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Stock Market Contagion in Central and Eastern Europe: Unexpected Volatility and Extreme Co-exceedance

Roman Horváth*, Štefan Lyócsa**, and Eduard Baumöhl***

* Institute of Economic Studies, Charles University, Prague, Czech Republic. ** Institute of Economics and Management, University of Economics in Bratislava, Slovakia. *** Institute of Economics and Management, University of Economics in Bratislava, Slovakia.
Corresponding author: roman.horvath@gmail.com; Opletalova 26, Prague 1, 110 00, Czech Republic

Institut für Ost- und Südosteuropaforschung
Institute for East and Southeast European Studies
Landshuter Straße 4
D-93047 Regensburg

Telefon: (09 41) 943 54-10
Telefax: (09 41) 943 54-27
E-Mail: info@ios-regensburg.de
Internet: www.ios-regensburg.de
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Abstract

We examine whether there is contagion from the U.S. stock market to six Central and Eastern European stock markets. We use a novel measure of contagion that examines whether volatility shocks in the U.S. stock market coupled with negative returns are followed by higher co-exceedance between U.S. and emerging stock markets. Using our approach and controlling for a set of market-related variables, we show that during the period from 1998 to 2014, financial contagion occurred, i.e., unexpected negative events in the U.S. market are followed by higher co-exceedance between U.S. and Central and Eastern European stock markets. Even though contagion is stronger during the financial crisis, it also occurs in tranquil times.

JEL-Classification: G01, G14, G15

Keywords: contagion, co-exceedance, volatility, stock markets

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1 Introduction

The global financial crisis was largely triggered by financial imbalances in the U.S. economy that consequently spread around the world. The financial frictions in developed countries significantly affected economic activity in many emerging economies, including those in Central and Eastern Europe (CEE), where GDP growth has fallen by double-digit numbers in some countries during the crisis. Although the overall evidence is somewhat mixed, several studies suggest that financial contagion has taken place in emerging economies in the past. Bae et al. (2003) and Bekaert et al. (2005) find evidence for contagion among Latin American countries and in Asia, respectively. This stream of literature focuses on examining the existence of financial contagion in emerging economies, especially during periods when emerging economies suffered from various forms of financial imbalances or even financial crises. As a result, it is not surprising that researchers find evidence of financial contagion under such circumstances.

However, to the best of our knowledge, evidence is lacking on whether financial contagion also occurs in emerging economies in the opposite situation, i.e., when developed countries suffer from financial imbalances but the financial sectors in the emerging economies of interest remain largely stable. This is what largely occurred during the current global financial crisis, which began in the summer of 2007. While financial markets in the U.S. and Western Europe had to obtain large financial injections from their governments, the financial sectors (dominated by banks) in Central European countries such as the Czech Republic, Slovakia and Poland remained largely stable and received no government support.[1]

In addition, there is an extensive stream of literature examining stock market linkages between Central and Eastern European countries vis-à-vis Western Europe (see Wang and Moore, 2008; Syllignakis and Kouretas, 2011, among many others). Nevertheless, these studies largely focus on correlations and do not examine contagion, i.e., correlations going beyond what would be implied by the fundamentals (Forbes and Rigobon, 2002; Bekaert et al., 2005, 2014). In this paper, we build upon the measure of financial contagion developed by Bae et al. (2003), who define financial contagion as the joint occurrence of return co-exceedances between two financial

[1] See, for example, the financial stability reports of the respective countries' central banks (Czech National Bank, 2015, National Bank of Poland, 2015), which show that local banks are well-capitalized and are able to withstand large negative shocks.

markets.[2] We extend this measure and define financial contagion as “the joint occurrence of return co-exceedances between two financial markets following an increase in unexpected volatility in one of the markets in the case where that market experiences negative returns”.

The main contribution to the existing literature is the decomposition of the U.S. stock market volatility into expected and unexpected components and examination of how unexpected volatility component increases the left tail co-exceedance between stock markets. Within the quantile regression framework we address specifically the left tails of the distribution of return co-exceedances, i.e. extreme market co-movements and their relationship to unexpected volatility component. Our notion of contagion is also conceptually in line with Bekaert et al. (2005) and Bekaert et al. (2014), who define contagion as excessive co-movement over and above the predictions of a factor model, i.e. what global equity market co-movements should be, based on existing fundamentals. Compared to Bekaert et al. (2005) and Bekaert et al. (2014), our approach is different in that the return series is first filtered-out of the effects of global factors and the resulting standardized residuals are used to compute co-exceedances, which are then linked to the unexpected part of the volatility.

We focus on six stock markets in the CEE. These markets represent a meaningful sample of the whole region of CEE markets in the European Union, which might be considered by international investors for diversification purposes. Our results provide evidence that an increase in the unexpected volatility in U.S. stock market, at the time US stock market falls markedly, leads to extreme negative joint co-movements between CEE and U.S. stock markets. This result holds for a number of robustness checks such as using non filtered measure of return co-movement, different time periods or different control variables in our quantile regression framework. As a consequence, our results indicate evidence of contagion from the U.S. stock market to CEE markets. While we find that contagion is stronger during the financial crisis, it also occurs in good times.

The paper is organized as follows. Section 2 discusses the related literature. Section 3 presents the data. Section 4 provides our empirical methodology. The results are presented in Section 5. Concluding remarks are available in Section 6. An Appendix with additional results follows.

[2] More specifically, Bae et al. (2003) define financial contagion as the fraction of extreme returns that are not explained by fundamentals but rather by extreme returns in another country/region. Extreme returns are those below the 5th or above the 95th quantile of the marginal return distribution and are referred to as return exceedances. Co-exceedances are defined as the joint occurrence of i exceedances of positive or negative returns on a given day.

2 Related Literature

2.1 Unexpected Volatility and Contagion

We define financial contagion as the occurrence of extreme return co-exceedances between two financial markets following an increase in unexpected volatility in one of the markets in the case where that stock market is plummeting. In line with the literature on contagion (e.g., Forbes, 2012; King and Wadhwani, 1990), a contagious event should be perceived by investors negatively. Therefore, contagion should be typically associated with bearish market conditions. Investors cannot be systematically surprised by fundamentals, i.e., we expect that fundamentals are on average expected, and therefore contagion should also be unanticipated. Otherwise, these events would have been already priced in. Even if investors are awaiting some news, expectations are already priced in, but the reality might be worse than expected. This negative and unexpected part of the news is what may cause contagion.

An important aspect of our definition of contagion is that we are not limited to identifying any crisis period *a priori*. A contagious event might be short-term (one day) event, somewhat negligible from a historical perspective, but still might induce excess co-movement between markets, unexplainable by fundamentals.

The existing literature examining contagion as an outcome of market over-reactions to unexpected events provides the rationale for our research. Studies examining the overconfidence of investors (e.g., Daniel et al., 1998; Odean, 1998; 1999; Barber and Odean, 2001; Grinblatt and Keloharju, 2008) suggest that after unexpected events, investors might react irrationally by ignoring fundamentals, thus propagating spillovers between international stock markets. More specifically, overconfidence can lead to excessive trading and volatility as investors over-react to new information (Daniel et al., 1998; Barber and Odean, 2001). Similar to the prospect theory of Kahneman and Tversky (1979), Hirschleifer (2001) argues that investors' overconfidence follows from the fact that people in general tend to underestimate the probability of rare events. Investors are easily surprised by unforeseen contingencies, which lead to market over-reactions. The irrationality of investors is of course not the only possible explanation for increased co-movement during times of distress. Increased unexpected market volatility typically leads to increased observed volatility; thus, through volatility, our approach is related to the literature in which pricing is explained by market volatility.

For example, an increase in market volatility might increase the required return on equity, which leads to declines in stock prices, i.e., the volatility feedback effect (e.g., Pindyck, 1984; French et al., 1987; Wu, 2001). Alternatively, volatility and returns act in a different causal order: negative returns increase financial leverage, which makes equities riskier; thus, equity prices become more volatile, i.e., the leverage effect (e.g., Black, 1976; Christie, 1982, Bekaert and Wu, 2000). Regardless of the underlying causes, an increase in unexpected market volatility signals mispricing. Such mispricing might be picked up by international investors, which leads to shock propagation across international equity markets (e.g., Boyer et al., 2006; Kodres and Pritsker, 2002).

2.2 Financial Co-movements in the CEE Region

The research on stock market integration (co-movements) in CEE countries is voluminous; however, contagion has rarely been investigated.

Syllignakis and Kouretas (2011) analyze co-movements between two developed markets (U.S. and Germany) and seven Central and Eastern European markets. They find that the estimated dynamic conditional correlations are systematically higher during the recent period of financial crisis in the U.S.

Samarakoon (2011) examines the spread of the financial crisis from the U.S. stock market to 62 emerging and frontier stock markets, including those of the CEE region. His results suggest that what we observe is not contagion but rather a high sensitivity of emerging markets to events in the U.S. market, i.e., interdependence. According to his results, actual contagion is rare. Surprisingly, he finds contagion from emerging markets to the U.S. market. However, this result might be a consequence of not considering non-synchronous trading effects.

Other studies apply some version of the multivariate GARCH model in an attempt to measure a “significant increase in cross-market linkages” in line with the simplest and most utilized definition of contagion by Forbes and Rigobon (2002). Such studies include, inter alia, those of Cappiello et al. (2006), Savva and Aslanidis (2010) and Kenourgios and Samitas (2011). For most of the CEE countries, a significant increase in dynamic correlations has been confirmed during the recent financial crisis, thus indirectly implying the presence of contagion.

Correlation analysis is, however, only suitable to measure the contagion within the definition of Forbes and Rigobon (2002). In broader terms, “true” contagion (when all fundamental channels are controlled for) is much more difficult to capture. Some attempts to explain dynamic conditional correlations among developed and CEE stock markets through fundamentals have been made (e.g., Wang and Moore, 2008 or Büttner and Hayo, 2011). However, cross-market linkages between the CEE region and developed markets appear to be driven by factors other than macroeconomic or financial fundamentals; perhaps they are driven by international investors and their herding behavior. The goal of our study is to bridge this gap and analyze the phenomenon of financial contagion in the CEE region in a more comprehensive way.

Compared to the most of existing studies, Bekaert et al. (2014) use industry level stock market data to uncover how contagion spreads within countries and within similar industries. They find support for the "wake-up call" hypothesis, i.e. that the shocks in one market induce investors to re-valuate fundamentals in other markets, which is observed as the increased co-movement across markets (industries). Reboredo et al. (2015) examine time-varying dependence among several CEE markets (the Czech Republic, Hungary, Poland, and Romania). Using dynamic copulas, they also find that this dependence intensified during the recent global financial crisis.

3 Data

We use data from January 1, 1998 to December 31, 2014. The sample covers the dotcom bubble, the subsequent steady growth of the U.S. stock market, peak of the recent global financial crisis in 2008 and its consequences for the real economy of the CEE countries, the surge in oil prices, uncertainty over the U.S. debt ceiling and the sovereign debt crisis in Europe, particularly including the uncertainty in the government bond market. Such a diverse sample should be sufficiently long to capture any contagious tendencies from the U.S. stock market to the CEE stock markets. We use continuous returns of the S&P 500 stock market index to proxy the daily developments in the U.S. stock market.

