. In our case, the DAX and BUX indices are dividend-included, while the PX and WIG indices are dividend-excluded. This causes different behaviors in the opening periods due to the possible issuance of dividends.[3] The initial cut-off can have a negative effect on the data since I do not consider the first moments of returns, where markets react to overnight events.[4] This has to be taken into account when I infer financial implications. The cut-off at the end of the trading day is performed for similar reasons, i.e., the end of the day also might have similar extreme events, so cutting off the end avoids a possible bias in the data. In addition, the cut-off occurs long after the US markets open,

[3]For a description of the dividend structures, see the official web pages for the four stock exchanges: www.bcpp.cz; www.bse.hu; www.gpw.pl; www.deutsche-boerse.com.

[4]This can even cause the data to show the opposite reaction to the events since markets could in the very first moments react negatively to negative events, and after an abrupt negative reaction, they could positively correct the price. Since I could cut off the first reaction, I would see the positive correction only. In addition, for an illustration of how the dividend process influences the price process, see Fengler, Hardle and Mammen (2007) for a discussion of various financial variables for the dividend-included DAX index.

Figure 1: Distribution of returns (LHS) and standard deviation of returns (RHS) over the trading day.



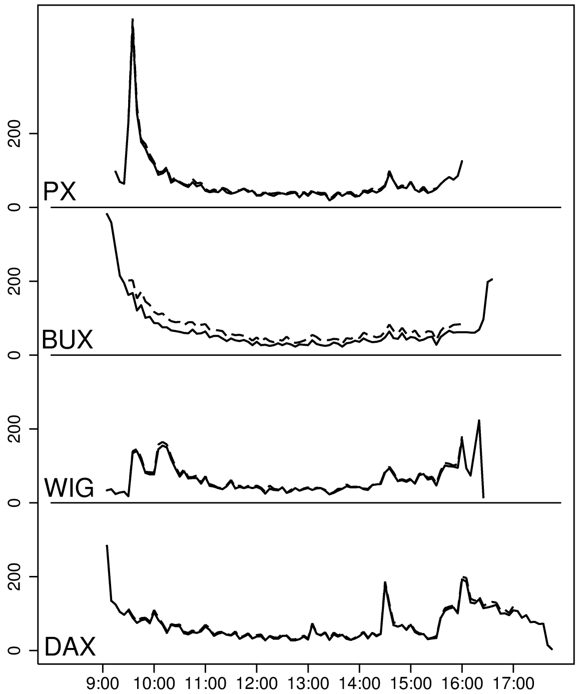
Note: The LHS figure describes the distribution of returns over a trading day using a 5-minute frequency. Plotted are distributions for all four indices: the PX, BUX, WIG, and DAX indices. The RHS figure captures the distribution of the standard deviation over a trading day using a 5-minute frequency for the four indices depicted in the same order. The initial double peak for the WIG index is caused by the fact that the stock exchange changed its operating hours in the middle of the sample from 10:00 to 9:00.

therefore the main trading events that are connected with the beginning of the US market day are explicitly included.

Cutting off the initial phase of the market is also necessary when I want to treat markets in a parallel manner. The reason stems from the fact that the stock exchanges open at different times. When the markets open they usually accommodate information that happened overnight. Thus, comparing markets at the beginning/end of the day can result in a situation where one of the markets is just opening/closing while others are at the end of their trading day. This could produce some false signals.

In order to provide a clear picture, I first summarize in Figure 1 the distribution

Figure 2: Distribution of extreme returns over the trading day.



Note: Shown is the distribution of extreme returns over a trading day using a 5-minute frequency. Extreme returns are defined as returns below the 2.5th centile or above the 97.5th centile calculated over the entire period. The solid line takes into account the entire trading day, while the dashed line refers to the trading day with the beginning and end cut off. The double peak for the WIG index is caused by the fact that the stock exchange changed its operating hours in the middle of the sample from 10:00 to 9:00.

of returns and the standard deviation over the entire trading day (without any cut-off) for all four indices at a 5-minute frequency. The figure on the left shows that the three emerging markets have on average negative returns during the opening period, i.e., the three markets drop during the first moments. On the contrary, the mature market does the opposite, i.e., it slightly increases in value. In addition, the PX has the most abrupt changes, which is further supported on the right of the figure, where the distribution for the standard deviation is depicted. Besides the U-shape during the trading day, which is the most strong for the PSE and less strong for the mature market, I can see a small increase in volatility during the lunch period and during the opening of US markets.

More specifically, the trading hours are: i) PX: opening hours from 9:15 to 16:00 and trading period from 9:30 to 15:30; ii) DAX: opening hours from 9:00 to 17:30 and trading period from 9:30 to 17:00; iii) BUX: opening hours from 9:00 to 16:30 and trading period from 9:30 to 16:00; and iv) WIG: opening hours from 9:00 to 16:20 [5] and trading period from 9:30 to 16:00. In the following, I also distinguish between two types of times, clock time and trading time, where trading time runs during trading periods only, i.e., the last minute at the end of the trading period is followed by the first minute of the next trading period.

The effect of cutting off the very first and very last moments of the trading period on the distribution of extreme movements is depicted in Figure 2. The figure depicts the distribution of the number of extreme returns over the trading day for both the entire trading day without any cut-off (solid line), and for the day with the cut-off (dashed line). Extreme returns are defined as those that are below the 2.5th centile or above the 97.5th centile calculated over the entire sample. The two lines tend to coincide for all four indices, except for a small deviation for the BUX index. The coincidence of the two lines combined with the information in Figure 1 means that the initial and/or final periods do not contain significantly more price jumps. The smile pattern, as can be seen on the LHS of Figure 1, suggests that the initial moments consist of returns with the same sign rather than being dominated by extreme downward movements. However, the RHS of Figure 1 still shows that the spread of returns will be higher in the initial period.

