Market integration among foreign exchange rate movements in central and eastern European countries

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ABSTRACT

This study focuses on the level of interdependence across the Central and Eastern European (CEE) foreign exchange markets (Hungary, Poland, the Czech Republic, Romania and Croatia) from September 2008 to September 2017, using the return spillover measure proposed by Diebold and Yilmaz (2009; 2012). We mainly find a bidirectional volatility spillover among these assets and the cross-market linkages in the CEE region have become stronger over time. Furthermore, the Czech exchange market has a significant influence on the rest of the foreign exchange markets. The total spillover remained very high over the periods 2010–2012 and 2015–2017, despite the noteworthy fluctuations in other periods. These results would also be useful for portfolio managers, policy makers and speculative traders to develop exploitable strategies, by providing knowledge of the transmission mechanisms of the volatility of foreign exchange markets. The results may support the distribution of assets in a financial portfolio, especially after financial integration.

KEYWORDS

exchange rates, volatility spillovers, spillover index, CEE countries

JEL-CODES

C22, F31

1. INTRODUCTION

The growing role of Central and Eastern European (CEE) financial markets in the world economy has recently attracted much attention to the issue of volatility shock spillovers within the region.
and beyond (e.g., Bubák et al. 2011; Hung 2018; Hung 2019). Return spillovers are prominent determinants for many market participants, they influence decisions to hedge open foreign exchange positions on the foreign exchange market (Barunik et al. 2017). As per Kanas (2000), volatility transmission might increase the nonsystematic risk which diminishes gains from international portfolio diversification. Specifically, the analysis of interdependence in foreign exchange markets, and its volatility spillovers, has been a subject of a considerable volume of research (Barunik et al. 2017). In this article, we attempt to evaluate the degree of market interdependence and innovation transmission between foreign exchange markets of five selected countries (Hungary, the Czech Republic, Poland, Romania and Croatia) over the period of 2008–2017, after the global financial crisis. By doing so, the purpose of this research is to provide new evidence on return spillovers by examining the spillover index on the selection of five national foreign exchange markets. The size and scope of this research allows us to take into account the intra-regional impact of return spillovers, rather than the global impact of volatility transmission.

Recent literature has centered on the correlations among forex markets of developed countries (Barunik et al. 2017; McMillan – Speight 2010; Wang-Yang 2009). These papers show that developed forex markets are interconnected and there is bidirectional volatility spillover among them. In the last 20 years, the significant role of exchange rate policies for economic development has remained a controversial issue. According to Guzman et al. (2018), there are two central and interrelated problems in connection with exchange rate policies in the macroeconomic literature on emerging economies. Namely, the role the exchange rate plays in facilitating economic growth, and how the exchange rate regime and capital account management help manage cyclical swings in external financing and terms of trade fluctuation. Briefly, pursuing a stable and competitive exchange rate can promote economic development, and this requires flexible and sustained interventions. The recent academic literature regarding spillovers of volatility across foreign exchange markets largely began with Engle et al. (1990), and was further considered by, for instance, McMillan – Speight (2010), Hong (2001), Patton (2006), Herwartz – Reimers (2002).