The sample of CEE stock markets includes the following countries: Croatia, the Czech Republic, Estonia, Hungary, Poland, and Romania. We choose these CEE countries because their stock markets are sufficiently capitalized, which is not the case in some other CEE countries such as Slovakia. The development of the CEE emerging stock markets is measured via daily continuous returns of the following market indices: CROBEX, PX, OMX Tallinn, BUX, WIG20, and BET.

We estimate return co-exceedances from prices denominated in local currencies, as we do not want to blur the extent of market co-movements with fluctuations on the foreign exchange market (Mink, 2015). However, we use daily returns on the foreign exchange market in the subsequent analysis as one of explanatory variables for co-exceedance. We use exchange rates between the U.S. dollar and the corresponding local currency with one exception, for Estonia, where we use the exchange rate between the U.S. dollar and the euro because before the adoption of the euro in 2011, the Estonian Kroon was fixed to the euro.

The fluctuations in the developed stock markets are captured using the daily continuous returns of the STOXX Global 1800 (excluding North America) index denominated in the U.S. dollar (R_t^{STX}). We make use of this index to account for common price-determining factors. When predicting U.S. market volatility, we use the implied stock market volatility, the VIX, to account for the overall uncertainty of investors. We have also utilized a fundamentally different index to measure the uncertainty in the U.S. economy: changes in the daily news-based Economic Policy Uncertainty Index (P_t) (Baker et al., 2013). The index is based on the number of articles in over 1000 U.S. newspapers about the economy. For a recent application, see Mensi et al. (2014), who use the policy index to explain returns on the BRICS stock markets.

Turbulent periods on stock markets may be accompanied by flight to quality, which drives the yield on low-risk bonds down. The recent period of ultra-low low-risk bond rates is by all standards unique. Decreases in low-risk bond yields decrease the required return, which might drive investors to emerging markets seeking new investment opportunities. Measuring such market conditions and tendencies is based on market yields on U.S. Treasury securities at 20-year constant maturity (Rt^{TB}).

We also use continuous daily returns from the Europe Brent Spot Price (Rt^{OIL}) and the Gold spot price (at PM fix; R_t^{GOLD}), both in U.S. dollars, to control for short term shocks which might be induced in these two commodity markets.

4 Methodology

Our methodology consists of three steps: (1) we compute return co-exceedances based on the standardized residuals from ARMAX(p, q)-EGARCHX(r, f) models; (2) we estimate expected and unexpected volatility components using range-based heterogeneous autoregressive (RB-HAR) model; (3) we link together co-exceedances with decomposed volatility within the quantile regression approach.

4.1 Return Co-exceedances

Our testing procedure is essentially based on the work of Baur and Schulze (2005), who modify the co-exceedance measure of Bae et al. (2003) and analyze it using a quantile regression approach. Their modification allows us to measure the extent of excess market co-movement. To measure co-exceedances we use formula similar to Baur and Schulze (2005):

$$C(s_{it}, s_{jt}) = \begin{cases} \min(s_{it}, s_{jt-1}) & s_{it} > 0 \wedge s_{jt-1} > 0 \\ \max(s_{it}, s_{jt-1}) \quad \text{if} & s_{it} < 0 \wedge s_{jt-1} < 0 \\ 0 & s_{jt} s_{jt-1} < 0 \end{cases} \tag{1}$$

where s_{it} and s_{jt} denote standardized residuals with zero mean and variance of 1 and subscripts i and j ($i \neq j$) correspond to two examined markets. The local (or potentially infected) market is denoted as i and the potentially contagious market as j. In all of the regression specifications, the potentially contagious market is the U.S. market, and the local market is one of the six stock markets, namely those in Croatia, the Czech Republic, Estonia, Hungary, Poland, and Romania.

With daily data frequency, we must address the non-synchronicity of returns. We employ the fact that the U.S. stock markets end their trading sessions last on a given calendar day t to our advantage and align the returns of the CEE markets at time t with the returns at t – 1 on the U.S. market. This approach allows us to study the spread of contagion, i.e., the direction of contagion from the U.S. market to the other CEE stock markets.

We report the results where the return co-exceedances are based on the standardized residuals derived from an ARMAX(p, q)-EGARCHX(r, f) model. One might consider our filtering procedure of returns to be a factor model of returns (Forbes and Chinn, 2004), which assumes, that market returns are a function of global factors (oil, gold prices), cross-country factors (foreign exchange returns and returns on other stock markets), and other market moving factors (U.S. treasury bond yields). This way, we isolate shocks which originate in a given country and we are therefore in the domain of *"pure/true contagion"*[3] instead of *"monsoonal"*[4] effects .

For each series of returns r_t, $t \in T$ we estimate an ARMAX (p, q) model:

$$
\begin{aligned}
& r_t = \alpha_0 + \alpha_1 R_{t-1}^{OIL} + \alpha_2 R_{t-1}^{FX} + \alpha_3 R_{t-1}^{TB} + \alpha_4 R_{t-1}^{GOLD} + \alpha_5 R_{t-1}^{STX} + z_t \\
& \left(1 - \sum_{i=1}^{p} \phi_i L^i\right) z_t = \left(1 + \sum_{j=1}^{q} \theta_j L^j\right) \varepsilon_t \qquad (2) \\
& \varepsilon_t = \sigma_t \eta_t, \quad \eta_t \sim iid(0,1)
\end{aligned}
$$

where α_k, ϕ_i, θ_j and σ_t are model parameters. To account for the movements in the oil, foreign exchange, bond, gold, and other developed equity stock markets (proxied by the STOXX 1800 index), we include the following returns in the mean equation: R_{t-1}^{OIL}, R_{t-1}^{FX}, R_{t-1}^{TB}, R_{t-1}^{GOLD}, and R_{t-1}^{STX}.

We model the evolution of σ^2_t via Nelson's (1991) exponential GARCH model with exogenous variables, i.e., the EGARCHX model:

$$
\ln\left(\sigma_t^2\right) = \omega + \sum_{n}^{N} \lambda_n D_n(t) + \sum_{k=1}^{r} \left(\alpha_i s_{t-k} + \gamma_i \left(\left|s_{t-k}\right| - E\left[\left|s_{t-k}\right|\right]\right)\right) + \sum_{l=1}^{s} \beta_l \ln\left(\sigma_{t-l}^2\right) \qquad (3)
$$

where s_t denotes standardized innovations, and α_i and γ_i control for the leverage and sign effects, respectively. We use the EGARCH specification because it allows the dependent variable to take on negative values, which is a convenient property when estimating such non-linear models with exogenous variables.[5]

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[3] This approach is also used by Koch (2014), who first filters the return series using a VAR model with exogenous, potentially common factors (e.g., S&P 500 equity index, credit spread) and only then studies extreme return co-exceedances in energy markets (WTI crude oil, heating oil, gasoline, natural gas, etc.).

[4] Common shocks driving co-movement are described as "monsoonal effects" by Masson (1998).

[5] We estimate several ARMAX(p, q)-EGARCHX(r, f) models with orders p, q, r, f up to 2. We select those models for which the resulting standardized residuals do not display autocorrelation and conditional heteroscedasticity. For this purpose, we use the test developed by Peña and Rodríguez (2006) using Monte Carlo critical values (see Lin and McLeod, 2006). If more suitable models remain, we prefer the more parsimonious models, that is, those with the least number of estimated parameters (p+q+r+f). If necessary, the chosen specification is selected using the Bayesian information criterion (BIC, Schwartz, 1978). Because we are unable to identify fully suitable models for Estonian and Romanian stock market returns, we choose the final specifications according to the BIC criterion. For both Estonia and Romania the autocorrelation of first order of standardized residuals was statistically significant, but the dependence is small 0.052 for Estonia and just 0.049 for Romania. For Romania statistically significant ARCH effects are identified as well, but only with a test testing up to 20 lags. Therefore, we consider our filtering procedure to be reasonable also for these two markets.

Since the studies by Lamoureux and Lastrapes (1990) and Hamilton and Susmel (1994), it is known that the persistence of market volatility is better explained by classifying the data into different time period regimes. Moreover, if volatility regimes are not taken into account, the persistence of market volatility tends to be overestimated. Therefore, we include dummy variables $D_n(t)$, n = 1, 2, …, N to account for potential shifts in the unconditional volatility. These breaks in market volatility are identified via the $\kappa 2$ test of Sansó et al. (2004), which is used within the Iterative Cumulative Sum of Squares algorithm of Inclán and Tiao (1994).[6]

In addition, we assume that η_t follows the SU-normal distribution of Johnson (1949a, b) with the probability density function defined as:

$$f(x) = (2\pi)^{-1/2} Je^{-\frac{z^2}{2}} \tag{4}$$

where $z = \varsigma^{-1}(sinh^{-1}(x) - \lambda)$ and $J = \varsigma^{-1}(x^2 + 1)^{-1/2}$. λ and ς are shape parameters that specify the skewness and kurtosis of the distribution. Choi and Nam (2008) show that Johnson's SU is a suitable distribution able to capture asymmetric and leptokurtic properties of heteroskedastic returns. The detailed results from ARMAX-EGARCH models are available in Table A.2 in the Appendix.

4.2 Range-based Heterogeneous Autoregressive Models

Based on the discussion in Section 2, we hypothesize that coupled with over-reactions, panic and signals of potential mispricing, the larger the level of unexpected market volatility during bearish market conditions is, the larger the probability of excess return co-movement will be. To measure the extent of unexpected events, we focus on market volatility because it is known that compared with returns, market volatility tends to be highly persistent, which makes it more suitable for forecasting purposes and thus for estimating the expected and unexpected events on a market.

The variance decomposition is based on the heterogeneous autoregressive (HAR) model of Corsi (2009). The original HAR model uses realized variances (RV), and currently one can use several competing specifications of the RV-HAR model (for an overview of the leading models,

[6] Within the κ_2 test, the estimation of the variance of squared demeaned returns is conducted via the non-parametric long-run variance estimator with automatic bandwidth selection of Newey and West (1994) and the Bartlett kernel weighting scheme. The script, including the ICSS algorithm of Inclán and Tiao (1994), is coded in R and is available upon request.

see Sévi, 2014). Because high-frequency data with a long history are not available for emerging markets, we forecast market variances using range-based volatility estimators and the corresponding HAR models, which we denote as RB-HAR models. On a sample of equity markets, Molnár (2015) demonstrates that the predictions of market variances based on the range-based HAR (RB-HAR) model are as accurate as the standard RV-HAR model.

We define $h_t = \ln(H_t/O_t)$, $l_t = \ln(L_t/O_t)$, and $c_t = \ln(C_t/O_t)$, $j_t = \ln(O_t/C_{t}{-}1)$, where O_t, H_t, L_t, C_t, are the open, highest, lowest and closing prices in a given day t, respectively. The Garman and Klass (1980) estimator is given by[7]:

$$\hat{\sigma}_t^2 = 0.511(h_t - l_t)^2 - 0.019(c_t(h_t + l_t) - 2h_t l_t) - 0.383c_t^2 + j_t^2 \tag{5}$$

The jump component j^2_t was proposed by Molnár (2012) to account for the gaps between closing and subsequent opening prices. Molnár (2012) argues that this is an unbiased approach to estimate market return variance over a whole day.