4.1 Descriptive Statistics

The descriptive statistics of returns provide the first hints about the possible properties of price jumps. The first four centered moments can be found in Table 1. In addition, the table shows the Jarque-Bera statistics (Jarque and Bera, 1980) to test the data coming from a standard Gaussian distribution. The Jarque-Bera statistics

[5]The WSE originally operated from 10:00 to 16:00. From October 3, 2005, exchange trading started at 9:30 and closed at 16:10. Currently, the trading hours span from 9:00 to 16:20.

Table 1: Basic statistics of returns.

Index	f	N	μ	σ	S	K	JB-stat.
PX	5	99 802	-9.13e-07	.00096	-0.2914	33.13	3.77e06
	10	49 807	-1.34e-06	.00147	-0.6364	28.77	1.38e06
	15	33 333	1.86e-07	.00191	-0.6301	29.28	9.61e05
	30	16 594	-1.01e-06	.00279	-0.7119	21.08	2.27e05
BUX	5	10 890	-1.55e-05	.00123	-0.2485	78.42	2.58e06
	10	55 138	-2.70e-05	.00181	-0.5953	48.33	4.72e06
	15	37 222	-3.83e-05	.00227	-1.2000	44.58	2.69e06
	30	19 298	-7.57e-05	.00338	-0.6181	22.91	3.20e05
WIG	5	104 075	-4.69e-06	.00145	0.1046	12.61	4.00e05
	10	52 130	-8.51e-06	.00204	0.0152	11.62	1.61e05
	15	34 746	-9.11e-06	.00246	0.0662	11.06	9.41e04
	30	17 443	-2.66e-05	.00349	0.2007	13.01	7.30e04
DAX	5	127 661	-2.14e-06	.00106	-0.1076	34.06	5.13e06
	10	64 521	-5.07e-06	.00151	-0.0778	31.70	2.21e06
	15	43 480	-6.69e-06	.00184	-0.0997	24.19	8.13e05
	30	22 429	-1.42e-06	.00286	3.5361	186.92	3.16e07

Note: The table summarizes the standard statistics of log-returns $r(t)$ for all four market indices used in this study; in the brackets is the corresponding stock exchange: PX (Prague Stock Exchange), BUX (Budapest Stock Exchange), WIG (Warsaw Stock Exchange) and DAX (Frankfurt Stock Exchange). All four frequencies were used: 5-, 10-, 15- and 30-minute.The table shows: (f) the number of observations (N), mean of returns (μ), standard deviation (σ), skewness (S), kurtosis (K) and Jarque-Bera statistics (JB-stat.).

is defined as $JB = \frac{N}{6}\left(S^2 + \frac{(K-3)^2}{4}\right)$ with S measuring the skewness, K measuring the kurtosis, and N the number of observations. The test is asymptotically equal to χ^2_2 and specifies the null hypothesis that data are i.i.d. and come from a Gaussian distribution.

Table 1 shows that the means of returns are shifted toward negative values. The standard deviation is increasing with decreasing frequency, or with increasing sampling intervals Δt, and is roughly in agreement with the known scaling law, see Stanley and Mategna (2000),

$$\sigma_{\Delta t} \propto \sqrt{\Delta t}\,.$$

A further measure reported in the table is skewness, which is a measure of the asymmetry of the distribution. The results show that the PX, BUX and DAX indices have negative skewness, with exception of the DAX index at a 30-minute frequency, and thus their distributions have longer negative tails. On the other hand the WIG index shows positive skewness over all the frequencies, which supports the claim that the WIG index is dominated by positive jumps. The distribution of this quantity differs a lot compared to the other 15 time series. The next column with reported kurtosis shows that all time series are leptokurtic, which supports the presence of a fat-tail, or in other words, the presence of extreme price jumps not coming from the Gaussian distribution. Finally, to statistically demonstrate that the data are not Gaussian-like, I report the Jarque-Bera statistics. The Jarque-Bera statistics reach large values when compared to the critical value 9.21 at the 1% confidence level. The strong deviation from the Gaussian distribution suggests the presence of price jumps.

5 Results

The analysis of returns suggests the presence of price jumps on all four frequencies used in this study. Therefore, I study price jumps using all four frequencies at different time scales. The different time scales are realized by setting up different time window lengths for the two statistical indicators of price jumps. The different lengths of time window resonate with the filtering properties of the indicators. In this study, I consequently employ the following set of time windows: $T = 12$, 24, 100, 1000, 2000 and 5000 time steps. Naturally, the length in minutes depends also on the used frequency. I applied steps $T = 12$ and 24 to focus on the immediate effects inside the trading day. Time widows $T = 100$ and longer are taken to inspect long-term averages.

5.1 Price Jump Indicators

The characteristic coefficient α, as introduced in relation (3), is estimated for both the price jump index and normalized returns. I first linearize relation (3) by recasting it into the form

