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Price jumps on European stock markets[☆]

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Abstract

We analyze the dynamics of price jumps and the impact of the European debt crisis using the high-frequency data reported by selected stock exchanges on the European continent during the period January 2008 to June 2012. We employ two methods to identify price jumps: Method 1 minimizes the probability of false jump detection (the Type-II Error-Optimal price jump indicator) and Method 2 maximizes the probability of successful jump detection (the Type-I Error-Optimal price jump indicator). We show that individual stock markets exhibited differences in price jump intensity before and during the crisis. We also show that in general the variance of price jump intensity could not be distinguished as different in the pre-crisis period from that during the crisis. Our results indicate that, contrary to common belief, the intensity of price jumps does not uniformly increase during a period of financial distress. However, there do exist differences in price jump dynamics across stock markets and investors have to model emerging and mature markets differently to properly reflect their individual dynamics.

JEL classification: C14; C58; F37; G15; G17

Keywords: Stock markets; Price jump indicators; Non-parametric testing; Clustering analysis; Financial econometrics; Emerging markets

1. Introduction: motivation and literature

It is widely accepted that periods of financial turbulence cause higher volatility on markets as investors tend to overreact to negative information (Anderson, Bollerslev, Diebold, & Vega, 2007). Further, price jumps have been recognized in the financial literature as a significant part of volatility since the seminal Merton (1976). A price jump is understood as an abrupt price change over a very short time that is related to a broad range of market phenomena that cannot be connected to a noisy Gaussian distribution (Lahaye, Laurent, & Neely, 2011; Lee, 2012; Zheng & Shen, 2008). However, so far research is surprisingly scarce on how the distribution of price jumps change during turbulent periods and whether its pattern differs across mature and emerging financial markets. In this paper we analyze price jumps in market indices reported by

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selected stock exchanges on the European continent and their behavior before and after the European debt crisis unfolded.

The financial literature considers a number of ways to classify market volatility. For our analysis the most important aspect is the decomposition of volatility into regular noise (the Gaussian-like component) and price jumps.[1] The literature supports two main explanations of the source of price jumps. First, price jumps can reflect the market reaction to unexpected information, which indicates that news announcements are the primary source of price jumps (Lahaye et al., 2011; Lee & Mykland, 2008). Second, Bouchaud, Kockelkoren, and Potters (2006) and Joulin, Lefevre, Grunberg, and Bouchaud (2008) advocate that jumps are mainly caused by a local lack of liquidity on the market, an event they term "relative liquidity." In addition, an inefficient provision of liquidity caused by an imbalanced market micro-structure can cause extreme price movements as well (see the survey in Madhavan (2000).

Hence, price jump identification is valuable for a number of reasons. Price jumps can serve as a proxy for information arrival and be utilized as tools for studying market efficiency (Fama, 1970) or phenomena like information-driven trading; see e.g., Cornell and Sirri (1992) or Kennedy, Sivakumar, and Vetzal (2006). Further, non-Gaussian price movements influence the models and indicators employed in finance, such as value-at-risk, or the performance of various financial vehicles (Bates, 1996; Gatheral, 2006; Heston, 1993; Scott, 1997). Also, a good knowledge of price jump distribution is potentially useful for financial regulators to implement the most optimal policies; see Becketti and Roberts (1990) or Tiniç (1995).

The financial literature identifies the key reason underlying the importance of detecting price jumps: the presence of jumps has serious consequences for financial risk management and pricing. The recent literature offers empirical support of this claim. Broadie and Jain (2008) show that the pricing of swaps significantly differs when jumps are taken into account and one cannot appropriately price risk while ignoring jumps. Arshanapalli, Fabozzi, and Nelson (2013) support the need to include the jump component into risk measures to estimate the proper risk-return relationship. Carr and Wu (2010) use a jump diffusion model to simultaneously price stock options and credit default swaps and find a significant presence of the interplay between credit and market risks. A similar confirmation of the change in the pricing mechanism was also shown by Duffie, Pan, and Singleton (2000), Liu, Longstaff, and Pan (2003), and Johannes (2004). Jarrow and Rosenfeld (1984), Nietert, and Pan (2002) study pricing in the presence of jumps and all of them confirm the presence of the jump risk premium. Further, Caporin, Rossi, and Santucci de Magistris (2011) analyze even the presence of price jumps in volatility. Another strand of the literature identifies presence of co-jumps and, for example, Li and Zhang (2013) show the stronger co-jump behavior on the US and Chinese stock markets since the subprime crisis.

Despite the importance of analyzing jumps, the literature on jumps in European stock markets is rather limited. Novotný, Hanousek, and Kočenda (2013) analyze the behavior and performance of multiple price jump indicators across developed and emerging markets by employing high-frequency stock market data from Japan, Germany, France, the United Kingdom, the USA, the Czech Republic, Poland, and Hungary. They identify clusters of price jump indicators with similar performance and show that clusters differ in size and are stable across stock market indices and over time. In this respect the recent 2007–2008 financial crisis did not seem to affect the overall jumpiness of mature or emerging stock markets. Further, Hanousek, Kočenda, and Novotný (2013) show that many price jumps identified on emerging European stock markets are due to foreign macroeconomic news. Further, a significant transfer of price jumps from EU and U.S. markets is also noted, with the latter having a stronger influence. Finally, Hanousek and Novotny (2013) analyze the impact of the Lehman Brothers collapse on volatility and price jumps in the US and Czech stock markets, and show only limited reaction to this type of financial distress.

In this paper we analyze how the financial distress affects the distribution and dynamics of price jumps on several stock markets. The financial distress is represented by the European debt crisis that fully unfolded in May 2010 and evolved into a state where it was difficult or impossible for several Eurozone member countries to repay or re-finance their government debts without the assistance of third parties. We aim to analyze the effect of this market-exogenous event on jump behavior across markets. In particular, we aim to study to what extent one can observe the similarities and transfers of price jumps from developed capital markets to emerging stock markets in Europe. Our choice to study both developed and emerging capital markets in Europe is based on several reasons. First, compared to other emerging stock markets, European emerging markets do not suffer so much from potential economic and political instability. Second, they are under the strong influence of developed stock markets (Hanousek, Kočenda, & Kutan, 2009; Horvath & Petrovski, 2013), hence, the potential for influence is one-directional. In the end we analyze data from developed stock markets in the UK and Germany, while emerging markets are represented by the Czech Republic, Poland, Hungary, Romania, Croatia, Slovenia, and Turkey. The emerging markets share several common features: their overall liquidity and number of traded stocks are rather small, the price formation mechanism is under the strong influence of foreign news originating in mature EU and US markets, and despite their smaller size, the share of overall trading volume performed by foreign investors in the emerging stock markets is substantial (Hanousek & Kočenda, 2011).

The paper is structured as follows. First, we define price jumps and connect them to the period of distress. Second, we

[1] This separation can be seen in the first pioneering papers dealing with price jumps (see e.g., Merton (1976) or a summary in Gatheral (2006)). Recently, the division of the Gaussian-like component and price jumps was used by Giot, Laurent, and Petitjean (2010). Although the original motivation for this decomposition was of a purely mathematical nature, it can be advocated by practitioners as well.

describe our methodology to detect price jumps and to measure intensity. We also formulate our testable hypotheses. In Section 3 we describe our high-frequency data. We employ a number of stock market indices and show that there is a sound reason for potential price jump transfers and overall dynamics between jumps originating in and transferred among countries. Then we analyze the price jump patterns that materialized in our selected stock market indices and analyze how the behavior of price jumps changed after the European debt crisis unfolded. The results of our analysis are presented in Section 5 along with specific policy implications. Finally, we summarize the findings and implications in the concluding section.