In this study, we use the following specification of the RB-HAR model:

$$\begin{aligned}\hat{\sigma}_t^2 = {} & \alpha_0 + \alpha_1\hat{\sigma}_{t-1}^2 + \alpha_2\left(\hat{\sigma}_{t-1}^2 I(c_{t-1} < 0)\right) + \alpha_3\hat{\sigma}_{t-1,t-5}^{2(+)} + \alpha_4\hat{\sigma}_{t-1,t-5}^{2(-)} + \\ & \alpha_5\hat{\sigma}_{t-1,t-22}^{2(+)} + \alpha_6 v\hat{\sigma}_{t-1,t-22}^{2(-)} + \alpha_7 VIX_{t-1} + e_t\end{aligned} \tag{6}$$

$I(.)$ is an indicator function that is defined as 1 if the returns during the trading on the U.S. market are negative and 0 otherwise. Patton and Sheppard (2011) suggest that the negative realized semi-variances may be more important when predicting the future variance on the U.S. stock market. Negative semi-variances in our model are represented by the average of the daily variances over the period from $t - k$ to $t - 1$ for days when the return was negative ("–"). Positive ("+") semi-variances are defined in a similar manner. Finally, we also include the transformed values of the volatility index (VIX_t), denoted as V_t, as they should represent investors' expectations about future equity market volatility. V_t is considered to represent a sentiment index of investors' fear and uncertainty. The transformation scales the VIX_t to daily values, i.e., $V_t = (VIX_t/100)^2/252$.

[7] With daily data, range-based variance estimators have a much higher efficiency compared with the simplest estimator of the daily variance (c_t^2), i.e., the Garman and Klass (1980) estimator is 7.4 times more efficient. For a more detailed treatment of range-based estimators, see Molnár (2012) or McLeish (2002).

We forecast the variance for time t using the specification (6) based on the previous 500 observations. We use the resulting coefficients to forecast the one-day-ahead variance[8]. Subsequently, we denote one-day-ahead volatilities as $\tilde{\sigma}_t$. The unexpected market volatility is calculated as $\hat{\sigma}_t - \tilde{\sigma}_t$. Rolling data one observation ahead and re-estimating the model leads to another forecasted variance at time $t + 1$. In this way, we obtain the series of expected and unexpected market volatilities. Our analysis shows that the correlation between the predicted and proxied true market volatility is 0.66.

4.3 Quantile Regressions

Because we are interested in excess return co-movements, we use the quantile regression framework to study the left tails of the distribution of return co-exceedances. Such a framework is most closely related to the studies of Baur and Schulze (2005), Baur (2013), and Mensi et al. (2014).

Let $\mathbf{C}_{ij}$ denote the $(T \times 1)$ vector of co-exceedances, where T is the number of observations, $\mathbf{X}$ is a $(T \times k)$ matrix of $k - 1$ exogenous variables and a constant, $\boldsymbol{\beta}(\tau)$ is the $(k \times 1)$ vector of unknown parameters and $\boldsymbol{\varepsilon}(\tau)$ is the $(T \times 1)$ vector of disturbances. We assume that the return co-exceedances $\mathbf{C}_{ij}$ are linearly dependent on a vector of exogenous variables. The τ-th conditional linear quantile regression model is defined as:

$$\mathbf{C}_{ij} = \mathbf{X}^{\mathrm{T}}\boldsymbol{\beta}(\tau) + \boldsymbol{\varepsilon}(\tau) \tag{7}$$

The τ-th quantile of the error term conditional on $\mathbf{X}$ is assumed to be equal to zero, i.e., $Q_{\boldsymbol{\varepsilon}(\tau)}(\tau|\mathbf{X}) = 0$. Given the linear functional form in (7), the τ-th conditional quantile of $\mathbf{C}_{ij}$ is:

$$Q_{Cij}(\tau \mid \mathbf{X}) = \mathbf{X}^{\mathrm{T}}\boldsymbol{\beta}(\tau) \tag{8}$$

We denote $\mathbf{x}^{\mathrm{T}}_t$ as a vector of exogenous variables at time $t = 1, 2, \ldots, T$. The quantile regression coefficients are estimated by solving the following minimization of weighted absolute deviations between co-exceedances and a linear combination of exogenous variables:

$$\mathbf{b}(\tau) = \underset{\beta(\tau)\in \mathrm{R}^k}{\arg\min} \left\{ \sum_{t:C_{ijt} \geq \mathbf{x}_t^{\mathrm{T}}\boldsymbol{\beta}(\tau)} \tau \left| C_{ijt} - \mathbf{x}_t^{\mathrm{T}}\boldsymbol{\beta}(\tau) \right| + \sum_{t:C_{ijt} < \mathbf{x}_t^{\mathrm{T}}\boldsymbol{\beta}(\tau)} (1-\tau) \left| C_{ijt} - \mathbf{x}_t^{\mathrm{T}}\boldsymbol{\beta}(\tau) \right| \right\} \tag{9}$$

[8] For a few instances where the predicted volatility is negative, the value of the expected volatility is set to 0. This approach is also visible from descriptive statistics in Table 1, where there are 31 instances where forecasted market volatility is set to 0, i.e., the minimum value.

The optimization is performed using the Barroda and Roberts (1974) algorithm described within a more general quantile regression context in Koenker and d'Orey (1987, 1994). Following Baur et al. (2012), the standard errors of the quantile regression coefficients are estimated via the block bootstrap. We set the fixed length of the blocks at 10 observations, but we also experimented with blocks with lengths of 2 and 25, and the results remain largely unchanged.[9]

We consider the following specification to explain the co-exceedances:

$$\begin{aligned}Q_{Cij}(\tau \mid \mathbf{X}) = {} & \beta_0(\tau) + \beta_1(\tau)C_{t-1} + \varphi_1(\tau)R_{t-1}^{TB} + \varphi_2(\tau)\tilde{\sigma}_{t-1}^{TB} + \delta_1(\tau)R_{t-1}^{FX} + \delta_2(\tau)\tilde{\sigma}_{t-1}^{FX} + \upsilon_1(\tau)P_{t-1} \\ & + \lambda_1(\tau)R_{t-1}^{STOXX} + \lambda_2(\tau)\tilde{\sigma}_{t-1}^{STOXX} + \eta_1(\tau)R_{t-1}^{OIL} + \eta_2(\tau)\tilde{\sigma}_{t-1}^{OIL} + \nu_1(\tau)R_{t-1}^{GOLD} + \nu_2(\tau)\tilde{\sigma}_{t-1}^{GOLD} \\ & + \gamma_1(\tau)\tilde{\sigma}_{t-1}^{US} + \gamma_2(\tau)\tilde{\sigma}_{t-1}^{US} I\left(R_{t-1}^{US} < 0\right) + \gamma_3(\tau)\left(\hat{\sigma}_{t-1}^{US} - \tilde{\sigma}_{t-1}^{US}\right) + \gamma_4(\tau)\left(\hat{\sigma}_{t-1}^{US} - \tilde{\sigma}_{t-1}^{US}\right) I\left(R_{t-1}^{US} < 0\right)\end{aligned} \qquad (10)$$

As before, $I(.)$ is an indicator function that returns 1 if the corresponding return on the U.S. market was less than zero and that otherwise returns 0. If contagion from the U.S. market occurred, the estimates of ($\gamma_3 + \gamma_4$) should be negative; thus, unexpected events coupled with bearish market conditions will increase the size of the left-tail dependence.

Similarly, for the mean equations defined in (2), we study whether fluctuation in the foreign exchange market, other equity markets, the oil market, gold markets and the bond market in the U.S. help to explain the occurrence of extreme market co-movements. Close-to-close daily returns R_{t-1}^{FX}, R_{t-1}^{STOX}, R_{t-1}^{GOLD}, R_{t-1}^{OIL}, R_{t-1}^{TB} and estimated market return volatilities $\tilde{\sigma}_{t-1}^{FX}$, $\tilde{\sigma}_{t-1}^{STOX}$, $\tilde{\sigma}_{t-1}^{GOLD}$, $\tilde{\sigma}_{t-1}^{OIL}$, $\tilde{\sigma}_{t-1}^{TB}$ are included in specification (10).

Instead of using conditional volatility estimated from suitable ARFIMA(p,d,q)-GARCH(r,s) models (as in Christiansen and Ranaldo, 2009), we proxy market volatility with the forecasted (expected) volatility derived from a simple ARMA(1,1)-EGARCH(1,1) model of daily continuous returns r_t. The advantage of using such a specification is that all of the terms on the right-hand side of equation (10) are known before the return co-exceedances are known. Similarly, in the RB-HAR models, for each series, we use the previous 500 observations to estimate the ARMA(1,1)-EGARCH(1,1) model, and based on the model, a one-observation-ahead variance forecast is made. The ARMA(1,1)-EGARCH(1,1) models are re-estimated excluding the first 25 observations.

[9] These results are available as part of the Online Appendix. For some markets, the value of return co-exceedances is zero in nearly 50% of all observations. For this reason, we add jitter to the return co-exceedances by replacing 0-valued return co-exceedances with a random value from –0.001 to +0.001. Because the return co-exceedances are calculated from standardized residuals with mean 0 and variance of approximately 1, these imputed values are small and distort the overall distribution of co-exceedances only negligibly but improve the convergence of our estimator.

5 Results

5.1 Properties of Co-exceedances

In Table 1, we provide some descriptive statistics of the country-specific co-exceedances (C), foreign exchange rate returns (R_t^{FX}) and their estimated volatilities ($\tilde{\sigma}_t^{FX}$), the STOXX 1800 index (R_t^{STX}) and its estimated volatility ($\tilde{\sigma}_{t-1}^{STX}$), gold ($R_t^{GOLD}$) and its estimated volatility ($\tilde{\sigma}_{t-1}^{GOLD}$), oil ($R_t^{OIL}$) and its estimated volatility ($\tilde{\sigma}_{t-1}^{OIL}$), government bonds ($R_t^{TB}$) and its estimated volatility ($\tilde{\sigma}_{t-1}^{TB}$), and the Economic Policy Uncertainty Index (P_t), together with range-based volatility estimates for the U.S. market ($\hat{\sigma}_{t-1}^{US}$) decomposed to the expected ($\tilde{\sigma}_{t-1}^{US}$) and unexpected parts ($\hat{\sigma}_{t-1}^{US} - \tilde{\sigma}_{t-1}^{US}$).

All of the co-exceedances are on average negative and are negatively skewed in most of the cases (except Hungary); thus, joint extreme negative shocks are more common in our examined time period. Interestingly, the lowest joint negative returns occurred in all of the markets at almost the same time: October 10, 2008 (for the Czech Republic, Estonia, Poland, and Romania), October 16, 2008 (Hungary) and November 20, 2008 (Croatia). All of these days correspond to the peak of the recent financial crisis. Joint positive shocks were also recorded in autumn 2008 (although for Estonia only in March 2009), thus demonstrating the extremely high volatility of returns during this period.