An important issue that has emerged in the empirical literature associated with modelling financial spillovers is the means by which volatility is specified. Typically, a traditional approach related to GARCH-type models is used. For example, Hung (2018) employed a multivariate EGARCH model to analyze the volatility spillover effects of foreign exchange rates in the CEE markets and provides evidence of that foreign exchange markets have become more independent after the global crisis. Kumar et al. (2016) examined the volatility in foreign exchange markets of India and China using daily data covering the period between 2006 and 2015. Based on the framework of the EGARCH model, the findings capture the effect of good and bad news and provide evidence of bidirectional volatility between these markets. Herwartz – Reimers (2002) estimated the properties of the DEM/USD and DEM/JPK rates with a sample period from 1975 to 1998 using the GARCH model, and provided strong evidence of persistence in volatility and its serial correlation. Similarly, Pankova et al. (2010) analyzed the volatility and asymmetry of the EUR/USD exchange rate, using daily data from June 2008 to May 2010 under GARCH(1,1) and EGARCH(1,1). They confirmed that there is no asymmetry in the EUR-USD relation. McMillan – Speight (2010) focused on the interdependence of return and volatility spillovers in three Euro exchange rates including the US dollar, the Japanese yen and the British pound, using the realized variance method. The findings report substantial evidence of contemporaneous connectedness between the returns on these rates and their volatility. More importantly, the spillover index is employed in this study to examine the degree of cross-market spillover.
In the volatility spillover literature, departing from the common econometric methods, Diebold – Yilmaz (2012) provide new measures of return and volatility spillovers of international equity markets based on forecast-error variance decompositions in a vector autoregressive framework. The analysis of spillovers in Forex markets has widely adopted the novel approaches developed by Diebold and Yilmaz. For example, Salisu – Ayinde (2018) employ Diebold and Yilmaz’s approach to test for spillovers in the Nigerian naira’s exchange rates. The findings reveal that the electioneering process in Nigeria appears to have had greater spillover effects on the naira than the global financial crisis. This result is strong to alternative measures of exchange rates. Baruník et al. (2017) provided evidence for asymmetric volatility interrelatedness on the Forex market using high-frequency, intra-day data of the most actively traded currencies. They showed that negative spillovers are due to bad rather than good volatility, by applying Diebold and Yilmaz spillover index. In the same vein, Greenwood-Nimmo et al. (2016) found that aggregate spillover intensity is countercyclical with respect to the federal funds rate and increased in periods of financial stress.

In the Central and Eastern European context, the analysis of volatility spillovers of foreign exchange markets as well as their interrelatedness has been recognized in the literature (Bubak 2009; Fidrmuc – Horvath 2008; Hsing 2016; Kbor – Szekely 2004; Kocenda – Valachy 2006; Kumar – Kamaiah 2014; Petrica – Stancu 2017). Nevertheless, most of these studies also employ the common econometric methodologies (GARCH-type models) to capture the dynamics of returns and volatility spillovers across Forex markets. In this paper, dynamic volatility interrelatedness and directional characterization of return spillovers among the Forex markets in the CEE countries are perfectly captured by the spillover index proposed by Diebold – Yilmaz (2009; 2012). There has not been evidence of the dynamics of return spillover effects related to the Forex markets in the CEE countries using the spillover index so far. In our study, therefore, we cover this issue and provide a primary contribution. Namely, we employ the Diebold and Yilmaz methodology to analyze the return spillovers among CEE currencies. The economic contribution of this empirical analysis is that we quantify the directional return spillover effects that a particular exchange market receives from the other markets. These spillovers effects are informative of the price discovery in a particular market, which might then be transmitted to other markets owning to cross-listing of firms and fund investments. Finally, we shed light on a richer extent of time-varying detail than is found in previous studies.

This paper proceeds as follows. We outline the methodology and data in Section 2. In Section 3, we present the main findings for total and directional connectedness. Finally, we conclude in Section 4.

2. METHODOLOGY AND DATA

2.1. Vector autoregression (VAR)

As a starting point, we present the concept and measure of the spillover index from Diebold – Yilmaz (2009; 2012). Taking into account a covariance stationary Vector Autoregression (VAR) model of order $P$ and $N$ variables, $x_t = \sum_{i=1}^{P} \phi_i x_{t-i} + \epsilon_t$, where $\epsilon \sim (0, \Sigma)$ is a vector of independent and identically distributed (IID) distances. We can turn the VAR into a moving average (MA) representation, that is, $x_t = \sum_{i=0}^{\infty} A_i \epsilon_{t-i}$ where $N \times N$ coefficient matrix $A_i$ is obtained by the recursive substitution, $A_i = \phi_1 A_{i-1} + \phi_2 A_{i-2} + \cdots + \phi_p A_{i-p}$, with $A_0 = I_n$. 
which is an identity matrix of order \( n \), and \( A_i = 0 \) for \( i < 0 \). The MA presentation can be employed to forecast the future with the H-step-ahead. We rely on variance decompositions to determine the fraction of the H-step-ahead error variance in forecasting \( x_i \) that are due to shocks to \( x_i \) and the fraction that is due to shocks to \( x_j, \forall i \neq j \), for each \( i \). Furthermore, we use the KPPS (Koop et al. 1996) generalized forecast error variance decomposition (GFEVD) to develop spillover indices.