2. Price jumps and European debt crisis

In this section, we provide a model of log-price dynamics and formalize the effect of the financial distress due to the European debt crisis in a model of volatility and in particular of price jumps. Consequently, the identification of price jumps is elaborated in detail.

2.1. Price jumps

Generally, a price jump is understood as an abrupt price movement that is very large when compared to the current market situation. The advantage of this definition is that it is model-independent: it does not require any specific underlying price-generating process. On the other hand, this definition is too general and rather vague and hence not useful for any statistical inference or testing. Therefore, we formalize the general approach by assuming that the log-price $Y=\{Y_t\}_{0\leq t\leq 1}$ is defined on the probability space $(\Omega, F, \{F_t\}_{0\leq t\leq 1}, P)$ over time interval [0,1]. The log-price process is a semi-martingale and its dynamics in continuous time can be specified by the stochastic differential equation

$$\mathrm{d}S_t = \mu_t\,\mathrm{d}t + \sigma_t\,\mathrm{d}W_t + \mathrm{d}J_t, \tag{1}$$

where μ_t and σ_t are processes driving the drift and volatility, $\mathrm{d}W_t$ is a standard Brownian motion and the term $\mathrm{d}J_t$ represents the pure jump Levy process; see, for example, Merton (1976) or Jacod and Shiryaev (1987). In the following, we consider finite activity jumps (Aït-Sahalia & Jacod, 2011) and factorize the Levy processes as $Y_t\mathrm{d}N_t$. The first component corresponds to a random process driving the magnitude of price jumps, while the latter one drives the arrival.

For the arrival process, we assume that the jumps arrive at finite activity. Therefore, the arrival process $\mathrm{d}N_t$ takes a value of 0 or 1 and can be expressed as $\mathrm{d}N_t = E[\mathrm{d}\lambda_t|I_t]$, where the instantaneous intensity $\mathrm{d}\lambda_t$ is time dependent and may depend on the exogenous economic variables and I_t is the information set available up to time t. In this paper, we focus on the long-term variation in the levels of intensity at a particular sampling of the data $\mathrm{d}t$. We therefore define the average intensity $\lambda_{[0,T]} = \int_0^T \mathrm{d}\lambda_t = \int_0^T E[\mathrm{d}N_t]$ with the meaning of the probability of a price jump arrival being at any time step $\mathrm{d}t$ out of the interval [0,T]. The average intensity captures the long-term variation in the probability of price jump arrivals while it smooths out the fact that price jumps arrivals are rare events and thus most of the time there are no arrivals.

2.2. Financial distress: European debt crisis

The global financial crisis in 2008 emerged as a consequence of excessive lending in the US debt market. The consequences of this crisis transferred to the European continent where the increased sensitivity to risk uncovered the structural fiscal problems of many European economies. Hence, following the worsened global economic development during 2008–2009, the European debt crisis evolved into a situation where it was difficult or impossible for several Eurozone member countries to repay or re-finance their government debts without the assistance of third parties. The situation was made even worse by the undercapitalization and liquidity problems of Eurozone banks. As a side effect, the crisis also exerted a major political impact on many European countries. Therefore, in this study, we explicitly focus on the European debt crisis that fully unfolded in May 2010.

This event was not by its nature preceded by a drop in capital markets. We therefore consider this event an exogenous trigger with the potential to affect capital markets. To understand the impact of a financial event like this, we associate the distressed period with a structural break in the sample. The distress period begins on May 1, 2010 and ends on June 30, 2013. From a technical point of view the beginning date coincides with the date when the Greek government announced a series of austerity measures in order to receive an external loan from the rest of the Eurozone and the IMF worth 110 billion euro, payable in three years at a 5.5% interest rate (Lane, 2012).[2] Other actions with respect to other Eurozone countries followed later on. In general, the period after May 2010 is characterized by the contagion of financial risk, increased volatility, and financial distress. This motivates us to choose May 1, 2010 as an exogenous breakpoint, since it is when the European debt crisis fully appeared and affected the performance and behavior of individual European stock markets.

To capture financial distress formally, i.e. following the data-generating process assumed in equation (1), we define the

[2] A brief note about the Greek financial problems in this period: around 2000, the Greek economy had a large structural deficit along with fast growth. However, the Greek economy was severely affected by the global financial crisis, especially because global trade collapsed at the same time that tourism declined. Greece responded with a pseudo-Keynesian plan to taking on huge government debt to support economic performance. Unfortunately, markets reacted negatively to this plan, worried about the negative consequences of such debt as the debt grew more rapidly than expected. The debt problem resulted in Greece not able to borrow on the open market. A loan of 45 billion Euro was requested by Greece from the IMF and EU in April 2010 just to keep basic government operations going, and this request itself plunged Greece's government bonds to below investment grade. Soon after, in May 2010, the Greek government responded to public protest by announcing a series of austerity measures and admitting the difficulty of the situation. For more information, see IMF (2012), Malkoutzis (2011), and Nechio (2010).

indicator (dummy) variable F_t as the risk factor indicator that takes a value of one during financial distress and zero otherwise.

First, the stylized facts suggest that spot volatility σ_t will be a function of F_t with the following effect:

$$\sigma_t = \sigma_t(F_t) \quad \text{with} \quad E[\sigma_t(F_t)|F_{t-}=1] > E[\sigma_t(F_t)|F_{t-}=0], \tag{2}$$

which in plain English means that the expected spot volatility during the distress period is strictly bigger than that during usual market conditions. Second, the distress period will have an effect on the price jump term as well. There are two possible channels how distress can impact the price jump term $Y_t \mathrm{d}J_t$:

$$\begin{aligned} &Y_t = Y_t(F_t) \quad \text{with} \quad E[Y_t(F_t)|F_{t-}=1] > E[Y_t(F_t)|F_{t-}=0], \\ &\mathrm{d}J_t = \mathrm{d}J_t(\lambda_t(F_t)) \quad \text{with} \quad E[\lambda_t(F_t)|F_{t-}=1] > E[\lambda_t(F_t)|F_{t-}=0], \end{aligned} \tag{3}$$

where the first line means that the magnitude of price jumps increases during distress, while the second line tells us that rate of price jumps increases during distress without influencing the magnitude. The effect of financial distress expressed in equations (2) and (3) reflects the obvious intuition: financial distress increases market volatility as well as the rate and significance of rare and substantial price movements (price jumps). One can measure the arrival of price jumps by their average intensity as

$$\boldsymbol{\lambda}_{[0,T]} = \frac{N_{\text{jumps}}}{N_{\text{jumps}} + N_{\text{non-jumps}}}, \tag{4}$$

where N_{jumps} and $N_{\text{non-jumps}}$ denotes the number of jumps and the number of non-jumps, respectively, over a given time interval $[0,T]$.[3]

We employ two different methods for the identification of price jumps (defined in detail in the methodology section) and aim to verify the intuition related to the price jump term; in particular, that we observe different intensities of price jumps during financial distress. For that purpose, we need to define the distress period exogenously and hence we use the European debt crisis as an exogenous factor defining the distressed period. Later, we will use equations (2)–(4) and different identifications of price jumps to statistically analyze to what extent we observe significant differences in the volatility and jump process during the financial distress period.