Table 1 Descriptive statistics

		Mean	SD	AC(1)	Skew.	Kurt.	min.	min. date	max.	max. date	KPSS	ADF-GLS
Croatia	C	-10.29	439.03	0.06	-1.95	26.24	-5017.43	20.11.2008	3350.70	19.09.2008	0.11	-9.24[c]
	R_t^{FX}	-0.13	6.47	0.01	-0.17	5.53	-46.19	20.03.2009	38.29	22.12.2008	0.14	-13.40[c]
	$\tilde{\sigma}_t^{FX}$	0.04	0.02	0.99	2.42	12.49	0.01	05.09.2014	0.17	22.01.2009	0.31	-2.29[b]
Czech Republic	C	-4.87	507.05	0.05	-1.22	21.02	-6296.82	10.10.2008	4293.35	24.11.2008	0.12	-13.51[c]
	R_t^{FX}	-0.14	7.78	0.01	-0.02	6.64	-52.19	20.03.2009	55.40	11.08.2013	0.18	-13.30[c]
	$\tilde{\sigma}_t^{FX}$	0.06	0.04	1.00	3.39	16.85	0.01	30.07.2014	0.35	25.02.2009	0.61[b]	-2.89[c]
Estonia	C	-17.02	515.65	0.06	-1.59	22.10	-5337.02	10.10.2008	4208.80	24.03.2009	0.17	-8.15[c]
	R_t^{FX}	-0.11	6.28	0.00	-0.17	5.79	-46.17	20.03.2009	38.44	22.12.2008	0.14	-10.08[c]
	$\tilde{\sigma}_t^{FX}$	0.04	0.02	0.99	2.16	11.40	0.00	01.03.2000	0.16	28.01.2009	0.28	-2.23[b]
Hungary	C	-1.02	508.88	0.08	0.46	38.05	-5721.50	16.10.2008	8050.92	29.10.2008	0.12	-10.67[c]
	R_t^{FX}	-0.09	9.37	0.02	0.06	6.46	-52.00	30.10.2008	63.05	16.10.2008	0.09	-39.89[c]
	$\tilde{\sigma}_t^{FX}$	0.08	0.07	0.99	2.36	9.30	0.02	03.05.2002	0.48	10.11.2008	1.01[c]	-2.47[b]

Table 1 (continued)

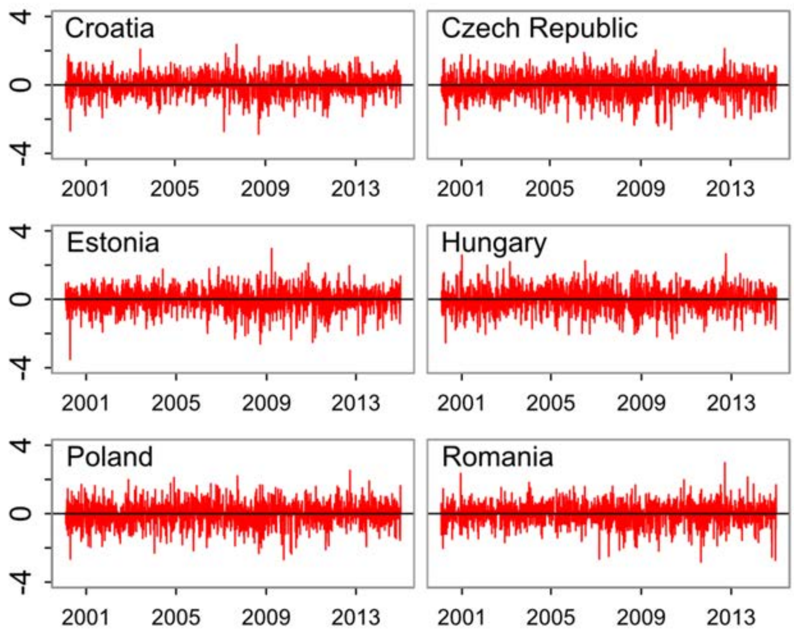
		Mean	SD	AC(1)	Skew.	Kurt.	min.	min. date	max.	max. date	KPSS	ADF-GLS
Poland	C	-6.84	491.77	0.07	-0.56	21.09	-5402.41	10.10.2008	4818.47	24.11.2008	0.53[a]	-10.18[c]
	R_t^{FX}	-0.14	8.77	0.03	0.05	7.71	-66.97	30.10.2008	56.96	23.10.2008	0.06	-8.69[c]
	$\tilde{\sigma}_t^{FX}$	0.07	0.06	0.96	2.98	14.76	0.01	07.01.2003	0.57	19.02.2009	0.58[b]	-4.30[c]
Romania	C	-11.76	465.21	0.07	-1.75	24.33	-6275.23	10.10.2008	3359.78	19.09.2008	0.11	-9.91[c]
	R_t^{FX}	0.12	7.29	-0.02	0.34	12.76	-52.61	30.10.2008	73.60	07.12.2004	0.38[a]	-9.82[c]
	$\tilde{\sigma}_t^{FX}$	0.06	0.09	0.94	6.18	63.59	0.00	22.12.2000	1.44	09.12.2004	0.84[c]	-3.92[c]
US	$\hat{\sigma}_{t-1}^{US}$	8.28	5.99	0.67	3.37	23.28	1.38	25.11.2014	77.62	15.10.2008	0.33	-4.45[c]
	$\tilde{\sigma}_{t-1}^{US}$	0.87	5.76	0.91	2.91	17.41	0.00	31 dates	59.15	17.10.2008	0.14	-3.38[c]
	$\hat{\sigma}_{t-1}^{US} - \tilde{\sigma}_{t-1}^{US}$	-0.43	4.28	0.17	1.57	23.13	-29.36	21.10.2008	50.37	07.05.2010	0.13	-6.11[c]
STOXX	R_t^{STX}	0.02	11.75	0.10	-0.39	8.81	-86.81	15.10.2008	79.93	30.10.2008	0.10	-1.69[a]
	$\tilde{\sigma}_{t-1}^{STX}$	0.12	0.12	0.97	5.57	49.14	0.02	16.06.2014	1.69	29.10.2008	0.12	-5.77[c]
Gold	R_t^{GOLD}	0.30	11.57	0.00	-0.31	8.26	-95.96	16.04.2013	68.36	20.03.2009	0.15	-12.17[c]
	$\tilde{\sigma}_{t-1}^{GOLD}$	0.13	0.10	0.94	3.40	20.06	0.03	05.05.2000	1.11	26.11.2008	0.49[a]	-3.53[c]
Oil	R_t^{OIL}	0.06	22.19	0.00	-0.44	8.56	-198.91	25.09.2001	128.53	21.11.2001	0.09	-9.54[c]
	$\tilde{\sigma}_{t-1}^{OIL}$	0.52	0.33	0.98	2.09	9.82	0.07	10.06.2014	2.76	26.09.2001	0.70[b]	-3.54[c]
TB	R_t^{TB}	-0.38	14.33	0.00	0.02	5.92	-89.06	19.03.2009	81.04	12.08.2011	0.03	-4.99[c]
	$\tilde{\sigma}_{t-1}^{TB}$	0.19	0.18	0.99	2.64	11.61	0.04	04.06.2007	1.38	03.11.2011	2.60[c]	-3.05[c]
P_t		-8.20	585.48	-0.36	0.03	4.04	-2904.28	22.10.2013	2919.37	09.05.2001	0.11	-44.12[b]

Notes: Significance at 10%, 5%, and 1% levels are denoted by "a", "b", "c" superscripts, respectively. SD – standard deviation, AC(1) – autocorrelation coefficient of the first order. KPSS – test statistics of the Kwiatkowski et al. (1992) test with the long-run variance estimator of Sul et al. (2005). ADF-GLS – test statistics of the Elliott et al. (1996) test, where in the auxiliary regressions, the lag length was determined via the modified Akaike criterion, as described in Perron and Qu (2007). Mean, SD, min and max are multiplied by 1000.

The co-exceedances display very low autocorrelation, which is practically zero in all of the cases. Therefore, this measure of stock market co-movement is not persistent, in contrast to, for example, the dynamic conditional correlations from multivariate GARCH models. Using co-exceedances might therefore be beneficial from a methodological perspective as well because highly correlated time series in regressions usually lead to large size distortions, and even if robust standard errors are applied, the model remains mis-specified (see Granger et al., 2001 and Su, 2008).

The return co-exceedances in Figure 1 do not appear to have any clear, specific pattern because before calculating the co-exceedances, when the returns are filtered via the ARMAX-EGARCHX models. It is therefore of particular interest whether we are able to measure any systematic effects on the return co-movement even after such a strong filtration procedure. A reader may compare Figure 1 with Figure A1 in the Appendix, where the return co-exceedances are calculated for non-filtered returns. There are sizeable differences, as we can observe large variability in the return co-exceedances during the recent crisis period in Figure A1 in Appendix, but not in Figure 1. As a consequence, we conduct a robustness check to examine whether the regression results (presented in the following sub-section) are influenced by the different filtering procedure.

Figure 1 Return co-exceedances from standardized residuals



5.2 Evidence of Financial Contagion: Full Sample

In Table 2, we provide the results from the quantile regressions based on the co-exceedances computed from the standardized residuals through the ARMAX-EGARCH model. Because we focus on contagion, we present the results from the left tail of the return co-exceedances.[10] All of the asymmetric terms of the expected and unexpected volatilities are highly significant (γ_2, γ_4). In addition, all of the coefficients are negative, suggesting that an increase in both expected and unexpected volatility accompanied with market declines tends to produce negative joint co-movements. The size of this effect is larger in the left tails and it gradually weakens through the other quantiles, although it remains significant, even in the OLS estimates.

[10] The results for the right tail of the return co-exceedance distribution are available in the Online Appendix.

Within our definition of contagion, the sum of the estimated coefficients of unexpected volatility and its asymmetric term should be negative ($\gamma_3+\gamma_4$). According to our findings, this result holds in all cases; thus, unexpected events coupled with market declines increase the size of extreme market co-movements. As a consequence, our results suggest that contagion from the U.S. market to the CEE region has taken place.

Figure 2 shows the striking difference in the size of the coefficients of unexpected volatility with respect to the different predicted quantiles, including those in the right tail of the co-exceedance distribution. We can clearly see that the unexpected part of the market's volatility matters not only for contagion (negative return co-exceedances) but also for positive return co-exceedances.

Regarding the fundamental variables that we control for in our regressions, only a few of them are significant. This result justifies our view that most extreme market co-movements are investor over-reactions rather than fundamentally based decisions.

Several fundamentals are significant for the OLS estimates, but these results should not be overemphasized because they capture the average conditions in the stock markets rather than the extremes, which is our focus. The STOXX 1800 index returns are statistically significant in all countries and the coefficient λ_1 is positive, which is in line with our expectations that if world-wide stock prices increase, it is likely that national stock markets will increase as well. The other fundamentals are significant only for certain countries, including the volatility of gold (significant in Croatia and Romania) and bond yields (significant in Croatia, the Czech Republic, Estonia and Romania).