### 2.2. Variance shares

Diebold – Yilmaz (2012) define “own variance shares” as the fraction of the H-step-ahead error variances in forecasting \( x_i \) due to shocks to \( x_i \) for \( i = 1, N \), and “cross variance shares” (spillovers) as the fraction of the H-step-ahead error variances in forecast \( x_i \), for \( i, j = 1, N \) such that \( i \neq j \). The KPPS H-step-ahead forecast error variance decomposition is

\[
\phi_{ij}^g(H) = \sigma_{ij} \frac{\sum_{h=0}^{H-1} (e_i A_h \sum e_i)^2}{\sum_{h=0}^{H-1} (e_i A_h \sum A_h e_i)}
\]

where \( \Sigma \) is the variance matrix of the error vector, \( \sigma_{ij} \) is the standard deviation of the error term for the \( i \)th equation, and \( e_i \) is the selection vector with 1 as the \( i \)th elements, and 0 otherwise. According to the properties of generalized VAR, we have \( \sum_{i=1}^{N} \phi_{ij}^g(H) \neq 1 \). Each entry of the variance decomposition matrix is normalized by the row sum as

\[
\tilde{\theta}_{ij}^g = \frac{\theta_{ij}^g(H)}{\sum_{j=1}^{N} \theta_{ij}^g(H)}
\]

where \( \sum_{j=1}^{N} \tilde{\theta}_{ij}^g(H) = 1 \) and \( \sum_{i,j=1}^{N} \tilde{\theta}_{ij}^g(H) = N \).

### 2.3. Total and directional volatility spillovers

We can construct a total volatility spillover index proposed by Diebold – Yilmaz (2012) as follows:

\[
S^g(H) = \frac{\sum_{i,j=1,j \neq i}^{N} \tilde{\theta}_{ij}^g(H)}{\sum_{i,j=1}^{N} \tilde{\theta}_{ij}^g(H)} \times 100 = \frac{\sum_{i,j=1,i \neq j}^{N} \tilde{\theta}_{ij}^g(H)}{N} \times 100
\]

The total spillover index is used to measure the contribution of spillovers across all five foreign exchange rates to the total forecast error variance. As the KPPS framework solves the ordering problem, we can measure the directional volatility spillovers received by market \( i \) from all other markets \( j \) as:
Similarly, we can calculate the directional spillovers transmitted by market $i$ to all other markets $j$ as:

$$S_{ij}^g(H) = \frac{\sum_{j=1, j \neq i}^{N} \tilde{\theta}_{ij}^g(H) \times 100}{\sum_{j=1}^{N} \tilde{\theta}_{ij}^g(H)}$$

(4)

2.4. Net pairwise spillovers

The net pairwise spillover of volatility between markets $i$ and $j$ is the difference between gross volatility shocks transmitted from market $i$ to market $j$ and those transmitted from $j$ to $i$, which Diebold – Yilmaz (2012) define as:

$$S_{ij} = \left( \frac{\sum_{i,k=1}^{N} \tilde{\theta}_{ik}^g(H) - \sum_{j,k=1}^{N} \tilde{\theta}_{jk}^g(H)}{\sum_{i,k=1}^{N} \tilde{\theta}_{ik}^g(H)} \right) \times 100$$

$$= \left( \frac{\sum_{i,j=1, i \neq j}^{N} \tilde{\theta}_{ij}^g(H) - \sum_{i,j=1, i \neq j}^{N} \tilde{\theta}_{ji}^g(H)}{\sum_{i,j=1, i \neq j}^{N} \tilde{\theta}_{ij}^g(H)} \right) \times 100$$

(7)

2.5. Data

The dataset used in this study contains time series of US dollar exchange rates with daily frequency for a sample of five countries located in Central and Eastern European region: Hungary, Poland, Czech, Romania, and Croatia.