The dependence of the diffusive and price jump terms on the risk factor F_t allows us to analyze the changes in the price jump intensities across different markets. Our distress model does not contain any explicit correlation across markets since we do not aim to model the immediate response of price jumps in one market to another as was done by Aït-Sahalia, Cacho-Diaz, and Laeven (2010). Rather, we use high-frequency data to describe the change in market regimes due to financial distress, where the driver of the distress is believed to be exogenous to the markets and any correlation is therefore realized through the distress factor. Our model framework thus resembles the approach in the Mixed Data Sampling (MIDAS) literature; see Ghysels, Sinko, and Valkanov (2007). It is worth noting that this methodology can be reverted to identify the distress period. Thus, by assuming that the distress period is defined as a regime with increased volatility and increased price jump arrival, or, alternatively, an increased contribution of price jumps to the overall market volatility, we may devise an algorithm to search for a period where these conditions are significantly satisfied. For the purpose of this analysis, however, we work with the exogenously given distress period.

3. Methodology

In this section, we describe how to test the impact of the European debt crisis on the price-generating process with a special focus on price jumps. In our analysis we employ two different approaches for price jump detection. Method 1, devised by Lee and Mykland (2008), primarily aims to isolate price jumps using integrated variance. Method 2, suggested by Aït-Sahalia and Jacod (2009), is based on the detection of extreme returns using percentiles. Both methods also differ in the way they identify price jumps from a purely statistical perspective. In this sense, we employ two methods that can be linked to two extreme cases with respect to hypothesis testing and were identified in a large simulation study in Hanousek, Kočenda, and Novotný (2012). Specifically, Method 2 is identified as a Type-I Error-Optimal indicator that maximizes the identification of true price jumps. Method 1 can be understood as a Type-II Error-Optimal indicator, which minimizes incorrect price jump identification.[4] In other words, in our analysis Type-I error identification (Method 2) would capture both price jumps and the volatility structure, while Type-II error identification (Method 1) would target primarily the price jumps.

In order to study the effects of the European debt crisis on stock market behavior we will compare the intensities of detected price jumps over different periods and markets. We introduce the form of both methods below.

3.1. Method 1: integrated-variance-based method

In order to estimate the key variable of this paper, the average intensity $\lambda_{[0,T]}$, we have to date and count the total number of price jump arrivals over time interval $[0,T]$. For that purpose, we employ the Lee and Mykland (2008) test statistics given as

[3] Definition (4) is an empirical counterpart of the theoretical considerations mentioned in equation (1). In particular, because of the discrete character of the price jump process, the average intensity defined in equation (4) corresponds to the original definition $\lambda_{[0,T]} = E[\mathrm{d}N_t]$. Originally (the theoretical definition of) intensity corresponds to the probability of price jump arrival at time step $\mathrm{d}t$ in the interval $[0,T]$, In equation (4) the meaning remains the same. It is an estimate of the proportion, i.e., of the probability of jump occurrence in the interval $[0,T]$.

[4] In the literature, the Type-I error criterion is known as optimization with respect to the power of the test; in diagnostic analysis it is usually called the optimization of the positive–negative probability. Similarly, Type-II error optimality is usually presented as optimality with respect to the size of the test, while in diagnostic analysis it is typically called the optimization of the false-negative probability.

$$L_t = \frac{r_t}{\sqrt{\mathrm{IV}_t}}, \tag{5}$$

where r_t is a log-return and IV_t is an instantaneous integrated variance, which captures the variance of $\sigma t\ \mathrm{d}Wt$ while neglecting the contribution from $\mathrm{d}J_t$. Then, the test itself is based on the variable ξ_n, which is defined as

$$\frac{\max_{t \in A_n} |L_t| - C_n}{S_n} \to \xi_n, \tag{6}$$

where A_n is the tested region with n observations and C_n and S_n are parameters depending on n only as specified in Lee & Mykland (2008). This statistics was found in a large simulation study performed by Hanousek et al. (2012) as being the optimal price jump indicator with respect to Type-II error. This method minimizes the probability of the false detection of jumps.

To estimate the integrated variance, we use Andersen, Dobrev, and Schaumburg (2012)'s median-based method, for which the estimator for IV_t is given as

$$\mathrm{IV}_t = \mathrm{MedRV}_t$$
$$= \frac{\pi}{6 - 4\sqrt{3} + \pi} \frac{n}{n-2} \sum_{i=2}^{n-1} \mathrm{med}(|r_{t-i+1}|, |r_{t-i}||r_{t-i-1}|)^2, \tag{7}$$

where n denotes the number of past returns in the window to estimate the integrated variance for the return r_t.

3.2. Method 2: detecting price jumps using extreme returns

Aït-Sahalia and Jacod (2009) defined types of jump indicator where the price process is assumed to be decomposed into the Gaussian component corresponding to normal (white) noise and the non-homogenous Poisson component corresponding to price jumps. Therefore, when a significant price jump appears, the price increment is dominated by the non-homogenous Poisson element. On the other hand, when the price movements are governed solely by Gaussian noise, the average and/or maximum magnitudes of such increments can be estimated. Therefore, one can use these properties and set a threshold value that will effectively distinguish the two components, i.e. predict jumps.

Let us assume that the underlying price increment (ΔS) process is given as $\Delta S = \sigma \Delta X + \Delta J$, where the price increment is defined as $\Delta S = S_t - S_{t-1}$, and further assume that we observe the realization of prices in equidistant time steps Δt. In this definition, X corresponds to a Brownian motion and J to a β-stable process. The increments of the two components can be expressed as $\Delta X = (\Delta t)^{½} X_1$ and $\Delta J = (\Delta t)^{1/\beta} J_1$ with equalities in distribution.

The different magnitudes in the two components can be used to discriminate between the noise components and the big price jumps coming solely from the J-process.[5] The big price jumps cause $\Delta S = \Delta J$ (in distribution) with X having a negligible effect, while in the presence of no big price jumps, which is most of the time, $\Delta S = \sigma(\Delta t)^{½} X_1$. Therefore, we can, for a given Δt, choose a threshold value equal to $\alpha(\Delta t)^{\gamma}$, with $\alpha > 0$ and $\gamma \in (0,½)$, such that if $\Delta S \propto (\Delta t)^{\gamma}$ then ΔS is at a given moment dominated by J with a certain probability.

This argument can be reverted: Assuming the knowledge of the rate of the arrival of big jumps, we can imply a corresponding threshold using centiles. Centiles, therefore, serve as a prior to form a threshold for discriminating price jumps from the noise. The standard approach is (Aït-Sahalia & Jacod, 2009) to decompose these processes by employing appropriate threshold levels, or certain percentiles, of the distribution of returns observed over the entire sample. We employ the 99.5th/0.5th centiles as the upper/lower thresholds and define price jumps as those returns that are higher/lower than a given upper/lower centile.