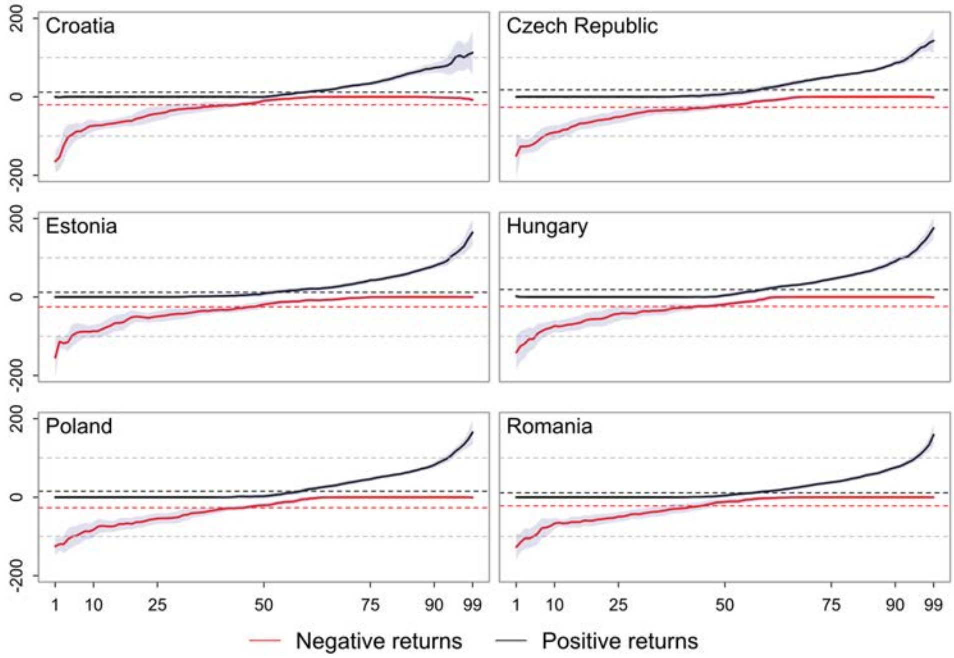
Table 2 Quantile regression estimates: co-exceedances based on standardized residuals

	τ	β_0	β_1	γ_1	γ_2	γ_3	γ_4	δ_1	δ_2	λ_1	λ_2	ν_1	ν_2	η_1	η_2	φ_1	φ_2	υ_1	R^2
Croatia	0.01	-7.88	-0.25	-0.30	**-169.42**^{d}	-0.70	**-163.92**^{d}	170.38	122.37	1.39	31.83	122.91	-119.64	-11.17	9.19	79.39	28.73	1.11	0.48
	0.05	-0.12	0.04	0.04	**-110.15**^{d}	0.00	**-95.89**^{d}	0.40	-0.27	0.02	-0.83	0.78	-0.53	0.10	0.09	1.55	-1.00	-0.02	0.42
	0.10	**-0.10**^{d}	0.01	**0.04**^{a}	**-77.64**^{d}	0.02	**-73.68**^{d}	0.51	-3.24	**0.02**^{b}	-0.61	0.30	-0.77	0.20	0.25	0.53	0.05	-0.01	0.39
	0.25	-0.01	0.01	0.03	**-39.78**^{d}	0.00	**-42.89**^{d}	0.21	-6.08	0.01	-1.01	-0.42	-1.25	0.10	0.59	**0.96**^{a}	0.01	0.00	0.20
	OLS	**6.21**^{d}	**-4.33**^{a}	**16.01**^{d}	**-38.69**^{d}	**11.82**^{d}	**-32.23**^{d}	68.61	-460.61	**2.98**^{d}	-76.86	-6.49	**-146.58**^{b}	-2.26	31.10	**123.73**^{b}	-1.17	0.06	0.28
Czech Republic	0.01	-8.70	-1.16	-1.87	**-205.12**^{d}	-1.47	**-214.66**^{d}	276.10	169.10	1.92	323.35	-12.33	-441.30	-21.96	8.37	10.22	63.05	0.18	0.42
	0.05	-0.28	-0.02	0.08	**-133.63**^{d}	0.04	**-140.18**^{d}	-1.18	9.33	0.09	3.37	-0.60	-7.55	-2.49	-0.71	0.22	-1.08	0.00	0.37
	0.10	-0.11	-0.03	0.03	**-95.62**^{d}	0.03	**-98.30**^{d}	0.30	0.97	0.02	0.34	0.28	-0.27	-0.28	-0.05	0.58	-0.11	0.01	0.35
	0.25	**-0.06**^{b}	-0.03	0.02	**-48.40**^{d}	0.03	**-52.74**^{d}	0.43	6.55	0.01	3.47	-1.06	-0.35	-0.62	-0.34	0.49	-1.06	0.00	0.24
	OLS	2.28	**-5.93**^{c}	**18.50**^{d}	**-48.67**^{d}	**17.90**^{d}	**-44.50**^{d}	-14.15	413.57	**3.38**^{c}	119.52	14.31	-91.47	-33.80	7.95	**127.59**^{a}	-42.46	-0.60	0.30
Estonia	0.01	-9.54	-0.29	-1.18	**-178.33**^{d}	-0.13	**-171.98**^{d}	45.76	-70.94	0.98	237.12	-76.00	-492.97	-3.15	41.38	70.76	101.51	3.25	0.43
	0.05	-0.12	0.00	0.00	**-122.56**^{d}	-0.02	**-102.57**^{d}	2.28	9.05	0.04	2.22	-0.86	-10.46	0.16	-0.01	0.91	0.92	-0.01	0.41
	0.10	**-0.10**^{d}	-0.01	0.04	**-89.38**^{d}	0.03	**-85.75**^{d}	1.28	-2.35	**0.02**^{a}	-0.42	-0.39	-1.07	0.16	0.24	0.60	0.03	-0.01	0.38
	0.25	-0.05	-0.01	0.04	**-48.34**^{d}	**0.04**^{a}	**-43.83**^{d}	-0.60	3.48	0.01	-0.68	-0.83	0.54	0.05	0.34	1.03	-0.28	-0.02	0.24
	OLS	2.83	**-6.75**^{d}	**16.69**^{d}	**-44.55**^{d}	**12.03**^{d}	**-37.21**^{d}	81.15	266.37	**4.27**^{d}	-58.68	-4.03	-84.07	2.93	38.12	**150.73**^{b}	5.09	-0.84	0.31
Hungary	0.01	**-24.95**^{b}	2.35	11.49	**-166.54**^{d}	3.35	**-152.28**^{d}	118.82	-47.37	0.25	-99.07	-80.23	-318.32	86.02	-30.93	67.93	143.80	-2.25	0.38
	0.05	-0.41	0.12	0.22	**-125.67**^{d}	0.01	**-124.23**^{d}	-5.30	3.96	0.04	0.86	-1.16	-9.41	-1.16	-1.74	-1.36	0.95	0.05	0.38
	0.10	**-0.10**^{d}	0.02	0.01	**-91.82**^{d}	0.02	**-82.93**^{d}	-1.06	-0.76	0.00	0.47	-0.65	-0.50	-0.31	0.34	0.40	0.28	0.01	0.36
	0.25	-0.03	0.03	0.01	**-46.60**^{d}	0.01	**-42.66**^{d}	-0.70	0.79	-0.01	0.64	-0.50	**-2.35**^{c}	0.06	0.41	0.67	0.57	-0.01	0.23
	OLS	**2.77**^{a}	-0.97	**18.32**^{d}	**-47.17**^{d}	**18.98**^{d}	**-42.91**^{d}	-19.00	-38.81	**2.76**^{b}	35.13	-31.11	-38.06	-53.66	36.61	84.27	29.14	-1.64	0.29
Poland	0.01	**-25.39**^{b}	3.31	5.03	**-179.25**^{d}	1.47	**-163.29**^{d}	11.02	12.40	0.99	162.50	-188.75	-489.78	15.04	44.18	86.51	100.07	**-10.21**^{a}	0.39
	0.05	-0.18	0.02	0.04	**-132.62**^{d}	0.00	**-109.87**^{d}	-0.95	2.35	0.05	1.80	-2.67	-5.13	-1.18	-0.17	-0.78	-0.03	-0.02	0.38
	0.10	**-0.10**^{d}	0.00	0.03	**-95.17**^{d}	0.01	**-82.23**^{d}	0.41	0.31	0.02	0.80	-0.48	-1.01	-0.27	0.00	-0.09	-0.01	0.00	0.37
	0.25	**-0.05**^{c}	0.01	0.01	**-47.50**^{d}	0.03	**-56.09**^{d}	-0.27	2.26	0.01	1.60	-0.15	-1.09	-0.12	0.31	0.33	-0.24	0.00	0.22
	OLS	**3.08**^{a}	-2.53	**18.68**^{d}	**-46.09**^{d}	**15.29**^{d}	**-42.25**^{d}	-92.83	**301.62**^{a}	**2.71**^{b}	98.08	-20.34	-116.89	**-67.13**^{a}	-27.26	105.55	-17.81	-0.89	0.28
Romania	0.01	-9.61	1.63	2.07	**-183.96**^{d}	1.65	**-191.72**^{d}	39.83	-20.63	0.85	91.97	27.39	-124.55	19.92	9.92	114.10	-75.77	3.37	0.41
	0.05	-0.25	-0.11	0.00	**-123.76**^{d}	0.01	**-111.76**^{d}	1.75	-3.10	0.06	1.93	-1.32	-4.65	1.14	0.56	4.77	-0.83	0.08	0.39
	0.10	-0.11	-0.02	0.01	**-89.22**^{d}	0.02	**-81.36**^{d}	-0.07	-1.10	0.02	0.16	-0.17	0.29	0.18	0.26	1.62	-0.71	0.01	0.36
	0.25	**-0.05**^{c}	0.00	0.00	**-43.07**^{d}	0.01	**-39.43**^{d}	0.44	0.38	**0.02**^{b}	0.26	0.35	-0.22	-0.24	0.50	**1.14**^{b}	0.02	0.01	0.21
	OLS	**3.25**^{a}	**-5.43**^{c}	**15.87**^{d}	**-39.65**^{d}	**11.23**^{d}	**-33.25**^{d}	100.63	82.92	**4.81**^{d}	13.99	4.82	**-215.72**^{c}	-31.50	24.24	**211.27**^{c}	25.11	1.39	0.28

Notes: τ denotes respective quantile. The coefficients const, β_1, δ_1, ν_1, η_1, φ_1, υ_1 are multiplied by100. Significance at 10%, 5%, 1%, and 0.1% is denoted by "a", "b", "c", and "d" superscripts, respectively. For the quantile regressions, R^2 denotes the pseudo R^2 as defined in Koenker and Machado (1999, Eq. 7), while for the OLS regressions, the usual adjusted coefficient of determination is used. The standard errors of the estimated OLS regression coefficients were derived from the HAC matrix and calculated using the quadratic spectral kernel weighting scheme with automatic bandwidth procedure, as in Newey and West (1994).

$$Q_{Cij}(\tau \mid \mathbf{X}) = \beta_0(\tau) + \beta_1(\tau)C_{t-1} + \varphi_1(\tau)R_{t-1}^{TB} + \varphi_2(\tau)\tilde{\sigma}_{t-1}^{TB} + \delta_1(\tau)R_{t-1}^{FX} + \delta_2(\tau)\tilde{\sigma}_{t-1}^{FX} + \upsilon_1(\tau)P_{t-1} + \lambda_1(\tau)R_{t-1}^{STOXX} + \lambda_2(\tau)\tilde{\sigma}_{t-1}^{STOXX} + \eta_1(\tau)R_{t-1}^{OIL} + \eta_2(\tau)\tilde{\sigma}_{t-1}^{OIL} + \nu_1(\tau)R_{t-1}^{GOLD} + \nu_2(\tau)\tilde{\sigma}_{t-1}^{GOLD} + \gamma_1(\tau)\tilde{\sigma}_{t-1}^{US} + \gamma_2(\tau)\tilde{\sigma}_{t-1}^{US} I\left(R_{t-1}^{US} < 0\right) + \gamma_3(\tau)\left(\hat{\sigma}_{t-1}^{US} - \tilde{\sigma}_{t-1}^{US}\right) + \gamma_4(\tau)\left(\hat{\sigma}_{t-1}^{US} - \tilde{\sigma}_{t-1}^{US}\right) I\left(R_{t-1}^{US} < 0\right)$$

Figure 2 Unexpected market volatility effects at different quantiles



Notes: The Figure reports the size of coefficients from quantile regression results for quantiles (τ) from 1 to 99. Negative returns corresponds to the sum of two coefficients ($\gamma_3 + \gamma_4$), while positive returns are just γ_3. The horizontal dashed lines represent OLS coefficient estimates.