Table 1. Foreign exchange market indices

<table>
<thead>
<tr>
<th>Country</th>
<th>Code</th>
</tr>
</thead>
<tbody>
<tr>
<td>Hungary</td>
<td>USDHUF</td>
</tr>
<tr>
<td>Poland</td>
<td>USDPLN</td>
</tr>
<tr>
<td>Czech</td>
<td>USDCZK</td>
</tr>
<tr>
<td>Romania</td>
<td>USDRON</td>
</tr>
<tr>
<td>Croatia</td>
<td>USDHRK</td>
</tr>
</tbody>
</table>
Poland, Czech Republic, Romania and Croatia. The sample period spans from September 2008 to September 2017. The exchange rate series are obtained from the Bloomberg database and represent the amount of US dollars per one unit of local currency. They are detailed in Table 1. The number of observations across the market is 2,368, which is less than the total number of observations because the joint modeling of five markets requires matching returns. The daily return data series are calculated as $R_t = 100 \times \ln(P_t/P_{t-1})$, where $P_t$ is the price level of the market at time $t$. The logarithmic stock returns are multiplied by 100 to approximate percentage changes and avoid convergence problems in estimation.

2.6. An overview of CEE foreign exchange markets

The evolution of exchange rates currently illustrates a significant source of concern from both a micro and a macroeconomic perspective. The exchange rate is one of the most synthetic prices in an economy and it is also the expression of a general equilibrium among the market for real goods and services, the currency market and capital market, which has the apparent potential of affecting the general economic equilibrium in any economy. The behavior of the exchange rate is influenced, by the rate of economic growth, the changes in the general level of prices, the industrial structure of the economy, the country’s level of international competitiveness and its degree of trade and financial openness, political stability and government’s ability to deal with internal crises. This diversity of determinants impacting directly or indirectly on the exchange rate raises the issue of the ease of managing such a complex and dynamic macroeconomic variable.

Over the past several decades, the number of countries running de jure floating exchange rate regimes has steadily grown. Some papers (Bubak 2009; Hsing 2016; Kumar – Kamaiah 2014) show that there is a discrepancy between de jure and de facto, and countries appear to actively restrict fluctuations in the external value of their national currencies (Table 2).

The diversity in the exchange rate regime choices also reflects different stabilization strategies and the availability of alternative monetary policy frameworks. Achieving price stability remains the main stabilization task. The exchange rate regimes of the former Communist countries in the region are quite diverse, ranging from stabilized arrangements to free floating. This diversity can

<table>
<thead>
<tr>
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<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Croatia</td>
<td>8</td>
<td>4</td>
<td>6</td>
<td>6</td>
<td>6</td>
<td>6</td>
<td>6</td>
</tr>
<tr>
<td>Czech Republic</td>
<td>10</td>
<td>10</td>
<td>10</td>
<td>10</td>
<td>10</td>
<td>8</td>
<td>4</td>
</tr>
<tr>
<td>Hungary</td>
<td>9</td>
<td>9</td>
<td>9</td>
<td>9</td>
<td>9</td>
<td>9</td>
<td>9</td>
</tr>
<tr>
<td>Poland</td>
<td>10</td>
<td>10</td>
<td>10</td>
<td>10</td>
<td>10</td>
<td>10</td>
<td>10</td>
</tr>
<tr>
<td>Romania</td>
<td>9</td>
<td>9</td>
<td>9</td>
<td>9</td>
<td>9</td>
<td>9</td>
<td>9</td>
</tr>
<tr>
<td>Mean</td>
<td>9.2</td>
<td>8.4</td>
<td>8.8</td>
<td>8.8</td>
<td>8.8</td>
<td>8.4</td>
<td>7.6</td>
</tr>
<tr>
<td>Standard Deviation</td>
<td>0.83</td>
<td>2.50</td>
<td>1.64</td>
<td>1.64</td>
<td>1.64</td>
<td>1.51</td>
<td>2.50</td>
</tr>
</tbody>
</table>

Notes: 4 = Stabilized arrangement; 6 = Craw-like arrangement; 7 = Managed floating with no pre-determined path for the exchange rate; 8 = Other managed arrangement; 9 = Floating; 10 = Free floating.