Method 2 for price jump identification maximizes the probability of the correct price jump detection, and it is thus optimal with respect to Type-I error. However, there is a chance that it may suffer from the overidentification of price jumps: almost any period with an extreme return is identified as a jump, even if the extreme value is driven by increased market volatility.

3.3. Hypotheses

In this paper, we aim to answer the following questions:

Question A. Is the intensity of price jumps on financial markets different following the European debt crisis?
Question B. Is the homogeneity of financial markets with respect to price jump intensity different following the European debt crisis?

The first question is based on the intuition that an extreme event such as the European debt crisis would result in an increase in overall volatility as well as an increase in the number of extreme price movements that would result in a greater intensity of jump occurrence. In the second question, we explicitly ask whether the European debt crisis caused a change in the distribution of price jumps, for example a higher variability in the arrival rate of price jumps and intensity. This means that during financial distress, we are likely to observe days with an extremely high rate of price jump arrivals, while there can be days that are rather calm as well.

To answer the above-mentioned questions we use the corresponding statistically testable hypotheses. First, we divide the sample of trading days into two sub-samples corresponding to periods of standard market conditions and financial distress. Then, we use the daily figures of arrived price jumps and form the following two hypotheses.

Hypothesis A. H_0: The mean of price jump intensity for the two sub-samples, i.e., during and not during distress, is the same.

[5] The J-process contributes to a large amount of small price jumps; however, we want to focus on big price jumps only. The goal is not to completely determine the properties of the J-process but rather to determine how to discriminate extreme price movements.

The main scope of this test is to compare whether the estimated number of price jumps changes during the crisis. For that we employ the two-sample Wilcoxon test, which is a non-parametric test comparing whether two observed samples come from the same distribution (Mann & Whitney, 1947; Wilcoxon, 1945). Here we test whether the estimated price jump measures for the two sub-samples come from the same distribution. The observations in each of the two sub-samples is combined into one sample and then ranked. The z-statistic is composed based on the mutual comparison of ranks between the two samples. For large samples, the z-statistic follows a standard normal distribution; 20 and above observations is usually sufficient (see Mann & Whitney, 1947; Wilcoxon, 1945). The null hypothesis of the test states that both observed samples come from the same distribution or there is no significant asymmetry in the rankings for the two groups. When the calculated z-statistics exceeds the critical value, we reject the null hypothesis. In addition, the sign of the z-statistics can suggest the position of the medians of the two compared samples.

Hypothesis B. H_0: The variance in the jump intensity of the two sub-samples, i.e., during and not during distress, is unchanged.

This test asks the question whether the trading days in either of the two sub-samples were on average more heterogenous. In other words, this procedure tests the heterogeneity of the trading days between the sub-samples. To answer the question we employ the standard F-test and compare whether the variance of the estimated price jump measures changed during the crisis. The F-test is defined as

$$\frac{S^2_{\mathrm{C}}}{S^2_{\mathrm{No-C}}} \sim F(N_{\mathrm{C}}-1, N_{\mathrm{No-C}}-1), \qquad (8)$$

where S^2 is the standard deviation of the characteristic coefficient calculated during the crisis “C” and not during the crisis “No-C”. N_{C} is the number of days the crisis lasts and $N_{\mathrm{No\text{-}C}}$ is the complement to the total number of days in the sample.

We aim to test these two hypotheses for different markets. In particular, we plan to analyze how price jumps in a developed capital market compare with emerging European markets, and also how price jumps transfer from one to the other. Focusing on two types of markets allows us to study changes in the price jump distribution in terms of the differences between these markets and compare the states of each market both before and after the distress.

4. Data description

Developed European markets are represented by the UK and Germany, while emerging markets in Central and South-Eastern Europe are represented by the Czech Republic, Poland, Hungary, Romania, Croatia, Slovenia, and Turkey. We used the maximum country-data coverage for the available high-frequency stock market data. The other countries in the regions studied either do not have enough liquidity to consider high-frequency trading or their intraday data are not available at all.

We employ high-frequency (5-min interval) data of realized prices for each of the market indexes. Data from all stock exchanges – except the Borsa Istanbul – cover the period from January 1, 2008 to June 30, 2013 and thus cover a sufficiently long enough period before and after the European debt crisis. High-frequency data for the Istanbul Stock exchange were available to us only for the period July 1, 2011 to June 30, 2013, which provides still enough data for similarity and response analyses.

The key characteristics of the markets and indices under research are presented in Table 1. We show the market capitalization and turnover ratio on each market at the beginning of our research span (in 2008) and one year before its end (in 2012). We also provide data for the year when the European debt crisis unfolded (in mid-2010). There is overwhelming evidence that until the crisis the market capitalization rose but dropped afterward; exceptions are Prague, where market capitalization is the same in 2008 and 2010 and Ljubljana, where market capitalization decreases over time. We can also witness a drop in the turnover ratio on the markets under research; exceptions are Bucharest and Ljubljana that record increases.

For our analysis we use the following set of indices with the corresponding tickers. For the European developed markets we use:

Table 1
Market capitalization and turnover of analyzed stock markets.

Stock exchange (country)	Stock market capitalization			Turnover ratio		
	2008	2010	2012	2008	2010	2012
London (United Kingdom)	69.9%	137.7%	124.0%	227.2%	101.9%	84.0%
Frankfurt (Germany)	30.6%	43.5%	43.7%	193.3%	103.0%	91.8%
Budapest (Hungary)	12.0%	21.5%	16.8%	93.0%	94.5%	54.6%
Prague (Czech Republic)	21.7%	21.7%	19.0%	70.4%	29.4%	27.0%
Warsaw (Poland)	17.0%	40.5%	36.3%	45.7%	47.6%	42.6%
Bucharest (Romania)	9.7%	19.7%	9.4%	11.3%	5.4%	11.5%
Zagreb (Croatia)	38.5%	42.3%	38.2%	7.4%	4.1%	2.3%
Ljubljana (Slovenia)	21.6%	20.1%	14.2%	6.9%	2.6%	6.2%
Istanbul (Turkey)	16.1%	41.9%	39.1%	118.5%	158.4%	136.5%

Note: data were obtained from the World Bank database and accessed on September 23, 2013. The database is at: http://databank.worldbank.org/data/views/variableselection/selectvariables.aspx?source=world-development-indicators.