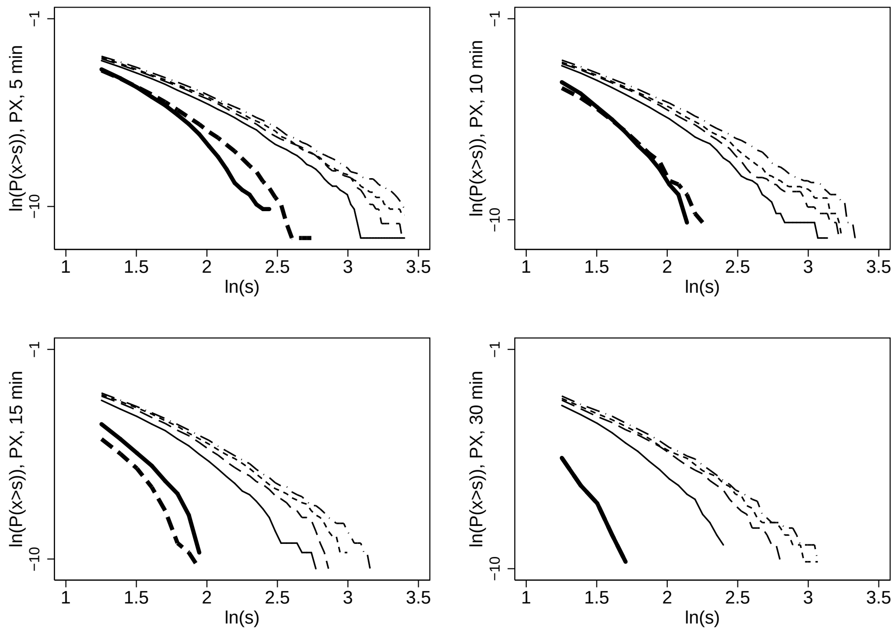
$$\ln P(j > s) \propto -\alpha \ln s \,. \tag{5}$$

The linearized relation for the PX index using all four frequencies and all six time windows is in Figure 3. The figure clearly shows that the longer the time window T, the higher the probability of the occurrence of extreme events. This is in agreement with Plerou et al. (1999), where the exponential behavior of tails was explicitly tested. This is also supported by the theoretical and empirical evidence presented in Kleinert (2009). The figure also suggests that a short time window produces a non-linear distribution, which is again in agreement with Plerou et al. (1999), where the authors claim that a short time window results in an exponential distribution for extreme price movements. In the following, I employ $T = 5000$ for all estimations of α.

In the next step, I employ the following algorithm to estimate the characteristic coefficient: using OLS, I estimate α in relation (5) for various tail intervals. I take the result that has the highest R^2. Such an algorithm is simple and in agreement with a visual observation of the linear region of tails; I also performed an eye check of the results to avoid spurious regressions. An alternative approach would be to use, e.g., MLE or Principal Component Analysis as in Vaglica, Lillo, Moro and Mantegna (2008).

First, I report in Table 2 the estimated characteristic coefficients for the price jump index using all four stock market indices and all four frequencies. Comparing the characteristic coefficients for the highest frequency, the PX index has the lowest significant value of all the indices. This suggests the presence of extreme price jumps

Figure 3: Log transformed version of the tail part of the price jump index distribution for the PX index.



Note: The figures capture the linearized empirical distribution of the price movements with the price jump index above the threshold value s. The distribution was calculated using all four frequencies and six different time windows T. The two short-term windows have a more suppressed occurrence of extreme events compared to the four long-term windows. The symbols used in this table are: $T = 12$ (thick solid) , $T = 24$ (thick dash) , $T = 100$ (solid), $T = 1000$ (dash), $T = 2000$ (short dash) and $T = 5000$ (dash dot).

Table 2: Estimated characteristic coefficient α_T for the price jump index.

$\alpha_T(\sigma_\alpha)$	5-minute	10-minute	15-minute	30-minute
PX	3.554 (.033)	3.313 (.031)	3.713 (.040)	4.167 (.085)
BUX	3.809 (.024)	3.403 (.027)	3.493 (.029)	3.465 (.059)
WIG	4.949 (.083)	4.825 (.096)	4.517 (.099)	3.927 (.063)
DAX	4.098 (.046)	3.773 (.030)	3.542 (.049)	2.973 (.032)

Note: The estimation was done for all four indices—PX (Prague Stock Exchange), BUX (Budapest Stock Exchange), WIG (Warsaw Stock Exchange) and DAX (Frankfurt Stock Exchange)—at all four frequencies—5-, 10-, 15- and 30-minute—and for the time window $T = 5000$. The value in the brackets is the standard deviation. The higher the standard deviation, the worse the estimation of the characteristic coefficient was found.

on the PX index. At the other pole stands the WIG index.

The smaller frequencies also reveal another important pattern that further distinguishes the behavior of the PX index compared to the other three indices. In the case of the PX index, the characteristic coefficient increases as the frequency decreases. This implies that less extreme events are present for lower frequencies. On the other hand, the remaining three indices reveal the completely opposite behavior: the characteristic coefficient decreases with decreasing frequency. Such a pattern tends to be supported by analogous results with shorter time windows. An analogous relationship is visible for returns where the tail distribution—for high frequencies—is exponentially suppressed. The exponential suppression can be viewed as a behavior with a very high characteristic coefficient. However, the PX index behaves in the opposite way, which I call the “PX puzzle”.

The explanation for the “PX puzzle” will probably lie in a characteristic specific to this market. One possible explanation, the different role of dividends, is not the case here. If it were so, I would also observe a “WIG puzzle”; however, I do not. Hence I argue that the explanation of the “PX puzzle” lies in the fact that several stocks traded at the PSE have relatively small market capitalization and liquidity. The price of such stocks could be easily influenced, especially over a short period of time. This explanation uses the parallel between the volume of traded assets and the mass in dynamics. The heavier an object is, the more effort has to be expended to make it move. Consequently, fast movements, when viewed from a longer perspective, are averaged out and the movements are not so jumpy. Another possible explanation for the “PX puzzle” can lie in the different policy regulations for margin lending. Namely, Fortune (2001) discusses the positive correlation between the rate of margin lending and market volatility. Taking into account the fact that the Prague Stock Exchange suffered during the period used in this study by a low regulation of trading margins, I can further explain the different behavior of the PX index with respect to the remaining three indices. Finally, the DAX index reveals for

Table 3: Estimated characteristic coefficient $\alpha_T^{\pm}$ for the price jump index.