Source: IMF’s Annual Reports on Exchange Arrangements and Exchange Restrictions, various years.
be explained by the structural diversity of these countries, on the one hand, and by the need felt by these countries to better control inflation and exchange rates at the same time. In general, there are some substantial differences for some countries and some years. We observed the volatility of exchange rates of these currencies against the US dollar over the same period (Fig. 1).

We plot the five foreign exchange market’s volatility in Fig. 2 and provide summary statistics of log returns in Table 3. Figure 2 sheds light on volatility trends over the sample period. We can note that foreign exchange markets of almost all countries under consideration reacted significantly to the global financial crisis of 2008, as well as the European stock market collapse of 2015. Other sharp declines in exchange rate changes can mainly be attributed to country-specific events when we take a close look at the patterns of changes in the logarithmic returns. Overall, most markets exhibit large volatility and the volatility dynamics appear to be highly persistent.

Table 3 presents the descriptive statistics for log daily returns of sample markets over the study period. Romania had the highest average return (5.5%) and the Czech Republic realized the lowest

![Figure 1. Exchange rate against the US dollar of five CEE currencies, 2008–2017. Source: author.](image-url)
return (2.7%). Volatility of the CEE exchange markets, measured by standard deviation, is generally high, and range from 10.78 (Croatia) to 16.19 (Hungary). It is clearly observed that neither of the return series has normal distribution, with respect to the Jarque-Bera test for normality. Finally, the augmented Dickey-Fuller (ADF) test provides evidence to support the hypothesis of stationarity for all return series at the 1% level, ensuring their suitability for further statistical analysis.

3. RESULTS

This section documents the empirical estimation results of our model using the generalized spillovers index methodology to analyze the magnitude and directions of return spillovers of foreign exchange rate movements among the CEE countries. To introduce a brief overview of the direction of spillovers, we begin with a full sample analysis, which highlights some stylized facts about the characteristics of the dynamic linkages in the region. We can then answer the

Figure 2. Daily volatility of five CEE foreign exchange markets
Source: author.
question of whether cross-market interconnectedness becomes stronger over time. Finally, we carry out robustness checks for the estimated spillover measures as well as pointing out possible limitations to their practical application.

3.1. Analysis of spillovers using the full sample

Table 4 reports the calculation of $\theta^x_{ij}(H)$ in Eq. (2) with full sample volatility spillovers. The ijth entry is the estimated contribution to the forecast error variance of market $i$ resulting from

**Table 3.** Descriptive statistics and unit root tests of log returns

<table>
<thead>
<tr>
<th></th>
<th>USDCZK</th>
<th>USDHRK</th>
<th>USDHUF</th>
<th>USDPLN</th>
<th>USDRON</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean</td>
<td>2.7%</td>
<td>2.725%</td>
<td>4.92%</td>
<td>5.05%</td>
<td>5.5%</td>
</tr>
<tr>
<td>Std. Dev</td>
<td>13.27%</td>
<td>10.78%</td>
<td>16.19%</td>
<td>13.36%</td>
<td>12.10%</td>
</tr>
<tr>
<td>Skewness</td>
<td>0.0837</td>
<td>-0.0606</td>
<td>0.1626</td>
<td>0.2060</td>
<td>0.1576</td>
</tr>
<tr>
<td>Jarque-Bera</td>
<td>1,189.89*</td>
<td>739.23*</td>
<td>1,296.64*</td>
<td>977.75*</td>
<td>1,164.90*</td>
</tr>
<tr>
<td>PP test</td>
<td>-48.77*</td>
<td>-48.73*</td>
<td>-48.38*</td>
<td>-48.28*</td>
<td>-46.49*</td>
</tr>
<tr>
<td>ADF test</td>
<td>-48.76*</td>
<td>48.72*</td>
<td>-48.37*</td>
<td>-48.21*</td>
<td>-46.54*</td>
</tr>
</tbody>
</table>

*Source:* author.