- Ticker UKX represents the FTSE 100 Index (a capitalization-weighted index) of the 100 most highly capitalized companies traded on the London Stock Exchange.[6]
- Ticker DAX that stands for the German (total return) Stock Index of 30 selected German blue chip stocks traded on the Frankfurt Stock Exchange. The equities use free-float shares in the index calculation.[7]

Emerging markets are represented by the following indices/tickers:

- Ticker BUX is the capitalization-weighted (total return) index adjusted for free float. The index tracks the daily price performance of large, actively traded shares on the Budapest Stock Exchange.[8]
- Ticker PX stands for the official index of the Prague Stock Exchange, a capitalization-weighted index based on the free float of all members.[9]
- Ticker WIG, the Warsaw Stock Exchange index, is a total return index that includes dividends and pre-emptive rights (subscription rights).[10]
- Ticker BET, the Bucharest Exchange Trading Index, is a capitalization-weighted index, comprised of the 10 most liquid stocks listed on the BSE tier 1. The index is a price index and was developed with a base value of 1000 as of September 22, 1997.
- Ticker CRO represents CROBEX, which is a capitalization-weighted index designed to measure the price movements of shares listed on the Zagreb Stock Exchange.[11]
- Ticker SBITOP stands for the Slovenian blue chip index. It is a free-float capitalization-weighted index comprising the most liquid shares traded at Ljubljana Stock Exchange.[12]
- Ticker XU100 is used for the Borsa Istanbul National 100 Index, which is a capitalization-weighted index composed of National Market companies except investment trusts.[13]

The general data characteristics are described in Table 2. Data for the covered stocked market indices (analyzed at a 5-min frequency) shows on average low negative returns with relatively small deviation. In the majority of cases the realized skewness is negative, which means that the distribution of returns have a fatter left tail, or in other words, that extreme movements down (large negative returns) tend to be more likely. Kurtosis is clearly higher than 3, which means that distributions of returns are fat-tailed (leptokurtic).[14] Further, the number of detected jumps is relatively large and is naturally higher for Method 2, which accounts not only for jumps but also heightened volatility.

5. Results

For testing the difference in the intensity of the price jumps we employ the Wilcoxon sign test. For Type-I Error-Optimal identification (Method 2) we see a clear pattern indicating that we observe higher jump intensity during the European debt crisis. The situation is reversed when we employ the Type-II Error-Optimal indicator for the detection of price jumps (Method 1). The main difference is that when we minimize the probability of incorrect jump identification (Type-II error), we see that the jump intensity did not dramatically increase during the period of financial distress. This discrepancy could be caused by an overall increase in market volatility without an unnecessary increase in the rate of price jumps. Because jump prediction minimizing the Type-I error uses centiles (i.e., is based on outliers), such a method could incorrectly identify a lot of false jumps during a volatile period.

5.1. Jump intensities

In Tables 3 and 4 we present a pair-wise comparison of the jump intensities across the stock markets under research. Tables 3 and 4 show the results of the Wilcoxon test on jump intensities obtained based on Methods 1 and 2, respectively. Each column in each table is divided into two sub-columns: in the left sub-column we present the results from before the European debt crisis in May 2010 while the right sub-column shows the results afterward. Individual entries in each table show the extent of intensity in price jumps between pairs of stock markets that are labeled by the names of the cities where stock exchanges operate. An entry (value of the z-statistics) in each table should be read in the following way: a positive (negative) number shows that price jump intensity on the

[6] The equities use investability weighting in the index calculation. Investability weighting gives a weight in the index based on a free float according to the following bands:Free float less than or equal to 15% = ineligible*Free float greater than 15% but less than or equal to 20% = 20%Free float greater than 20% but less than or equal to 30% = 30%Free float greater than 30% but less than or equal to 40% = 40%Free float greater than 40% but less than or equal to 50% = 50%Free float greater than 50% but less than or equal to 75% = 75% Free float greater than 75% = 100%The index was developed with a base level of 1000 as of January 3, 1984 (source: Bloomberg, London Stock Exchange).

[7] The DAX has a base value of 1,000 as of December 31, 1987. As of June 18, 1999 only XETRA equity prices are used to calculate all DAX indices.

[8] The BUX index accounts for 58% of the domestic equity market capitalization. BUX has a base value of 1000 points as of January 2, 1991.

[9] The index was calculated for the first time on March 20, 2006 when it replaced the PX50 and PX-D indices. The index took over the historical values of the PX50 index. The starting date was April 5, 1994 with a base of 1000 points. As of September 24, 2012, the composition fully reflects the free float of members due to methodology changes.

[10] The index includes all companies listed on the main market, excluding foreign companies and investment funds. The index base value is 1000 as of April 16, 1991.

[11] It is capped at a maximum 20% weighting of the index capitalization. CROBEX was developed with a base level of 1000 beginning September 1, 1997.

[12] Each stock's weighting is capped at 30%. The index was developed with a base level of 1000 as of March 31, 2006.

[13] The constituents are selected on the basis of pre-determined criteria for the companies to be included in the indices. The base date is January 1986 and the base value is 1 for the TL-based price.

[14] The null hypothesis stating that returns are i.i.d. following the normal distribution (Jarque–Bera (Jarque & Bera, 1980) statistics) implies a rejection of the null hypothesis at a very high confidence level, where the p-value does not exceed 0.0001 in any case.

Table 2
Summary statistics for stock market index returns.

Stock exchange	Number of observations	Characteristics based on a 5-min frequency						
		Mean return	Skewness	Kurtosis	Number of jumps detected		Number of jumps per day	
		Whole period	Whole period	Whole period	(1)	(2)	(1)	(2)
London	139,260	−2.11E−06	−1.25	134.5	800	1392	0.58	1.01
Frankfurt	145,248	−3.14E−06	−0.06	23.1	682	1452	0.49	1.04
Budapest	128,847	−9.79E−06	−0.40	40.8	689	1288	0.50	0.94
Prague	116,048	−1.60E−05	−1.45	68.4	1374	1160	0.99	0.84
Warsaw	129,173	−7.13E−06	0.16	20.0	905	1292	0.66	0.94
Bucharest	79,421	−1.10E−05	−0.35	55.9	711	794	0.51	0.57
Zagreb	85,500	−1.90E−05	0.08	505.7	731	854	0.53	0.62
Ljubljana	38,567	−2.00E−05	−0.77	64.4	803	386	0.59	0.28
Istanbul	39,586	−2.40E−06	−0.14	23.8	125	396	0.23	0.72

Note: columns denoted as (1) correspond to Method 1 for jump detection (integrated variance), while columns marked as (2) represent the results obtained for Method 2 (centile based). The different number of observations is mostly related to the different hours of operation. For example, while the Frankfurt Stock Exchange opens at 9 a.m. and closes at 5:30 p.m., the Ljubljana Stock Exchange opens at 9:30 a.m. at and closes at 1 p.m.; for continuous trading the open market session runs only from 9:30 a.m. to 12:50 p.m.

market in a given row is larger (smaller) than the price jump intensity on the market in a given column. Alternatively, a negative number can be interpreted as a stock market in a given column exhibiting greater price jump intensity than a stock market in a given row. The larger the coefficient, the larger is the difference in jump intensity between the two markets. This interpretation can be illustrated by a specific example: in the left sub-column of Table 3 the Frankfurt–London pair-wise result is −1.77, which means that Frankfurt stock exchange exhibits smaller intensity in jumps of its index (DAX) than does London Stock Exchange; however, the difference in jump intensities on both markets is not very large.

From Table 3 a pattern emerges: price jump intensity is different before and after the European debt crisis unfolded. In most cases the jump intensity increased during the crisis but several anomalies are present. As we already reported in our illustrative example above, the jump intensity before the crisis is smaller on the Frankfurt stock exchange than on the London exchange (−1.77; left sub-column) and even increases afterward (−3.21; right sub-column). Emerging stock markets almost uniformly exhibit larger intensity in jumps than both developed markets and the magnitude of the intensity is also greater. Out of the emerging stock markets only the Budapest stock exchange exhibits lower intensity than London during both periods (−1.52 and −0.06) but not with respect to

Table 3
Pair-wise testing for the equality of mean jump intensities (Method 1, using integrated variance).