$\alpha_T^{\pm}(\sigma_\alpha)$		5-minute	10-minute	15-minute	30-minute
PX	+	3.654 (.047)	3.721 (.058)	3.475 (.040)	3.516 (.077)
	-	3.435 (.041)	3.065 (.031)	4.028 (.053)	4.008 (.082)
BUX	+	3.887 (.027)	3.388 (.033)	3.712 (.062)	3.712 (.078)
	-	3.769 (.033)	3.365 (.046)	3.352 (.045)	3.359 (.063)
WIG	+	4.208 (.075)	4.103 (.096)	3.979 (.067)	3.277 (.081)
	-	6.205 (.293)	4.811 (.157)	4.769 (.159)	4.076 (.127)
DAX	+	3.836 (.037)	3.704 (.049)	3.310 (.044)	2.720 (.044)
	-	4.277 (.057)	3.792 (.043)	3.703 (.068)	3.233 (.037)

Note: The estimation was done for all four indices—PX, BUX, WIG and DAX—using all four frequencies—5-, 10-, 15-, and 30-minute—and the time window $T = 5000$. The characteristic coefficient is calculated separately for upward movements (+) and downward movements ($-$). The value in the brackets is the standard deviation.

the lowest frequency a Levy-like behavior, which, in theory, implies infinite volatility.

5.2 Asymmetry

The next step is to estimate the characteristic coefficients for positive and negative movements separately. In the case of normalized returns this comes naturally from the definition. In the case of the price jump index, I estimate the characteristic coefficients separately for positive and negative movements, while the average of absolute returns is composed of a given history no matter what the sign of the returns was.

Table 3 contains estimates using the price jump index, while Table 4 contains the estimates using normalized returns. Characteristic coefficients for positive and negative movements estimated separately are done for all four indices using all four frequencies and the longest time window.

The qualitative results are more important than the quantitative results. These results enable me to robustly compare the behavior of stock exchanges. Both tables clearly show that intuitive asymmetry favoring negative price jumps does not hold here. Table 5 analyzes this asymmetry. For every index and every frequency, the characteristic coefficient is calculated for negative and positive movements using

Table 4: Estimated characteristic coefficient $\alpha_T^{\pm}$ for normalized returns.

$\alpha(\sigma_\alpha)$		5-minute	10-minute	15-minute	30-minute
PX	+	3.659 (.066)	3.607 (.080)	3.651 (.038)	3.397 (.093)
	-	3.277 (.070)	3.186 (.027)	3.932 (.105)	3.654 (.141)
BUX	+	3.972 (.044)	3.636 (.060)	3.827 (.103)	4.144 (.138)
	-	4.060 (.058)	3.756 (.037)	3.689 (.072)	3.874 (.133)
WIG	+	3.992 (.092)	4.316 (.098)	4.140 (.103)	3.472 (.079)
	-	5.153 (.110)	4.872 (.215)	5.636 (.234)	4.652 (.246)
DAX	+	4.288 (.067)	4.025 (.036)	3.275 (.061)	2.699 (.115)
	-	4.064 (.095)	3.815 (.061)	3.830 (.088)	3.388 (.082)

Note: The estimation was done for all four indices: PX, BUX, WIG and DAX. The length of the time window is $T = 5000$. The value in the bracket is the standard deviation. The estimated characteristic coefficients are for both negative $(-)$ and positive $(+)$ sides of the normalized returns. Parameters were estimated using the standard OLS algorithm.

Table 5: Up/down asymmetry for the price jump index and normalized returns.

	5-minute		10-minute		15-minute		30-minute	
	PJI	NR	PJI	NR	PJI	NR	PJI	NR
PX	-	-	-	-	+	+	-	+
BUX	-	+	+	+	-	-	-	-
WIG	+	+	+	+	-	+	+	+
DAX	-	-	-	-	+	+	+	+

Note: The table summarizes the comparative study of the characteristic coefficients for the up and down movements. PJI stands for the case where the price jump index was employed, while NR is for the case with normalized returns. The estimation was done for all four indices—PX, BUX, WIG and DAX—and all four frequencies—5-, 10-, 15- and 30-minute. The length of the time window is $T = 5000$. In each entry, the characteristic coefficients for positive and negative price jumps are compared. The symbol $+$ means that α_T^+ is lower than α_T^-, i.e., more price jumps are observed in the upward direction. The analogy holds for the symbol $-$. Intuition suggests that entries should be dominated by the symbol $-$.

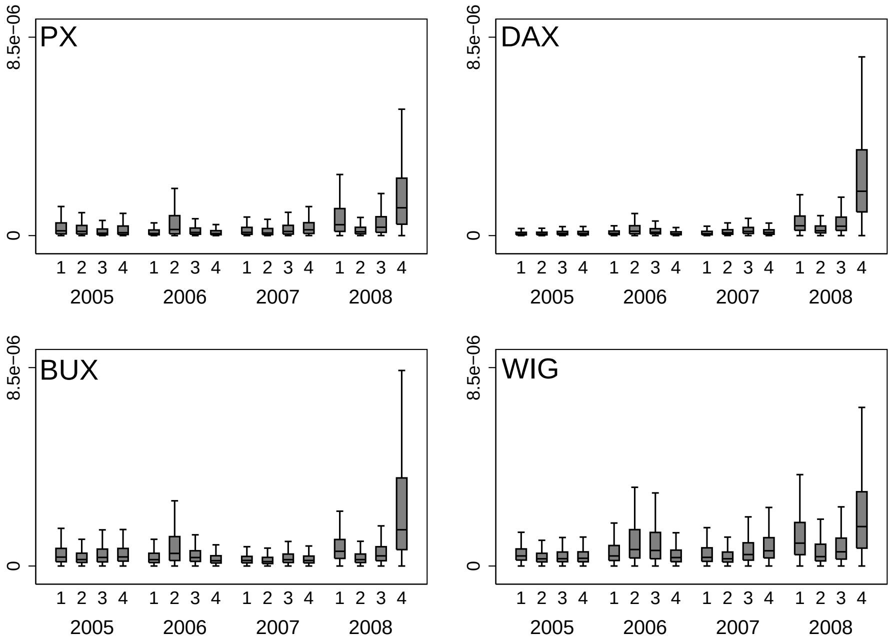
both indicators. The symbol in the table entry denotes whether the data favor price jumps up or down for a given indicator, i.e., if the entry contains a + symbol, $\alpha_T^{(+)}$ is smaller than $\alpha_T^{(-)}$ and, thus, more extreme price jumps occur in the upward direction.