*Notes:* Exchange rates are expressed as units of currencies per unit of US dollar. *denotes significance at the 1 per cent level. All returns are expressed in percentages. ADF and PP test represent the augmented Dickey and Fuller test and the Phillips-Perron test of stationarity respectively. Means and standard deviations are annualized as $r \times 250$ and $\sigma \times \sqrt{250}$ (Chevallier et al. 2018). The Jarque-Bera test examines the null hypothesis of normality of log returns.

**Table 4.** Return spillover table

<table>
<thead>
<tr>
<th></th>
<th>USDHUF</th>
<th>USDPLN</th>
<th>USDCZK</th>
<th>USDRON</th>
<th>USDRHK</th>
<th>Received</th>
</tr>
</thead>
<tbody>
<tr>
<td>USDHUF</td>
<td>27.38</td>
<td>20.51</td>
<td>18.60</td>
<td>17.19</td>
<td>16.31</td>
<td>72.6</td>
</tr>
<tr>
<td>USDPLN</td>
<td>20.45</td>
<td>27.50</td>
<td>19.05</td>
<td>17.03</td>
<td>15.95</td>
<td>72.5</td>
</tr>
<tr>
<td>USDCZK</td>
<td>18.06</td>
<td>18.48</td>
<td>26.46</td>
<td>18.38</td>
<td>18.62</td>
<td>73.5</td>
</tr>
<tr>
<td>USDRON</td>
<td>17.11</td>
<td>16.88</td>
<td>18.83</td>
<td>27.15</td>
<td>20.03</td>
<td>72.8</td>
</tr>
<tr>
<td>USDRHK</td>
<td>16.48</td>
<td>16.08</td>
<td>19.46</td>
<td>20.38</td>
<td>27.61</td>
<td>72.4</td>
</tr>
<tr>
<td>Transmitted</td>
<td>72.1</td>
<td>72.0</td>
<td>75.9</td>
<td>73.0</td>
<td>70.9</td>
<td>363.9</td>
</tr>
<tr>
<td>Including own</td>
<td>99.5</td>
<td>99.5</td>
<td>102.4</td>
<td>100.1</td>
<td>98.5</td>
<td>Total spillover index: 72.8%</td>
</tr>
<tr>
<td>Net spillover</td>
<td>-0.5</td>
<td>-0.5</td>
<td>0.6</td>
<td>0.2</td>
<td>-1.5</td>
<td>0</td>
</tr>
</tbody>
</table>

*Source:* author.
shocks to market $j$. Spillovers transmitted by market $i$ to market $j$ are depicted by numbers in the columns, excluding the contribution to its own variance (the number in the diagonal) which represents own market innovations. The numbers (excluding the diagonal) for market $i$ (across a row in the table) illustrate spillover received, or innovations resulting from innovation to market $j$. The off-diagonal column sums, labeled as “Transmitted,” and the row sums, labeled as “Received,” describe the total spillovers contributed towards and received from other markets. The difference between the spillovers originating from the market and the spillovers received from other markets is the net volatility spillovers for each market. Due to row normalization according to Eq. (2), the sum of the variances in a row equals 100%, while the column sum does not. The total volatility spillover index, which appears in the lower right-hand corner of the table, is calculated as the sum of all variance in the $5 \times 5$ matrix less the sum of the diagonal variances, summarizing the degree to which shocks are attributable to spillovers for the entire sample expressed as a percentage.

It is clear from Table 4 that we find that approximately 72.8% of shocks were owing to spillovers, which indicates that, on average, across our entire sample, 72.8% of the volatility forecast error variance in all five markets comes from spillovers. Let us consider what we learn from the rest of the table about directional spillovers. We can see that the receivers of volatility to other markets are not very different in magnitude. For example, the gross directional volatility spillovers from others (receivers) to the Czech Republic are highest, at 73.5%, followed by the Romania, with the spillovers from others explaining 72.8% of the forecast error variance, while the figures for Hungary, Poland and Croatia are slightly lower, standing at 72.6%, 72.5%, and 72.4% respectively. When considering the return spillover transmitted by each country separately, we find that the biggest transmitters of volatility to other markets are the Czech Republic (75.9%), Romania (73%) and Hungary (72.1%), while the corresponding data for Poland and the Czech Republic is 70.9% and 72%, respectively. As for the net directional return spillovers, we can observe the last row of the table, which shows that the largest are from the Czech Republic to others (0.6) and from others to Croatia (−1.5).