Stock exchange	London		Frankfurt		Budapest		Prague	
	Pre-crisis	Crisis	Pre-crisis	Crisis	Pre-crisis	Crisis	Pre-crisis	Crisis
Frankfurt	−1.77^{b}	−3.21^{a}						
Budapest	−1.52^{c}	−0.06	0.32	2.85^{a}				
Prague	5.52^{a}	7.46^{a}	5.98^{a}	7.41^{a}	6.03^{a}	7.38^{a}		
Warsaw	1.28^{c}	4.28^{a}	2.98^{a}	5.23^{a}	2.95^{a}	3.88^{a}	−5.11^{a}	−6.68^{a}
Bucharest	2.87^{a}	4.87^{a}	4.42^{a}	5.51^{a}	4.31^{a}	4.79^{a}	−3.92^{a}	−3.53^{a}
Zagreb	2.62^{a}	4.07^{a}	4.13^{a}	5.10^{a}	4.16^{a}	4.06^{a}	−3.92^{a}	−3.22^{a}
Ljubljana	6.42^{a}	7.29^{a}	6.42^{a}	7.35^{a}	6.42^{a}	7.20^{a}	6.06^{a}	3.39^{a}
Istanbul	N/A	−4.27^{a}	N/A	−2.98^{a}	N/A	−4.10^{a}	N/A	−6.74^{a}
Stock exchange	**Warsaw**		**Bucharest**		**Zagreb**		**Ljubljana**	
	Pre-crisis	Crisis	Pre-crisis	Crisis	Pre-crisis	Crisis	Pre-crisis	Crisis
Frankfurt								
Budapest								
Prague								
Warsaw								
Bucharest	1.74^{b}	2.82^{a}						
Zagreb	1.34^{c}	2.42^{a}	−0.36	0.03				
Ljubljana	6.42^{a}	6.63^{a}	6.36^{a}	5.16^{a}	6.34^{a}	4.91^{a}		
Istanbul	N/A	−5.56^{a}	N/A	−5.99^{a}	N/A	−5.59^{a}	N/A	−6.66^{a}

Note: the table contains the results of the Wilcoxon test (z-statistics, normally distributed) of the equality of jump intensities. Negative (positive) test statistics means that the stock market shown in a row has lower (higher) jump intensity than the market shown in the column. Superscript letters a, b, and c denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Frankfurt (0.31 and 2.85). Further, the Istanbul stock market during the crisis period shows lower jump intensity than developed (−4.26 and −2.98 with respect to London and Frankfurt, respectively; right sub-column) and the rest of the emerging stock markets. Another feature stands out: the magnitude of the jump intensity during the European debt crisis period is highest on the Prague and Ljubljana stock markets that also exhibit higher jump intensity than other markets (right sub-column). The feature is less pronounced during the pre-crisis period (left sub-column), though.

In Table 4 we present the results of the Wilcoxon test on price jump intensities derived by Method 2. There is not much inter-period change found for the Frankfurt–London pair (−0.93 and −0.76 for pre-crisis and crisis periods, respectively) and also the behavior of the Prague stock market with respect to both developed markets seems quite stable (0.46 vs. 0.61 for the Prague–London pair; 1.16 vs. 1.08 for the Prague–Frankfurt pair). On the other hand, the effect of the European debt crisis can be seen on the pairs of the rest of the emerging markets as the intensities of price jumps in Budapest, Warsaw, Bucharest, Zagreb, and Ljubljana do change with respect to other markets during the crisis period. Further, these intensities for many pairs switch signs. For example, the Warsaw and Bucharest markets exhibited higher intensity of jumps than other markets before the crisis, but during the crisis period both markets show chiefly lower intensity of jumps than the rest of the markets. The Istanbul stock market exhibits the opposite pattern during the post-crisis period as it shows higher jump intensity than all the other stock markets with the single exception of a lower jump intensity than the market in Ljubljana (−2.81; right sub-column). This finding indicates that when volatility is accounted for in price jump identification, the Istanbul stock market exhibits remarkable sensitivity to the European debt crisis.

It is also interesting to note that the very high magnitude of the jump intensity on the Prague market with respect to other markets detected by Method 1 (Table 3) disappeared when Method 2 was used. Only the Ljubljana market exhibits markedly higher intensity of price jumps than the rest of both developed and emerging markets during both periods (Table 4). The reason for this peculiar behavior might lie in the fact that the Ljubljana stock exchange is opened only a few hours each day for trading. For continuous trading the open market session runs only from 9:30 a.m. to 12:50 p.m. Naturally, in terms of information flow, the market aims to capture whatever happened before opening and take positions with respect to the future before closing. However, the short trading interval means that all this has to be done at a much faster pace than on other markets. Potentially higher nervousness and uncertainty might be behind the markedly different price jump intensity behavior on the Ljubljana market. The result is quite robust as it is captured by both methods.

Another interesting finding is represented by the visibly lowered jump intensity on the Warsaw stock market detected by Method 2 during the crisis period (Table 4, right sub-column). An explanation for this behavior should be sought behind the institutional set-up of the Polish financial market. Polish investment funds usually hold up to 40% of their assets in stocks: when stock prices rise (decrease) the same stocks are sold (bought) to keep the value of assets in balance. This process helps to smooth and lower market volatility. In other words, it does not prevent jumps but helps to avoid extreme returns. For that reason we can see mostly higher jump intensity of the Warsaw stock market during the crisis period with respect to other markets detected by Method 1 (Table 3, right sub-column) but lower jump intensity when volatility is accounted for (Table 4, right sub-column).

5.2. Differences in jump intensities and volatility

In Table 5 we present additional results that supplement our findings presented earlier in Tables 3 and 4. First, we formally test hypothesis A whether the (mean of) the jump intensity differs in the two periods under research. When we consider Method 1, the values of the z-statistics of the Wilcoxon test reveal that jump intensities are not different between periods for the whole group or individual markets (Table 5; Method 1). The single exception is the Ljubljana stock market for which we can safely assert that jump intensities are different in both periods. Specifically, with the help of Table 4, we can see that the jump intensity on the Ljubljana stock market was high and about the same with respect to other markets but during the crisis period it increased and decreased with respect to other markets in about the same proportions. When we consider Method 2 the results change dramatically. Values of the z-statistics show that jump intensities during both periods are markedly different (Table 5; Method 2). If we consult Table 4 again we can see that the difference in jump intensities do depend on the market pairs that exhibit an intensity increase or decrease without a firm pattern. Ljubljana is again an exception as it shows a uniformly huge increase in jump intensity with respect to all markets. We can sum up our supplementary findings in the following way. Our results indicate that jump intensity did not change in between periods when only jumps are considered. However, when the results of Method 2 are considered, volatility increased substantially but dramatic movements in values of indices did not. Hence, during the European debt crisis, the intensity of jumps did not increase but the uncertainty associated with the crisis transferred (only) to increased volatility.

Second, we present the results of the test for Hypothesis B of variance equalities for the two periods. To assess it, we employ the F-test specified in (12). Table 6 reports the results of the test for both methods. We present two pieces of information for every test. First, we decide whether we can reject the null of the equality of variances at a given confidence level with respect to a two-sided alternative hypothesis. If we are able to reject the null hypothesis, then we further provide an indicator whether the variance was higher (>) or lower (<) in the period before the crisis when compared to the period of the European debt crisis.