The inequalities agree in all but three cases. The comparisons for the PX index at the 30-minute frequency and for the BUX index at the 5-minute frequency differ, but the differences are very small in the absolute values of the characteristic coefficients and are statistically insignificant. The third disagreement is for the WIG index at the 15-minute frequency, which could come from the fact that the standard deviations for the WIG index are generally high and thus the OLS estimation is in this case less reliable.

The observed violation of intuitive asymmetry does not fit into the current empirical understanding of financial markets. It could be caused by the fact that emerging markets in the Visegrad region are relatively small and differ substantially from mature markets or from large Asian emerging markets. Our observation is supported by employing two independent price jump indicators on the same sample. Therefore, I believe that our findings are robust with respect to the methods used. Hence, the observed violation of intuitive asymmetry for the Visegrad stock markets reflects differences in market micro-structure and market responses to shocks rather than in the sensitivity of the methods.

Another plausible explanation can lie in the cutting-off of the beginnings and ends of the indices. This implies that for the indices and frequencies that show a violation of intuitive asymmetry, returns driving the intuitive asymmetry occur mainly in the truncated period, i.e., during the moments after opening and before closing. This would mean that at the highest frequency, that for example the BUX and WIG indices show during the very first and very last operating moments significant drops in value. This is confirmed by the data; see Figure 1. Figure 2 further suggests that the downward movements in the very first moments of the trading day are

Figure 4: Volatility quarterly.



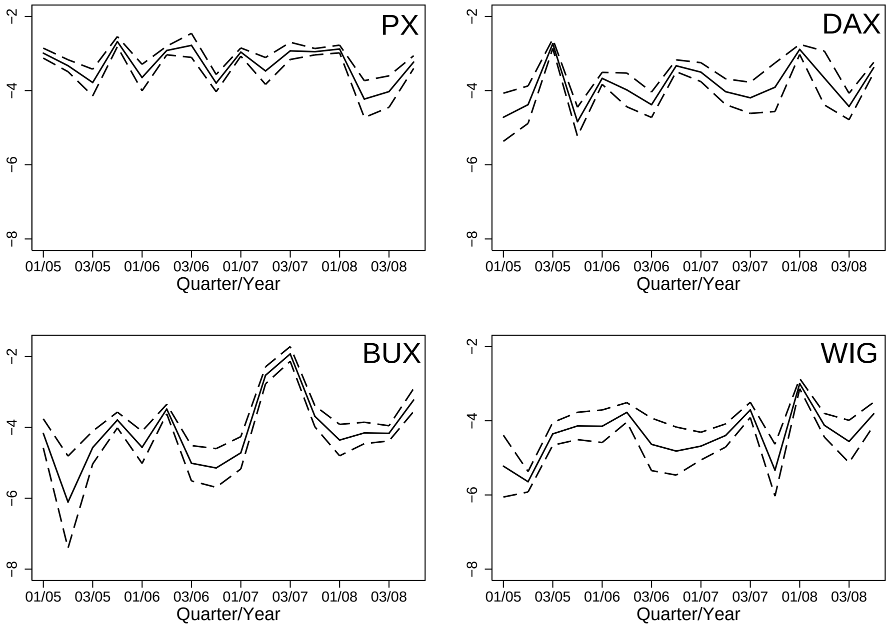
Note: Shown is the distribution of the volatility for each quarter for all four indices—PX, BUX, WIG and DAX—using 5-minute data and the shortest time window $T = 12$. In addition to the increase of volatility during the financial crisis, there is an increase for the three emerging markets in mid-2006. This increase was caused by negative investment recommendations by big financial institutions.

not dominated by extreme price movements but rather movements with the same downward orientation. This conclusion, however, would mean that for the case of the PX index the asymmetry is even more pronounced since the initial period, which is dropped, contains on average the most negative values for returns among all the indices.

5.3 Financial Crisis

Finally, I study the behavior of price jumps during the recent financial crisis, which hit economies at full strength in August 2008. It is generally believed that any financial crisis increases volatility as the impatience and nervousness of market participants increases. This is confirmed by Figure 4, where I report the standard deviation for all four indices at a 5-minute frequency and with a time window of

Figure 5: Characteristic coefficient estimated quarterly.



Note: This figure shows the estimated characteristic coefficient α_T for the price jump index using all four indices: PX, BUX, WIG and DAX. Estimation was done on quarterly basis for the period 2005 to 2008. The length of the time window is $T = 5000$. The dashed line in both sub-figures represent the 95% CI.