5.3 Is Contagion a Financial Crisis Phenomenon?

Bekaert et al. (2014) find that financial contagion from the U.S. stock market to the CEE markets occurred during the financial crisis. These results are intuitive and are supported by most of the literature finding excess co-movement during crisis period. Therefore, we examine: 1) whether our results are driven only by the recent financial crisis and 2) whether, in case that we observe contagion in both good and crisis times, contagion is stronger during the crisis.

5.3.1 Contagion in Good Times

We re-estimate the quantile regression models for two periods. The first period ends in June 2007, and the second period starts after March 2009 (crisis period is excluded). This division is similar to that presented in Baur (2012), Kontonikas et al. (2013) and Florackis et al. (2014). However, it is noteworthy that the comparison of these results with the results for full sample is not straightforward, as the corresponding quantiles will change. Despite that, it represents an important check whether financial contagion occurs only in specific periods such as financial crisis or whether it is a more general phenomenon occurring in good times too.

Our main results remain largely unchanged, as before and after the crisis period all of the coefficients of the asymmetric unexpected market volatility of the models predicting the left tail of the return co-exceedances remain negative and statistically significant.[11] In addition, after the 2007–2009 crisis, the sensitivity of the CEE stock markets has increased, i.e., when the markets plummet, a unit change in unexpected market volatility now leads to higher extreme market co-movements.

5.3.2 Contagion during Financial Crisis

We examine whether extreme negative co-exceedances are more intensively related to the unexpected market volatility during the recent financial crisis. We extend the specification in Eq. (10) by the regime dependent expected and unexpected market volatilities in the following way. We introduce two additional dummy variables to characterize the crisis regime and after-crisis regime. D_1 is equal to 1 for observations in the crisis (July 2007 – March 2009), 0 otherwise. D_2 is equal to 1 if the observation is from after-crisis period, i.e. from April 2009 onward, 0 otherwise. As a result, our regression specification is as follows:

$$Q_{Cij}(\tau \mid \mathbf{X}) = \mathbf{R\beta} + (1 + D_1 + D_2)\mathbf{Z\Gamma} \tag{11}$$

where

$$\begin{aligned}\mathbf{R\beta} = {} & \beta_0(\tau) + \beta_1(\tau)C_{t-1} + \varphi_1(\tau)R_{t-1}^{TB} + \varphi_2(\tau)\tilde{\sigma}_{t-1}^{TB} + \delta_1(\tau)R_{t-1}^{FX} + \delta_2(\tau)\tilde{\sigma}_{t-1}^{FX} + \upsilon_1(\tau)P_{t-1} \\ & + \lambda_1(\tau)R_{t-1}^{STOXX} + \lambda_2(\tau)\tilde{\sigma}_{t-1}^{STOXX} + \eta_1(\tau)R_{t-1}^{OIL} + \eta_2(\tau)\tilde{\sigma}_{t-1}^{OIL} + \nu_1(\tau)R_{t-1}^{GOLD} + \nu_2(\tau)\tilde{\sigma}_{t-1}^{GOLD} \\ \mathbf{Z\Gamma} = {} & \gamma_1(\tau)\tilde{\sigma}_{t-1}^{US} + \gamma_2(\tau)\tilde{\sigma}_{t-1}^{US} I\left(R_{t-1}^{US} < 0\right) + \gamma_3(\tau)\left(\hat{\sigma}_{t-1}^{US} - \tilde{\sigma}_{t-1}^{US}\right) + \gamma_4(\tau)\left(\hat{\sigma}_{t-1}^{US} - \tilde{\sigma}_{t-1}^{US}\right) I\left(R_{t-1}^{US} < 0\right)\end{aligned} \tag{12}$$

We report the results in Table 3. For the sake of simplicity, we do not present the estimates of $\boldsymbol{\beta}$ (available in the online Appendix) and focus instead on the estimates of expected and unexpected market volatilities, i.e. the $\boldsymbol{\Gamma}$, $D_1\boldsymbol{\Gamma}$, and $D_2\boldsymbol{\Gamma}$. These coefficients are denoted in Table 3 as γ_1, γ_2, γ_3, γ_4 for the first regime characterized by D_1 (γ_1 – expected market volatility, γ_2 – expected market volatility with decreasing markets, γ_3 – unexpected market volatility, and γ_4 – unexpected market volatility with decreasing markets), γ_5, γ_6, γ_7, γ_8 denote the change in coefficients during the crisis period, and γ_9, γ_{10}, γ_{11}, γ_{12} denote the change in coefficients (compared to the pre-crisis period) after the crisis. The coefficient γ_8 denotes the *change* in the effect of the unexpected market volatility when markets are decreasing, which is of prime interest for this study.

[11] The complete results from the Section 5.3 and 5.4 are available in the Online Appendix.

The results in Table 3 support findings reported in the literature that co-exceedances are higher during crisis period as: i) almost all γ_8 coefficients are negative suggesting that the sensitivity to unexpected negative events increased, i.e. extreme negative co-exceedance is higher for the same magnitude of "bad surprise" shock during the financial crisis, ii) compared to the γ_4 coefficient, the absolute value of the γ_8 coefficient for the most extreme quantile (0.01) is large (note that the overall effect is the sum $\gamma_4 + \gamma_8$, so that γ_8 denotes only the change), iii) the γ_8 coefficient for the extreme lower quantile is statistically significant at least at 10% for all countries except for Poland.

Table 3 Quantile regression re-estimates according to crisis period: co-exceedances based on standardized residuals

		Before the financial crisis				During the financial crisis				After the financial crisis				
	τ	γ_1	γ_2	γ_3	γ_4	γ_5	γ_6	γ_7	γ_8	γ_9	γ_{10}	γ_{11}	γ_{12}	R^2
Croatia	0.01	-0.34	**-148.52[d]**	-0.40	**-91.53[d]**	0.38	**-49.76[b]**	0.81	**-128.89[c]**	-0.39	**25.20[a]**	-0.67	15.37	0.72
	0.05	0.01	**-97.80[d]**	0.01	**-98.30[d]**	0.00	**-45.64[c]**	-0.01	-61.44	0.00	**14.83[b]**	0.00	**40.53[b]**	0.57
	0.10	0.04	**-74.10[d]**	0.01	**-81.61[d]**	0.01	**-42.56[c]**	0.03	-24.52	-0.01	9.80	0.01	**34.65[b]**	0.47
	0.25	0.03	**-33.19[d]**	0.02	**-38.10[d]**	0.02	**-27.43[d]**	0.01	-31.09	0.01	-6.10	0.03	-0.51	0.25
	OLS	**24.14[d]**	**-42.09[d]**	**13.73[c]**	**-35.23[d]**	2.89	-10.12	11.42	-20.42	-0.45	2.93	-6.06	15.87	0.35
Czech Republic	0.01	0.03	**-152.27[d]**	-0.02	**-123.88[d]**	0.01	**-46.59[a]**	0.07	**-101.67[a]**	0.00	-4.30	0.03	-2.68	0.68
	0.05	0.06	**-111.09[d]**	0.03	**-96.63[d]**	-0.01	-17.16	-0.01	-28.77	-0.01	-13.57	-0.02	-29.92	0.55
	0.10	0.01	**-85.18[d]**	0.02	**-81.05[d]**	0.00	**-24.20[a]**	0.05	-44.46	-0.01	-11.48	-0.02	-8.66	0.46
	0.25	0.05	**-46.21[d]**	0.04	**-36.01[d]**	0.00	**-14.80[b]**	0.10	**-39.60[a]**	-0.04	0.77	-0.02	-11.91	0.28
	OLS	**28.64[d]**	**-54.49[d]**	**23.65[d]**	**-46.15[d]**	2.29	**-10.58[a]**	3.21	-7.48	-2.59	0.76	-11.68	0.49	0.40
Estonia	0.01	-0.07	**-158.21[d]**	-0.11	**-109.94[d]**	0.01	**-45.59[a]**	0.11	**-121.57[a]**	-0.23	-24.72	-0.22	**-69.23[a]**	0.71
	0.05	0.01	**-112.45[d]**	-0.02	**-89.54[c]**	0.02	-14.89	0.01	-1.91	0.01	-14.58	0.03	-34.33	0.57
	0.10	0.07	**-79.89[d]**	0.03	**-66.05[d]**	-0.01	**-29.62[d]**	-0.05	-21.03	0.00	**-21.00[b]**	0.01	-32.64	0.50
	0.25	0.09	**-42.56[d]**	0.06	**-32.48[d]**	-0.01	**-26.34[d]**	-0.06	**-45.12[c]**	-0.01	**-8.77[a]**	0.02	-15.57	0.30
	OLS	**26.51[d]**	**-47.73[d]**	**7.01[a]**	**-31.31[d]**	-4.62	**-9.63[a]**	**13.76[a]**	**-25.63[b]**	2.96	-8.23	**19.51[a]**	-28.06	0.43
Hungary	0.01	0.15	**-150.41[d]**	0.05	**-104.43[d]**	0.12	-22.69	0.00	**-76.27[a]**	-0.05	-8.20	-0.10	-18.09	0.67
	0.05	0.04	**-113.09[d]**	0.02	**-68.72[d]**	-0.01	-14.94	-0.03	-75.67	0.00	-1.87	-0.03	**-47.44[b]**	0.54
	0.10	0.02	**-88.74[d]**	0.02	**-74.21[d]**	0.00	-19.39	-0.03	-8.28	-0.01	4.64	-0.02	-10.25	0.45
	0.25	0.05	**-46.40[d]**	0.02	**-39.01[d]**	-0.02	-5.56	0.00	3.11	-0.03	5.49	0.03	-8.64	0.24
	OLS	**25.90[d]**	**-56.88[d]**	**23.85[d]**	**-47.27[d]**	-0.71	-5.41	-0.52	5.89	-4.92	**9.17[a]**	-7.07	-3.11	0.35
Poland	0.01	0.13	**-161.87[d]**	-0.01	**-108.40[d]**	-0.05	-5.74	0.10	-36.99	-0.30	-18.68	-0.15	-10.78	0.66
	0.05	0.02	**-121.28[d]**	0.00	**-88.01[d]**	0.00	-5.09	0.00	-33.31	0.00	**14.65[a]**	-0.01	-15.41	0.54
	0.10	0.00	**-95.47[d]**	0.00	**-70.21[d]**	0.02	-4.83	0.00	**-51.09[b]**	0.02	**14.83[b]**	0.00	-4.51	0.46
	0.25	0.01	**-51.44[d]**	0.02	**-52.91[d]**	-0.01	-5.47	-0.03	**-38.56[b]**	0.00	**12.55[b]**	-0.01	13.26	0.25
	OLS	**27.59[d]**	**-57.52[d]**	**22.49[d]**	**-50.05[d]**	-0.48	2.07	-7.10	-7.61	-1.64	**10.16[b]**	-4.53	9.70	0.36
Romania	0.01	0.04	**-146.15[d]**	0.03	**-100.46[d]**	0.04	**-42.41[b]**	0.02	**-137.84[b]**	0.00	-20.01	-0.02	-19.09	0.70
	0.05	0.02	**-97.44[d]**	0.00	**-88.72[c]**	-0.01	**-35.16[b]**	0.00	-17.86	-0.01	**-27.31[b]**	0.00	-12.69	0.54
	0.10	0.04	**-70.74[d]**	0.01	**-43.29[c]**	0.00	**-46.42[d]**	0.02	**-65.45[b]**	0.00	**-18.68[b]**	0.02	**-32.97[a]**	0.46
	0.25	0.04	**-30.21[d]**	0.03	**-20.35[b]**	0.00	**-34.82[d]**	0.01	**-49.40[c]**	0.02	**-14.72[d]**	0.03	**-34.86[c]**	0.25
	OLS	**16.41[d]**	**-35.93[d]**	**6.43[b]**	**-15.92[c]**	2.83	**-17.94[b]**	14.22	**-48.02[c]**	**10.96[b]**	**-17.59[d]**	6.34	**-27.30[b]**	0.38

Notes: As for Table 2

$Q_{Cij}(\tau \mid \mathbf{X}) = \mathbf{R\beta} + (1 + D_1 + D_2)\mathbf{Z\Gamma}$

5.4 Robustness Analysis

5.4.1 Has Return Filtration Induced Spurious Contagion?

Filtering returns via the ARMAX-EGARCHX model might be considered too fine an approach to obtain residuals, and critics may argue that it distorts the "true" relationship between markets. We re-estimate our quantile regression models but with return co-exceedances calculated from standardized raw returns (E[r_t] = 0, V[r_t] = 1). The results for these non-filtered return co-exceedances are available in Table A1 in the Appendix.