For Method 1, we see that when all markets are taken together the variance significantly differs during the two periods. In particular, the variance of monthly intensities was

Table 4
Pair-wise testing for the equality of mean jump intensities (Method 2, using extreme values, i.e., centiles).

Stock exchange	London		Frankfurt		Budapest		Prague	
	Pre-crisis	Crisis	Pre-crisis	Crisis	Pre-crisis	Crisis	Pre-crisis	Crisis
Frankfurt	−0.93	−0.76						
Budapest	−1.13	−0.34	−0.69	0.48				
Prague	0.46	0.61	1.16	1.08	0.70	1.53[c]		
Warsaw	0.92	−2.42[a]	1.62[c]	−1.76[b]	1.10	−0.81	0.43	−2.98[a]
Bucharest	1.31[c]	−1.21	2.16[b]	−0.59	1.36[c]	0.13	0.51	−1.46[c]
Zagreb	1.13	−0.22	1.79[b]	0.34	1.44[c]	0.78	0.54	−0.43
Ljubljana	−2.9[a]	4.79[a]	−1.97[b]	4.56[a]	−2.30[b]	4.41[a]	−2.89[a]	4.77[a]
Istanbul	N/A	1.27	N/A	1.51[c]	N/A	1.87[b]	N/A	1.21
Stock exchange	Warsaw		Bucharest		Zagreb		Ljubljana	
	Pre-crisis	Crisis	Pre-crisis	Crisis	Pre-crisis	Crisis	Pre-crisis	Crisis
Frankfurt								
Budapest								
Prague								
Warsaw								
Bucharest	0.07	0.96						
Zagreb	0.25	1.99[b]	0.11	0.88				
Ljubljana	−3.39[a]	5.11[a]	−3.59[a]	4.91[a]	−3.56[a]	5.44[a]		
Istanbul	N/A	2,47[a]	N/A	1.79[b]	N/A	1.61[c]	N/A	−2,81[a]

Note: the table contains the results of the Wilcoxon test (z-statistics, normally distributed) of the equality of jump intensities. Negative (positive) test statistics means that the stock market shown in a row has lower (higher) jump intensity than the market shown in the column. Superscript letters a, b, and c denote statistical significance at the 1%, 5%, and 10% levels, respectively.

higher during the pre-crisis period before the Greek bailouts. This finding indicates also a higher variance in the jump-arrival process. The crisis therefore served as an element that homogenized the behavior of extreme price jump arrivals. In addition, a similar pattern is seen for the London market, while other markets do not show a significant difference between the two periods. The single difference is identified in Zagreb that shows the opposite behavior, albeit not as significant as in the London case. This suggests that the London Stock Exchange is the main driver of the difference between the two periods. This evidence can be understood by the fact that London was directly exposed to the US subprime mortgage crisis and post-Lehman turmoil, which falls into the pre-European debt crisis period. Therefore, the likely driver of the excessive variance on London market originates from the spill-over of the distress in the US in 2008.

Method 2 offers different insights as there is no lack of the statistical significance. In this case, all individual markets as

Table 5
Testing for the equality of the jump intensities before and during the crisis (after May 1, 2010).

	Method 1	Method 2
Stock market		
London	1.01	4.24[a]
Frankfurt	1.26	3.51[a]
Budapest	−0.84	3.58[a]
Prague	−0.21	3.97[a]
Warsaw	−0.31	5.15[a]
Bucharest	−0.90	5.25[a]
Zagreb	−0.99	4.99[a]
Ljubljana	3.66[a]	−3.57[a]
All markets	0.55	8.39[a]

Note: the row marked "All markets" does not contain data from the Istanbul stock exchange, because of missing data for the pre-crisis period. A negative (positive) number for the test statistics corresponds to the situation when jump intensity is lower (higher) before the financial crisis. Superscript letters a, b, and c denote statistical significance at the 1%, 5%, and 10% levels, respectively. The column denoted as "Method 1" corresponds to the Method 1 for jump detection (integrated variance), while the column marked as "Method 2" represents the results obtained for Method 2 (centile based).

Table 6
Testing for the equality of the variances of jump intensities before and during the crisis (after May 1, 2010).

	Method 1	Method 2
Stock market		
London	4.36[a] ">"	14.57[a] ">"
Frankfurt	1.42	6.99[a] ">"
Budapest	1.32	12.04[a] ">"
Prague	1.75	22.72[a] ">"
Warsaw	1.53	6.99[a] ">"
Bucharest	0.65	3.40[a] ">"
Zagreb	0.41[b] "<"	53.03[a] ">"
Ljubljana	0.60	0.43[b] "<"
All markets	1.485[a] ">"	7.85[a] ">"

Note: the row marked "All markets" does not contain data from the Istanbul stock exchange, because of missing data for the pre-crisis period. Superscript letters a, b, and c denote statistical significance the 1%, 5%, and 10% levels, respectively, for the two-sided alternative. Additionally, the sign ">" denotes that the variance is higher in the period before the crisis, and the sign "<" denotes that the variance is lower during the European debt crisis period. The column denoted as "Method 1" corresponds to Method 1 for jump detection (integrated variance), while the column marked as "Method 2" represents the results obtained for Method 2 (centile based). We apply the classic F-test, with a null hypothesis that the variances of jump intensities in two sub-periods are equal (the corresponding critical values are $F(27,37)$).

well as the result of the aggregated market exhibit statistically significant differences between the two periods. In particular, in all cases (with the single exception of Ljubljana) the variance of the price jump intensity is higher during the first period before the European debt crisis emerged. This confirms the sensitivity of Method 2 to the subprime mortgage crisis and post-Lehman turmoil. Therefore, we can conclude that in the ex-post analysis, Method 2 can lead us into a false sense of the increased variance of the arrival processes, which originates from the over-volatile markets after the Lehman Brothers collapse. Method 1, however, filters out the over-volatile bias of Method 2 and accentuates the Lehman Brothers' effect only for the London market.

If we combine the results of hypothesis B testing based on both methods we can conclude that with the exception of London and Zagreb, the variance of the price jump intensity could not be distinguished as different in the pre-crisis period from that during the crisis.

5.3. Turkey — brief case study

Finally, we aim to analyze the mutual relationship of the Turkish stock market with the rest of our sample as a case study. We apply the developed methodological framework described in the previous sections. The purpose of this section is to advocate quantitative results based on average intensity and assess the level of economic and financial integration (defined in terms of the spill-over of extreme events) of the Istanbul stock exchange with respect to different European markets.

We can split our sample into geographical regions: the two developed markets (London, Frankfurt); the Visegrad markets consisting of stock exchanges in Budapest, Warsaw, and Prague; the South European (SE) markets composed of stock exchanges in Bucharest, Zagreb, and Ljubljana. Our aim is to compare the Istanbul stock market with the three regions with respect to price jump-arrival properties and thus to establish a link with respect to the transmission of extreme events and their reaction to the distress caused by the European debt imbalances.