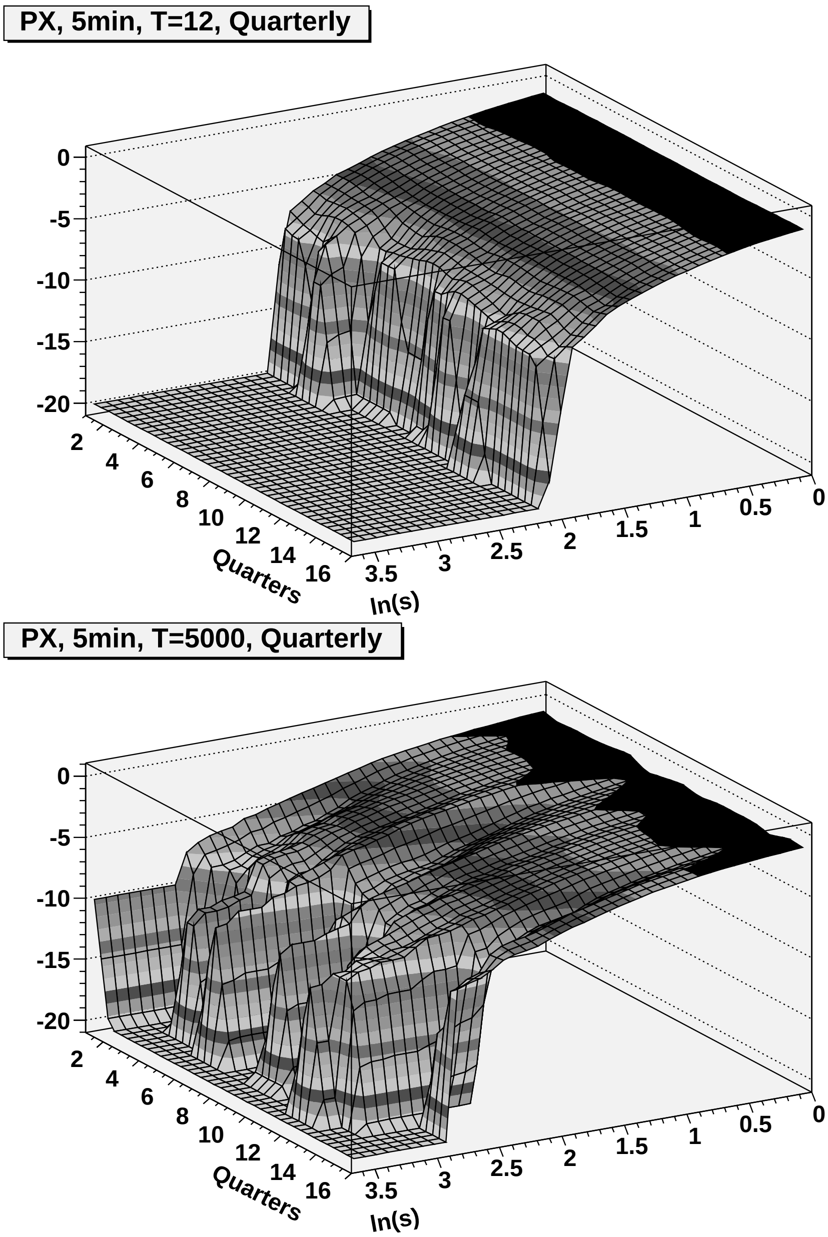
$T = 12$. The volatility is reported by quarters, where the confidence intervals are also reported. All of the indices show an extreme increase in uncertainty during the last quarter of 2008 at the onset of the financial crisis. In addition, a sharp increase in uncertainty can be seen during the first quarter of 2008, which can be understood as a signal of worsening conditions. Since the volatility in the second quarter of 2008 returned back to its usual levels, this signal was mostly ignored.

However, the unanswered question still remains: Did the current financial crisis have any significant effect on the behavior of price jumps? In the preceding sections it was shown that the price processes of all assets at all frequencies contain a significant amount of price jumps. The effect of the financial crisis can in fact be twofold. First, the entire price process could be scaled up by some factor. This results in increased volatility and the ratio of extreme price movements with respect to the recent history of the market remains unchanged. Second, the number of extreme price movements could be higher, meaning that the market will behave more irrationally and will tend to overreact to coming news and market signals. Therefore, a priori intuition is missing.

To answer the question whether the activity of price jumps increased or not during the crisis, I estimated the coefficients for both indicators and all frequencies using all four indices on a monthly and quarterly basis. The monthly basis does not seem to be useful since the study of price jumps as rare events calls for a rather high number of observations, which is not satisfied. The results are therefore statistically weak and one cannot obtain any meaningful conclusions. Therefore, I focus on the quarterly basis and estimate characteristic coefficients quarterly. The estimated characteristic coefficients for the price jump index, along with 95% confidence intervals, for all four indices at a 5-minute frequency and a $T = 5000$ time window are graphically depicted in Figure 5. Comparing the four indices, I can clearly see that the characteristic coefficient for the PX index dominates the other three markets. This means that the PX index reveals the highest rate of price jumps. The reason for that can be borrowed from the previous explanation of the "PX puzzle", namely from the loose regulation of margin lending. In addition, the characteristic coefficient for the PX index is constant in time while the coefficients for the remaining three indices tend to grow in time, i.e., the indices become more jumpy. However, the figure does not reveal any statistically significant change in the characteristic coefficients solely due to the financial crisis, which appeared in the second half of 2008. Thus, the results suggest that the rate of price jumps was not affected by the arrival of the financial crisis. The same conclusion holds for other frequencies.

To get a more proper view of how the distribution of price jumps behaves in time, I present the 3D Figure 6 with the log-log distribution of extreme events for the PX index, using data at 5- and 30-minute frequencies and time windows $T = 12$ and 5000. The time period spans from 2005 to 2008 and the distributions are plotted

Figure 6: Tail of the linearized distribution of the price jump index.



Note: Plotted is the tail part of the linearized distribution of the price jump index for the PX index. The vertical axis contains $\ln P(j > s)$, i.e., the linearized probability to observe a price jump with the price jump index above the thershold s. Data spans from 2005 to 2008 and were taken on a quarterly basis, where 1 stands for the first quarter of 2005 and 16 for the last quarter of 2008. The variable s is the same as was introduced in equation (3). This Figure is a 3D analogy to Figure 3.

on a quarterly basis, i.e., 1 stands for the first quarter of 2005 and 16 for the last quarter of 2008. The figure is an analogy to Figure 3 (the interpretation of $\ln(s)$ and the value on the vertical z-axis). Both sub-figures support the previous results and the claim that the financial crisis did not cause any absolute increase in price jumps. However, one has to bear in mind that the entire price process was scaled up, which cannot be seen in these figures. The other three indices and other frequencies reveal the same behavior.