Our main results again remain largely unchanged. An interesting observation is that the effects are slightly lower, as the negative coefficients of unexpected market volatilities are higher. It appears that although fluctuations in other markets seem to mitigate contagious tendencies from the U.S. stock market toward the CEE stock markets, they are not sufficient to eliminate the contagion.

5.4.2 Are Results Sensitive to Model Specifications?

Next, we investigate sensitivity of our results to the different regression model specifications. In the first specification, we include only the constant, the lagged return co-exceedance, and the expected and unexpected market volatilities. Therefore, we exclude fluctuations in other markets and the policy index (see Eq. 13). The results remain largely unchanged.

$$\begin{aligned} Q_{Cij}(\tau \mid \mathbf{X}) = \beta_0(\tau) + \beta_1(\tau)C_{t-1} + \gamma_1(\tau)\tilde{\sigma}_{t-1}^{US} + \gamma_2(\tau)\tilde{\sigma}_{t-1}^{US} I\left(R_{t-1}^{US} < 0\right) + \\ \gamma_3(\tau)\left(\hat{\sigma}_{t-1}^{US} - \tilde{\sigma}_{t-1}^{US}\right) + \gamma_4(\tau)\left(\hat{\sigma}_{t-1}^{US} - \tilde{\sigma}_{t-1}^{US}\right) I\left(R_{t-1}^{US} < 0\right) \end{aligned} \tag{13}$$

Previous findings led us to the second alternative specification, where we have included the constant and the lagged return co-exceedance together with variables capturing movements on other markets including the news-based economic policy uncertainty index, thus excluding expected and unexpected U.S. market volatilities:

$$\begin{aligned} Q_{Cij}(\tau \mid \mathbf{X}) = \beta_0(\tau) + \beta_1(\tau)C_{t-1} + \varphi_1(\tau)R_{t-1}^{TB} + \varphi_2(\tau)\tilde{\sigma}_{t-1}^{TB} + \delta_1(\tau)R_{t-1}^{FX} + \delta_2(\tau)\tilde{\sigma}_{t-1}^{FX} + \upsilon_1(\tau)P_{t-1} \\ + \lambda_1(\tau)R_{t-1}^{STOXX} + \lambda_2(\tau)\tilde{\sigma}_{t-1}^{STOXX} + \eta_1(\tau)R_{t-1}^{OIL} + \eta_2(\tau)\tilde{\sigma}_{t-1}^{OIL} + \nu_1(\tau)R_{t-1}^{GOLD} + \nu_2(\tau)\tilde{\sigma}_{t-1}^{GOLD} \end{aligned} \tag{14}$$

Contrary to the full model specification (Eq. 10), several variables become statistically significant across the whole range of quantiles for almost all countries especially global STOXX returns and its expected volatility, government bonds, and the expected volatility in the oil market. We find foreign exchange market important for the extreme negative co-exceedances for the Croatia, Estonia, and Romania, and gold market for the Czech Republic, Hungary, Poland, and Romania.

We compare the pseudo R2 (Koenker and Machado, 1999) between Eq. (10) and Eq. (14) to assess whether the inclusion of the expected and unexpected market volatility improves the fit of regressions. With the exception of the very extreme quantiles of 0.01, where the fit is comparable, the fit of the full model (Eq. 10) is superior because the average pseudo R2 is approximately 2.5 times higher for all left-tail quantiles (0.01, 0.05, 0.10, 0.25) and for all countries. These results indicate that expected and unexpected market volatility helps understand the joint occurrence of extreme events in stock markets.

6 Concluding Remarks

We analyze financial contagion in emerging markets using a new approach for measuring contagion, which stipulates that contagion should be observed as excess co-movement during negative unexpected events. More specifically, we examine whether unexpected negative events in the U.S. stock market propagate into emerging stock markets and increase the co-exceedance between these markets and the U.S. market. We interpret the results as evidence of financial contagion. Using quantile regressions, we specifically examine those periods when the U.S. market experienced the largest declines. We use the co-exceedance measure introduced by Bae et al. (2003) and a quantile regression framework, as in Baur and Schulze (2005), but we extend these two contributions by decomposing U.S. stock market volatility into expected and unexpected components and examining how this unexpected volatility component increases the co-exceedance between stock markets.

Using our approach with daily data from 1998-2014, we find evidence of financial contagion for all of our examined emerging markets (Croatia, the Czech Republic, Estonia, Hungary, Poland, and Romania). Therefore, the contagion is present regardless the monetary policy regime the countries adopted. We subject this finding to a series of robustness checks. First, we investigate whether our results hold for different time periods, i.e., before and after the 2007-2009 crisis and we confirm that contagion occurs both during the financial crisis as well as in good times. However, we find that contagion is stronger during the crisis. Second, instead of filtering the stock market returns through the ARMAX-EGARCHX model, we use non-filtered returns, but the results remain unchanged. Third, we control for the returns and volatilities of different asset classes – gold, oil, foreign exchange and government bonds. We observe that extreme negative co-movements are not driven by fluctuations in these markets, thus providing further evidence that the contagion is based on investor over-reactions rather than on fundamentally based decisions.

Overall, our results indicate that financial contagion from the U.S. stock market to the CEE markets occurs irrespective to the financial crisis period but we find that contagion is stronger during the crisis (sensitivity to unexpected negative events increases considerably), i.e. a result, which goes in the direction of findings by Bekaert et al. (2014).

In terms of future research, it would be worthwhile develop more structural approaches to assess financial contagion so that they can be systematically used for policy analysis at various institutions, such as international organizations, governments or central banks.

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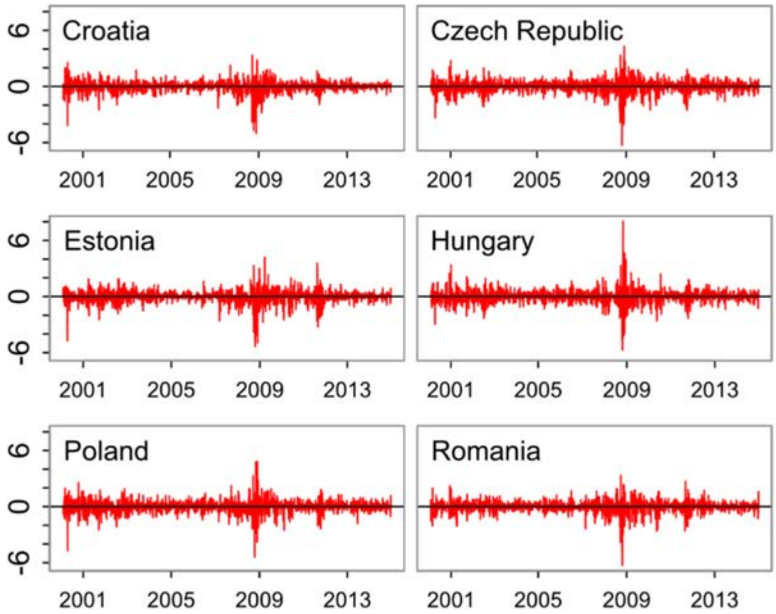
Appendix

Figure A1 Return co-exceedances from non-filtered returns



Note: Returns are not filtered but are standardized to E[r_t] = 0 and V[r_t] = 1.

Table A1 Quantile regression estimates: co-exceedances based on non-filtered returns