Table 7 presents a pair-wise comparison of the distribution of monthly intensities between Turkey and the three regions for both methods. In particular, we use only the overlapping sample to have comparable data. First, Method 1 suggests that the intensity of price jump arrivals on the Istanbul stock exchange is on average significantly smaller than any of the three regions where the difference is lowest with respect to the developed markets. Therefore, we may conclude that Istanbul resembles by its price jump-arrival properties stable developed markets rather than its counterparts in the SE and Visegrad markets that are regionally and economically more similar to Turkey. It may also suggest that Turkey is more affected by the large and developed European markets and the information spillovers flow from Europe mainly through the developed markets. In other words, the regional events contained within the boundaries of the SE and Visegrad markets do not have enough power to reach Istanbul. Despite the fact that Istanbul

Table 7
Pair-wise testing for the equality of mean jump intensities.

	Developed markets	Visegrad region	SE markets	Turkey
(Method 1, using integrated variance)				
Developed markets				
Visegrad region	5.98[a]			
SE markets	7.97[a]	4.84[a]		
Turkey	−3.38[a]	−5.90[a]	−6.92[a]	
(Method 2, using centiles)				
Developed markets				
Visegrad region	−0.78			
SE markets	2.16[b]	3.11[a]		
Turkey	1.49[c]	2.07[b]	−0.19	

Note: the table contains the results of the Wilcoxon test (z-statistics, normally distributed) of the equality of jump intensities. Negative (positive) test statistics means that the stock market shown in a row has lower (higher) jump intensity than the market shown in the column. Superscript letters a, b, and c denote statistical significance at the 1%, 5%, and 10% levels, respectively.

stock exchange is in terms of volatility closest to the SE markets, the similarity can be explained only through the overall periods of increased volatility, which are most likely to be driven by the existing European debt crisis. Moreover, Method 2 is not able to deliver a strong message since the difference in volatilities between Istanbul and the three other regions is not statistically significant in many cases.

Based on our previous results we can draw some conclusions. When perceived through the optics of the monthly price jump-arrival intensity, the Istanbul stock exchange seems to be closest to the developed markets. This suggests that the jump intensity of the Turkish stock market is linked to Europe through the main channel of the developed markets. Unfortunately, we do not have pre-crisis high-frequency data from the Borsa Istanbul. Therefore, we can use only the data from the crisis period, during which the Turkish stock market differs from other emerging European markets in terms of price jump behavior and its dynamics.

5.4. Policy implications

Our results suggest the existence of different correlation patterns in terms of extreme events. Based on this, we can draw specific policy implications. From the perspective of emerging-market investors, the Borsa Istanbul should be considered a relatively independent capital market with unique price dynamics. A global player investing part of his portfolio in emerging European markets usually forms a basket of similar assets and treats them in the same way across the whole region. Based on our price jump analysis, such an approach is rational in the case of the Visegrad stock markets, which correspond to countries with closely connected economies and currencies. However, such a strategy does not appear to be optimal for the entire region including the Turkish market, since the economic links and price jump dynamics are significantly different. Hence, a combination of assets from diverse markets could be too heterogenous to be treated as a consistent basket. In particular, the different risk profile and contagion dynamics would be the main source of inconsistency for the investor, as seen from different price jump behaviors.

The regulators, on the other hand, should consider different parameterizations of contagion effects and market panic for mainland Europe and Turkey and not include Turkey into existing European regional groups. Ignoring the above-mentioned different risk profiles and contagion dynamics would lead to the mistreatment of systemic financial stability for the entire European market. In addition, during the financial crisis, the underestimation of the complexity of financial institutions seems to be one of the major causes of the global market freeze. Our analysis, which focuses on the dynamics of price jumps, provides proxy information for the distressed period. In particular, the propagation of jumps across financial systems mitigates the contagion. Its properties may be different from the typical volatility spill-over effects and therefore an efficient regulatory policy has to properly distinguish them. Preparing for the contagion using tools calibrated to volatility spill-over patterns would produce a false sense of safety: this approach would in fact not only fail in the effect, but, due to the complex nature of financial markets, it could even amplify the contagion and worsen the crisis. Our paper thus points to the direction that regulators should follow to draw proper regulatory recommendations for suggesting efficient early warning systems that would prevent abundant losses.[15] These recommendations will become more and more important, as the economic recovery after the European debt crisis and economic and financial integration will progress.

6. Conclusion

In this paper we analyzed the impact of the European debt crisis on the volatility and especially the price jump intensity in stock market indices reported by the set of stock exchanges on the European continent. We employed data from the stock exchanges of two developed (Frankfurt, London) and six emerging (Budapest, Prague, Warsaw, Zagreb, Bucharest, Ljubljana, Istanbul) markets during the period January 2008 to June 2012.

It is rather obvious that even *ex post* identification of the price jumps would depend on the actual method used, i.e., on the employed price jump indicator. Therefore, one can conclude that any analysis of jump distributions during financial distress would be method-dependent. We use this apparent disadvantage in potentially useful way: to distinguish between a significant volatility increase and a change in price jump intensity. In order to do so, we employ two methods to distinguish stock price behavior from different perspectives. While Method 1 minimizes the probability of false jump detection (the Type-II Error-Optimal price jump indicator), Method 2 maximizes the probability of successful jump detection (the Type-I Error-Optimal price jump indicator). It means that Method 2 identifies not only price jumps but also periods with high volatility without any price jump appearance.

[15] See Tsai (2013) and Ari (2012) for examples of the early warning systems.

We employed both methods on a number of pairs of stock market indices reported by several stock exchanges on European continent. We tested a hypothesis that there was no effect of the European debt crisis on the price jump intensity. Our analysis suggests that Method 2, which captures both price jumps and volatility, rejects the null hypothesis. A number of mature and emerging markets show both increased as well as increased levels of volatility during financial distress. The results are limited by some lack of statistical significance, though. In addition, we found that differences in price intensity are less pronounced when using Method 1, which focuses more on price jumps. From our results notable exceptions stand out. The Ljubljana stock market is clearly the market with the highest jump intensity, especially during the European debt crisis period. The Istanbul stock market exhibits higher jump intensity during the crisis period than other markets (with the exception of Ljubljana). To sum up, during the European debt crisis, the intensity of jumps did not increase but the uncertainty associated with the crisis transferred (only) to increased volatility.

Further, we tested the hypothesis that the variance of price jump intensities was different during the two periods. Following Method 1, we show that the variance on all markets taken together was lower in the period before the European debt crisis. However, the results for most of the individual markets are not statistically significant. On other hand, the results based on Method 2 are statistically significant and show lower variance during the pre-crisis period for the majority of markets. Since Method 2 accounts not only for jumps but volatility on markets as well, we based our overall conclusion on Method 1 that filters out the over-volatile bias of Method 2. Hence, disregarding a couple of exceptions, the variance of the price jump intensity could not be distinguished as different in the pre-crisis period from that during the crisis.

The regulatory consequences of our results can be linked to the Basel approach to financial distress. First, there is a common belief among risk practitioners and policy makers that the intensity of price jumps does uniformly increases during a period of financial distress. However, our results indicate that this pattern does not correspond to stock market behavior during a crisis. Second, there do exist differences in price jump dynamics across stock markets. Hence, investors have to model emerging and mature markets differently to properly reflect their individual dynamics.

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