Briefly, the results are robust to methods of row and column normalization. Higher volatility spillover with other markets includes the Czech Republic, Hungary and Romania, while the Polish and Croatian exchange markets are the most closed in our sample.

3.2. Analysis of spillovers using a dynamic rolling sample

We illustrate the dynamics of interrelatedness in terms of the total return spillovers among the five exchange markets during the sample period in Fig. 3, which depicts the evolution of the spillover index over the period 2008–2017. Figure 3 also shows that return spillover is subject to instability, and experienced some remarkable peaks, particularly during, and in the aftermath of European stock market collapse of 2015. Obviously, many changes took place during the years in our sample.

We highlight some major events in the figure. First, from 2009 to 2011, the spillover index rose from 70% to 76% in the first window, implying that during high volatility periods, there was strong information spillover because of the transmission of tradeable information across these markets resulting in price movements and the contagion of high uncertain market conditions across the national markets. Second, the period of the highest volatility correlations of these exchange markets was from 2011 to 2012. The spillover reached its climax between 2011 and
2012, then decreased gradually from 2012 to 2014. The lowest number was around 65% during the European stock market collapse (Blundell–Wignall 2012). Third, the spillover index dramatically increased over the period 2015–2017 and stabilized thereafter.

Overall, the total spillover index fluctuates steadily during the study period, showing increased connectedness among CEE foreign exchange markets. This conclusion is based on Fig. 3 using a VAR(2) model with 200-day rolling samples fluctuating between 64% and 76% of error variance. This result reveals strong evidence of increased financial market interdependence. Spillover cycles are persistent, and high total spillover periods suggest that in highly volatile periods, investors might have to take into consideration other asset classes, as diversification might not be found in other international exchange markets. On the other hand, the flow of tradeable information has a substantial influence on the spillover index, and is a more significant driver during non-high volatility periods. This finding is consistent with Hung (2018) and Fidrmuc – Horvath (2008). We examine this issue further by taking into account spillover directions in the next section.

3.3. Directional spillover analyses

We now turn to the analysis of directional spillovers from foreign exchange markets. Figure 4 describes the directional volatility spillovers from each of the five asset classes to others (transmitted) for a sample of countries, Hungary, Poland, the Czech Republic, Romania and Croatia. They vary over time slightly. During peaceful times, the spillovers from each exchange market are below 60%, but at volatile times, the directional spillovers increase by close to 15%. It is crucial to note that the results of directional spillovers are extremely similar. Overall, the gross return spillovers of foreign exchange markets from Hungary and Poland are generally smaller than the spillovers from the other three markets.

In Fig. 5, we present the directional volatility spillovers from the others to each of the five foreign exchange markets (received). As we can see from the plot, the directional spillovers to others vary significantly over time. Nevertheless, the relative variation pattern is reversed, with directional volatility spillovers to Hungary and Poland increasing relatively more in the periods of 2012–2015.

In summary, based on Figs 4 and 5, each of five exchange markets exhibit more volatility in the index of spillovers received compared to spillovers transmitted.
Figure 6 gives interesting insights based on the dynamic patterns that show each currency’s net position in terms of the volatility spillovers transmitted or received. The positive domain contains net spillovers that a currency transmits to other currencies. The net spillovers in the

Figure 4. Directional return spillovers, from five asset classes
Source: author.
negative domain illustrate the situation when a specific currency receives net volatility spillover from others. The extent of spillover transmission among currencies is uniform. Nevertheless, the evidence shown in Fig. 6 describes quite the opposite. Two currencies relationships can be characterized by opposite extreme net positions: USD-HUF is a net volatility spillover receiver and USD-CZK is a net spillover transmitter; short periods when low net spillovers are in the

**Figure 5.** Directional return spillovers, to five asset classes
*Source:* author.
Figure 6. Net return spillovers, five asset classes

Source: author.
Figure 7. (continued)
opposite domains are the exception. Furthermore, Romania and Croatia clearly transmit more spillovers during most of the researched period. The Polish Zloty in Fig. 6 alternates between being transmitters or receivers, depending on the time.