6 Conclusion

I performed an extensive analysis of price jumps using high-frequency data (5-, 10-, 15- and 30-minute frequencies) for three emerging Visegrad indices (PX, BUX and WIG20), and for the DAX index to represent a geographically close mature market. The time period of the data ranges from June 2003 to December 2008. For the analysis I employed two different indicators of price jumps: the price jump index and normalized returns. The analysis of returns revealed that the data deviates from a Gaussian distribution and tends to support the presence of price jumps. Based on this observation, I estimated the price jump index and normalized returns. The results suggest that intuitive asymmetry favoring negative price jumps does not hold and this result was confirmed by both indicators.

Further, the Prague Stock Exchange differs with respect to the presence of price jumps when lower frequencies are used. Based on the theory, one would assume that the lower the frequency is, the more price jumps will be observed. However, the PX index reveals the completely opposite behavior, supporting the hypothesis that the behavior of the PX index significantly differs from the remaining three market indices. One can speculate that this difference could be explained by the composition of the PX index: the small number of components, the relatively high number (and weight) of stocks with dual trading and prices determined in other exchanges and the fact that some components are not traded with high frequency. Simply, a relatively small number of trades with a few stocks could have a large impact on the entire PX index. These explanations, however, would need additional analysis and the market micro-structure perspective should be tested across the markets, which is beyond the scope of this study.

Last but not least, I estimated the price jump properties quarter by quarter and then checked whether the recent financial crisis caused an increase in the number of price jumps. The results show that the number of price jumps remains roughly the same, while the overall volatility soared up.

Overall, I aim to cast light on the issue of extreme price movements, which frighten both market practitioners and financial regulators in the environment of small emerging markets. Understanding the distribution of price jumps can help to decrease the risk connected with price jumps and to develop various financial models. The empirical analysis–or the stylized facts–presented in this study can also serve as a starting point for further study of the integration of financial markets. Such a study could bear fruit especially for small emerging markets, like those of Central and Eastern Europe, where the measure of integration and its change in time is highly needed. The quantitative and qualitative differences in jump behavior can serve as a new way to view financial integration.

References

Andersen T.G., Bollerslev T., Diebold F.X., and Vega, C., 2007. Real-time price discovery in global stock, bond and foreign exchange markets. Journal of International Economics 73, pp. 251 – 277.

Bachelier, L., 1900. Théorie de la spéculation. Annales Scientifiques de l'École Normale Supérieure 3 (17), pp. 21 – 86.

Becketti, S., and Roberts, D.J., 1990. Will increased regulation of stock index futures reduce stock market volatility?. Economic Review, Federal Reserve Bank of Kansas City, Issue Nov, pp. 33 – 46.

Black, F., and Scholes, M., 1973. The pricing of options and corporate liabilities. The Journal of Lolitical Economy, Vol. 81, No. 3, pp. 637 – 654.

Bouchaud, J-P., Kockelkoren, J., and Potters, M., 2004. Random walks, liquidity molasses and critical response in financial markets. Science & Finance (CFM) working paper archive 500063, Science & Finance, Capital Fund Management.

Broadie, M., and Jain, A., 2008. The effect of jumps and discrete sampling on volatility and variance swaps. International Journal of Theoretical and Applied Finance, Vol. 11, No.8, pp. 761-797.

Cornell, B, and Sirri, E.R., 1992. The reaction of investors and stock prices to insider trading. Journal of Finance 47 (3), pp. 1031 – 1060.

Erb, C. B., Harvey, C. R., and Viskanta, T. E., 1994. Forecasting international equity correlations. Financial Analysts Journal, November-December 1994, pp. 32 – 45.

Eryigit, M., Cukur, S., and Eryigit, R., 2009. Tail distribution of index fluctuations in world market. Physica A, Vol. 388, pp. 1879 – 1886.

Fama, E., 1965. The behavior of stock-market prices. Journal of Business, Vol. 38, No. 1, DOI: 10.1086/294743.

Fama, E., 1970. Efficient capital markets: a review of theory and empirical work. Journal of Finance, Vol. 25, pp. 383 – 417.

Fengler, M.W., Hardle, W.K., and Mammen, E., 2007. A semiparametric factor model for implied volatility surface dynamics. Journal of Financial Econometrics, 2007, Vol. 5, No. 2, doi 10.1093/jjfinec/nbm005.

Fortune, P., 2001. Margin lending and stock market volatility. New England Economic Review, Vol. 4, pp. 4 – 25.

Gatheral, J., 2006. Volatility surface: A practitioner's guide. John Wiley & Sons, Inc., New Jersey.

Giot, P., Laurent, S., and Petitjean, M., 2010. Trading activity, realized volatility and jumps. Journal of Empirical Finance, Vol. 17, pp. 168–175.

Gopikrishnan, P., Plerou, V., Nunes Amaral, L. A., Meyer, M., and Stanley, H. E., 1999. Scaling of the distribution of fluctuations of financial market indexes. Physical Review **E**, Vol 60, No. 5, pp. 5305 – 5316.

Hanousek, J., Kocenda, E., and Kutan, A. M., 2008. The reaction of asset prices to macroeconomic announcements in new eu markets: evidence from intraday data. CERGE-EI Working Paper No. 349.

Jarque, C. M., Bera, A. K., 1980. Efficient tests for normality, homoscedasticity and serial independence of regression residuals. Economics Letters, Vol. 6, No. 3, pp. 255 – 259.

Jiang, J. , Li, W., Cai, X., and Wang, Q. A., 2009. Empirical study of recent chinese stock market. Physica A, Vol. 388, pp. 1893 – 1907.