	τ	const.	β_1	γ_1	γ_2	γ_3	γ_4	δ_1	δ_2	λ_1	λ_2	ν_1	ν_2	η_1	η_2	φ_1	φ_2	υ_1	R^2
Croatia	0.01	-0.53	-0.31	0.46	**-151.11[d]**	-0.25	**-134.03[d]**	35.16	83.88	0.38	-75.75	-14.17	-46.36	2.66	-5.97	6.76	14.11	-0.09	0.68
	0.05	-0.02	0.07	0.32	**-102.90[d]**	0.06	**-90.46[d]**	2.97	6.60	0.03	-35.60	0.53	-5.50	0.29	-0.45	0.56	1.99	-0.01	0.54
	0.10	-0.04	0.02	0.06	**-79.31[d]**	0.01	**-72.14[d]**	0.38	4.46	0.01	-4.75	0.14	-1.84	0.14	-0.40	0.35	0.33	0.00	0.45
	0.25	0.01	0.03	0.02	**-39.69[d]**	0.02	**-45.36[d]**	0.12	-1.36	0.01	-2.05	-0.63	-1.25	0.35	0.42	**1.18[a]**	0.03	0.01	0.24
	OLS	**3.96[a]**	-3.00	**25.96[d]**	**-45.00[d]**	**16.56[d]**	**-37.72[d]**	56.14	-441.79	**3.27[c]**	**-471.17[b]**	-156.22	**-260.67[b]**	2.67	30.74	**155.67[b]**	69.38	0.59	0.34
Czech Republic	0.01	-0.08	-0.01	-0.01	**-167.54[d]**	-0.01	**-150.33[d]**	1.94	1.81	0.02	0.78	-0.62	-2.27	0.61	-0.41	0.07	0.19	0.01	0.67
	0.05	-0.07	-0.04	0.10	**-120.84[d]**	0.04	**-120.90[d]**	-1.16	5.48	0.02	-7.63	-0.36	-3.32	0.16	-0.02	0.54	-0.53	-0.01	0.55
	0.10	-0.05	-0.02	0.05	**-95.10[d]**	0.04	**-90.63[d]**	0.22	5.38	0.02	-5.72	-0.39	-0.98	0.69	0.27	1.07	-0.72	0.00	0.46
	0.25	0.02	-0.03	0.02	**-49.81[d]**	0.03	**-51.29[d]**	0.01	3.47	0.01	-3.11	-1.43	-0.60	0.32	0.46	1.47	-0.11	0.00	0.27
	OLS	1.01	**-6.97[b]**	**29.59[d]**	**-58.12[d]**	**21.91[d]**	**-48.22[d]**	-115.76	**857.66[b]**	**3.53[c]**	-259.81	-88.22	-128.19	12.36	-10.10	**238.29[c]**	-74.30	-0.40	0.40
Estonia	0.01	-0.08	-0.07	-0.05	**-172.49[d]**	-0.06	**-154.42[d]**	-1.99	12.00	0.05	-1.37	-0.09	-4.22	0.24	-0.08	3.95	-3.87	-0.02	0.70
	0.05	-0.07	-0.01	0.02	**-120.77[d]**	0.00	**-97.68[d]**	-0.81	2.89	0.03	-3.20	0.14	-0.86	0.27	0.10	2.18	-0.78	0.00	0.57
	0.10	-0.04	0.01	0.08	**-94.48[d]**	0.03	**-87.04[d]**	0.24	10.17	0.03	-9.39	-0.40	-1.86	0.15	0.14	2.24	-0.48	0.01	0.48
	0.25	0.01	-0.06	0.10	**-51.71[d]**	0.05	**-49.61[d]**	0.46	4.53	0.07	-11.64	-0.79	-1.49	0.76	1.14	2.83	0.36	0.00	0.29
	OLS	2.62	**-8.38[b]**	**25.44[d]**	**-52.70[d]**	**16.67[d]**	**-46.24[d]**	243.92	758.52	**7.93[d]**	**-571.44[d]**	-49.97	-218.44	49.56	44.57	**266.12[c]**	50.34	-0.86	0.42
Hungary	0.01	-0.70	0.48	1.97	**-155.90[d]**	0.05	**-141.61[d]**	14.82	16.39	0.04	-83.56	25.19	-216.91	1.66	-9.69	1.93	38.22	-0.24	0.66
	0.05	**-0.08[d]**	0.01	0.04	**-116.85[d]**	0.01	**-107.20[d]**	-0.59	-0.97	0.01	-2.24	-0.30	-0.87	0.01	-0.17	0.26	0.26	0.00	0.53
	0.10	**-0.06[d]**	-0.01	0.03	**-90.94[d]**	0.01	**-73.65[d]**	0.30	0.30	**0.02[b]**	-2.99	-0.46	-0.23	0.13	-0.05	0.11	0.20	0.00	0.45
	0.25	0.00	-0.01	0.04	**-45.15[d]**	0.03	**-43.03[d]**	-0.97	1.97	0.00	-1.78	-0.32	-0.98	0.04	-0.14	0.22	-0.33	0.00	0.24
	OLS	0.91	-0.06	**24.11[d]**	**-56.72[d]**	**21.80[d]**	**-46.51[d]**	**-493.39[b]**	-194.43	0.22	172.53	-120.24	-145.90	-50.62	54.56	94.10	74.87	-0.87	0.35
Poland	0.01	-0.37	0.05	0.02	**-170.69[d]**	-0.05	**-125.01[d]**	-8.95	-22.74	0.06	4.67	0.56	-1.47	-1.02	0.62	-3.15	3.12	-0.05	0.65
	0.05	**-0.10[d]**	-0.02	0.03	**-116.36[d]**	0.00	**-100.21[d]**	-0.62	1.52	**0.02[a]**	-2.81	-0.89	0.12	0.04	0.04	0.09	-0.11	-0.01	0.53
	0.10	**-0.06[d]**	-0.01	0.02	**-92.85[d]**	0.01	**-82.99[d]**	-0.79	**2.56[a]**	0.01	-2.04	-0.51	-0.63	-0.19	0.14	0.06	-0.40	-0.01	0.46
	0.25	-0.01	0.00	0.02	**-48.27[d]**	0.01	**-54.42[d]**	**-1.94[a]**	0.61	0.00	-0.01	-0.35	-0.71	-0.29	-0.20	-0.28	0.17	-0.01	0.24
	OLS	0.23	-2.97	**28.40[d]**	**-54.18[d]**	**19.33[d]**	**-50.18[d]**	**-322.20[b]**	218.29	1.02	13.38	52.54	-166.16	**-89.00[b]**	-32.95	**155.02[b]**	11.78	-0.06	0.36
Romania	0.01	-0.12	-0.04	0.03	**-162.05[d]**	0.03	**-127.26[d]**	-0.75	0.71	0.03	1.74	-4.17	-18.40	0.65	0.02	1.73	2.74	0.05	0.68
	0.05	**-0.07[a]**	0.00	0.05	**-119.30[d]**	0.01	**-100.38[d]**	-0.91	-1.03	0.02	-4.19	-0.34	-1.89	0.22	0.08	0.73	0.25	0.01	0.53
	0.10	**-0.07[c]**	0.01	0.04	**-83.82[d]**	0.02	**-66.62[d]**	0.31	-0.26	**0.02[a]**	-3.01	-0.07	-0.46	-0.16	0.23	0.97	0.10	**0.02[a]**	0.44
	0.25	0.00	0.01	0.03	**-41.73[d]**	**0.04[a]**	**-49.53[d]**	0.22	-0.24	0.01	-1.43	0.00	-1.68	-0.15	0.24	**1.63[b]**	0.27	0.01	0.23
	OLS	2.89	-2.77	**20.89[d]**	**-45.62[d]**	**12.66[c]**	**-37.47[d]**	125.81	-99.59	**5.03[d]**	-104.01	-29.45	**-310.13[c]**	-37.77	42.10	**311.60[d]**	73.15	**1.78[b]**	0.36

Notes: τ denotes respective quantile. The coefficients const, β_1, δ_1, ν_1, η_1, φ_1, υ_1 are multiplied by100. Significance at 10%, 5%, 1%, and 0.1% is denoted by "a", "b", "c", and "d" superscripts, respectively. For the quantile regressions, R^2 denotes the pseudo R^2 as defined in Koenker and Machado (1999, Eq. 7), while for the OLS regressions, the usual adjusted coefficient of determination is used. The standard errors of the estimated OLS regression coefficients were derived from the HAC matrix and calculated using the quadratic spectral kernel weighting scheme with automatic bandwidth procedure, as in Newey and West (1994).

$$Q_{Cij}(\tau \mid \mathbf{X}) = \beta_0(\tau) + \beta_1(\tau)C_{t-1} + \varphi_1(\tau)R_{t-1}^{TB} + \varphi_2(\tau)\tilde{\sigma}_{t-1}^{TB} + \delta_1(\tau)R_{t-1}^{FX} + \delta_2(\tau)\tilde{\sigma}_{t-1}^{FX} + \upsilon_1(\tau)P_{t-1} + \lambda_1(\tau)R_{t-1}^{STOXX} + \lambda_2(\tau)\tilde{\sigma}_{t-1}^{STOXX} + \eta_1(\tau)R_{t-1}^{OIL} + \eta_2(\tau)\tilde{\sigma}_{t-1}^{OIL} + \nu_1(\tau)R_{t-1}^{GOLD} + \nu_2(\tau)\tilde{\sigma}_{t-1}^{GOLD} +$$
$$\gamma_1(\tau)\tilde{\sigma}_{t-1}^{US} + \gamma_2(\tau)\tilde{\sigma}_{t-1}^{US} I\left(R_{t-1}^{US} < 0\right) + \gamma_3(\tau)\left(\hat{\sigma}_{t-1}^{US} - \tilde{\sigma}_{t-1}^{US}\right) + \gamma_4(\tau)\left(\hat{\sigma}_{t-1}^{US} - \tilde{\sigma}_{t-1}^{US}\right) I\left(R_{t-1}^{US} < 0\right)$$

Table A2 Estimation of filtered returns: ARMAX-EGARCHX model estimates

	Croatia	Czech Republic	Estonia	Hungary	Poland	Romania	US
Mean Equation							
μ (x 100)	0.019	0.024	0.016	0.015	0.007	0.061	-0.010
ϕ_1	0.916^{d}	0.923^{d}	1.840^{d}			0.225^{d}	
ϕ_2			-0.847^{d}			-0.983^{d}	
θ_1	-0.898^{d}	-0.903^{d}	-1.739^{d}	0.005	0.005	-0.106^{d}	-0.054^{d}
θ_2		-0.006^{a}	0.673^{d}			0.962^{d}	
θ_3			0.078^{d}			0.124^{d}	
Additional mean equation variables							
Returns on the FOREX, R_{t-1}^{FX}	0.043	-0.058^{b}	0.060^{d}	-0.095^{d}	-0.074^{b}	0.046^{a}	0.735
Returns on the STOXX, R_{t-1}^{STX}	0.046^{d}	0.011	0.068^{d}	-0.025	-0.047	0.041^{d}	6.761^{d}
Returns on the gold market, R_{t-1}^{GOLD}	-0.018	-0.030	0.000	-0.030	0.024	-0.012	0.236
Returns on the oil market, R_{t-1}^{OIL}	0.008	0.011	-0.001	-0.004	0.001	-0.019^{d}	0.550
LIBOR and *T*-Bill 3M spread, R_{t-1}^{TED}	0.045^{d}	0.051^{d}	0.035^{d}	0.017	0.038^{a}	0.052^{d}	-0.027
Variance Equation							
ω	-0.146^{d}	-0.301^{d}	-0.117^{d}	-0.211^{d}	-0.153^{d}	-1.355^{d}	-0.213^{d}
α_1	-0.002	-0.055^{d}	-0.042	-0.062^{d}	-0.130^{d}	-0.055^{b}	-0.242^{d}
α_2	-0.025		-0.026		0.054		0.107^{d}
α_3			0.041		0.042^{a}		
β_1	0.983^{d}	0.966^{d}	0.984^{d}	0.975^{d}	0.978^{d}	0.628^{d}	0.977^{d}
β_2						0.205^{a}	
γ_1	0.390^{d}	0.236^{d}	0.453^{d}	0.172^{d}	0.046	0.453^{d}	-0.157^{d}
γ_2	-0.220^{d}		-0.088		-0.054		0.277^{d}
γ_3			-0.147^{d}		0.170^{d}		
Additional variance equation variables							
Unconditional variance break 1	-0.011^{a}		-0.033^{b}		0.010	-0.176^{d}	
Unconditional variance break 2	-0.023^{d}				-0.029	0.145^{d}	
Unconditional variance break 3					-0.016^{d}	0.152^{d}	
Unconditional variance break 4						-0.255^{d}	
Unconditional variance break 5						-0.132^{d}	
Distribution model							
ν (skewness)	0.005	-0.240^{b}	-0.026	-0.010	0.013	0.054	-0.771^{d}
κ (kurtosis)	1.466^{d}	2.256^{d}	1.388^{d}	2.048^{d}	2.347^{d}	1.615^{d}	2.410^{d}
Diagnostics of standardized residuals							
Peña – Rodríguez test for serial dependence	0.307	0.116	0.004^{d}	0.227	0.291	0.004^{d}	0.347
Peña – Rodríguez test for ARCH effects	0.096^{a}	0.701	0.486	0.422	0.104	0.044^{b}	0.235

Notes: The estimated coefficients correspond to an ARMAX-EGARCHX model of returns r_t, with the following general specification: $r_t = \mathbf{X}_t\mathbf{M} + z_t$; $(1-\phi L)z_L = (1+\theta L)e_t$; $e_t = \sigma_t \eta_t$, η_t ~ Johnson's Su $(0,1,\nu,\kappa)$, where $\mathbf{X}_t$ is a row vector of variables in the mean equation, **M** is the column vector of coefficients (both including the constant), L is the backshift operator and η_t follows the Johnson's Su distribution where ν and κ are skewness and kurtosis parameters. The Peña – Rodríguez (2002) test reports the minimum p-value where the test was performed to test dependence in standardized residuals (and its squares for ARCH effects) up to 22 lags. Superscripts a, b, c, d denote significance at the 10%, 5%, 1% and 0.1% levels.