Johannes, M. 2004. The statistical and economic role of jumps in interest rates. Journal of Finance, Vol. 59, pp. 227 – 260.

Joulin, A., Lefevre, A., Grunberg, D., and Bouchaud, J.-P., 2008. Stock price jumps: news and volume play a minor role. http://arxiv.org/abs/0803.1769.

Kennedy, D.B., Sivakumar, R., and Vetzal, K.R., 2006. The implications of IPO underpricing for the firm and insiders: Tests of asymmetric information theories. Journal of Empirical Finance, Vol. 13, Issue 1, pp. 49 – 78.

Kleinert, H., 2009. Path integrals in quantum mechanics, statistics, polymer physics, and financial markets, 5th Edition. World Scientific.

Knif, J., Kolari, J., and Pynnonen, S., 2005. What drives correlation between stock market returns? international evidence. Working Paper, available at: http://lipas.uwasa.fi/julkaisu/ewp/mat8.pdf.

Lahaye, J., Laurent, S., and Neely, C. J., 2009. Jumps, cojumps and macro announcements. Working Paper of Federal Reserve Bank of St. Louis, No 2007-032, Revised Version.

Lee, S. S., and Mykland, P. A., 2008. Jumps in financial markets: a new nonparametric test and jump dynamics. The Review of Financial Studies, Vol. 21, No. 6, pp. 2535 – 2563.

Levy, P., 1925. Calcul de probabilities II, Paris: Gauthier Villars.

Lillo, F., and Farmer, J. D., 2004. The long memory effect of the efficient market. Studies in Nonlinear Dynamics & Econometrics, Vol. 8, No. 3, Art. 1.

Madhavan, A., 2000. Market microstructure: A survey. Journal of Financial Markets, Vol. 3, Issue 3, pp 205 – 258.

Melvin, M., and Taylor, M.P., 2010. The crisis in the foreign exchange market. Journal of International Money and Finance, Vol. 28, Issue 8, pp 1317 – 1330.

Merton, R. C., 1976. Option pricing when underlying stock returns are discontinuous. Journal of Financial Economics, Vol. 3, No. 1-2, pp. 125 – 144.

Nietert, B., 2001. Pricing relevance of stock price jumps: capm and variance decomposition. EFMA 2001 Lugano Meetings, available at SSRN: http://ssrn.com/abstract=268546.

Pan, J., 2002. The jump-risk premia implicit in options: evidence from an integrated time-series study. Journal of Financial Economics, Vol. 63, pp. 3 – 50.

Plerou, V., Gopikrishnan, P., Nunes Amaral, L. A., Meyer, M., and Stanley, H. E., 1999. Scaling of the distribution of price fluctuations of individual companies. Physical Review **E,** Vol 60, No. 6, pp. 6519 – 6529.

Ribiero, R., and Veronesi, P., 2002. The excess comovement of international stock markets in bad times. Working Paper, International Economics workshop and Finance Lunch at University of Chicago.

Stanley, H. E., and Mantegna, R. N., 2000. An introduction to econophysics. Cambridge University Press, Cambridge.

Tinic, S.M., 1995. Derivatives and stock market volatility: Is additional government regulation necessary?. Journal of Financial Services Research, Vol. 9, No. 3-4, pp. 351 – 362.

Vaglica, G., Lillo, F., Moro, E., and Mantegna, R. N., 2008. Scaling laws of strategic behavior and size heterogeneity in agent dynamics. Physical Review **E**, Vol. 77, No. 2, 036110.

Budapest Stock Exchange: http://www.bse.hu, (accessed July 8, 2009).

Frankfurt Stock Exchange: http://www.deutsche-boerse.com, (accessed July 8, 2009).

Prague Stock Exchange: http://www.bcpp.cz, (accessed July 8, 2009).

Warsaw Stock Exchange: http://www.gpw.pl, (accessed July 8, 2009).

Working Paper Series
ISSN 1211-3298
Registration No. (Ministry of Culture): E 19443

Individual researchers, as well as the on-line and printed versions of the CERGE-EI Working Papers (including their dissemination) were supported from the European Structural Fund (within the Operational Programme Prague Adaptability), the budget of the City of Prague, the Czech Republic's state budget and the following institutional grants:

- Center of Advanced Political Economy Research [Centrum pro pokročilá politicko-ekonomická studia], No. LC542, (2005-2010);
- Economic Aspects of EU and EMU Entry [Ekonomické aspekty vstupu do Evropské unie a Evropské měnové unie], No. AVOZ70850503, (2005-2010);
- Economic Impact of European Integration on the Czech Republic [Ekonomické dopady evropské integrace na ČR], No. MSM0021620846, (2005-2011);

Specific research support and/or other grants the researchers/publications benefited from are acknowledged at the beginning of the Paper.

Published by
Charles University in Prague, Center for Economic Research and Graduate Education (CERGE)
and
Economics Institute ASCR, v. v. i. (EI)
CERGE-EI, Politických vězňů 7, 111 21 Prague 1, tel.: +420 224 005 153, Czech Republic.
Printed by CERGE-EI, Prague
Subscription: CERGE-EI homepage: http://www.cerge-ei.cz

Phone: + 420 224 005 153
Email: office@cerge-ei.cz
Web: http://www.cerge-ei.cz

The paper is available online at http://www.cerge-ei.cz/publications/working_papers/.

ISBN 978-80-7343-210-2 (Univerzita Karlova. Centrum pro ekonomický výzkum a doktorské studium)
ISBN 978-80-7344-200-2 (Národohospodářský ústav AV ČR, v. v. i.)

CERGE-EI
P.O.BOX 882
Politických vězňů 7
111 21 Praha 1
Czech Republic
http://www.cerge-ei.cz