Figure 7 includes net pairwise spillover plots, which provide a detailed analysis of the return spillovers. First, the bulk of return spillovers from USD-HUF were transmitted first to USD-
PLN, second to USD-CZK, third to USD-RON, then to USD-HRK. During this episode, the USD-HUF was a net receiver of volatility from other markets. However, in the case of HUF-PLN, the Hungarian currency was a net transmitter of volatility to another market in the periods of 2015–2017. The fact that the USD-HUF exchange rate was at the same time a net receiver from other exchange markets pointed out the connectedness between USD-HUF and USD-RON, USD-PLN, USD-CZK, USD-HRK. Second, return spillovers from USD-PLN were transmitted first to USD-CZK, USD-RON, then to USD-HRK. Overall, during the end of the research period, the USD-PLN rate was a net receiver of volatility from other markets, while a slight transmitter of volatility to other markets in the periods of 2011–2014. This simply meant that there was a weak relationship between the Polish exchange market and other markets in this region. Third, return spillovers from USD-CZK were transmitted to USD-RON and USD-HRK. Figure 7 highlights that the USD-CZK exchange rate was a net transmitter of volatility to other markets, with the exception of the period between 2013 and 2015. We can conclude that the exchange market in the Czech Republic has a dramatic influence on other exchange markets in CEE region. Finally, we consider the episode of return spillovers from the USD-RON rate were transmitted to USD-HRK. Throughout 2009–2014, the spillovers went in the direction of USD-RON, whereas between 2009–2010 and 2015–2017, USD-RON was a net transmitter of volatility to USD-HRK.

All in all, we highlight a complete picture of the return spillovers among the considered markets as well as their directional interrelatedness over the sample. As expected, the total spillover effects intensified during the first and last years of the research period. A close inspection of the graphs in Fig. 7 demonstrates that the integration of the foreign exchange markets is significant.

The stylized facts confirm previous studies. For example, Kumar – Kamaiah (2014) attempted to analyze the deterministic presence of chaos in the Forex markets in Bulgaria, Croatia, Czech Republic, Hungary, Poland, Romania, Russia, Slovakia and Slovenia. They confirmed that the Forex markets exhibited deterministic chaotic behavior. By contrast, Bubak (2009) relied on model-free nonparametric measures of ex-post volatility, and documented that daily returns on the EUR-CZK, EUR-HUF and EUR-PLN exchange rates are independent over time. Fidrmuc – Horvath (2008) reported asymmetric effects of the volatility of exchange rates in new EU members states including Czech Republic, Hungary, Poland, Romania and Slovakia. This result is also supported by Kocenda – Valachy (2006).

**Figure 8.** Total return spillovers to VAR lag structure

*Source:* author.
3.4. Robustness

In order to test for robustness, we slightly modify our baseline model to evaluate the sensitivity of our time-varying volatility spillover results. First, we calculate the dynamic indices for orders 2 through 6 of VAR, and plot the minimum, maximum and median values of the related estimations which are obtained in Fig. 8. We do not detect a significant distinction among these time-varying estimation results. Then, we examine the results for forecast horizons varying from 1 to 7 months at a 40 month rolling window VAR analysis. As we can see in the Fig. 9, the dynamic total spillover plot is not sensitive to the choice of the order and the forecast horizon of the VAR model. We can conclude that our results are robust to the above variations.

4. CONCLUSIONS

In this article, we employed the spillover index developed and extended by Diebold – Yilmaz (2009; 2012), based on the forecast error variance decomposition analysis to better fit the assessment of volatility spillovers on foreign exchange markets. Applying daily data over 2008–2017, we used the method on a set of the most actively traded currencies quoted against the US dollar, including the USD-HUF, USD-PLN, USD-CZK, USD-RON and USD-HRK exchange rates. Based on the analysis of the data, we provided a wealth of detailed estimations.

The results of our spillover analysis provide several straightforward insights about the level and the dynamics of foreign exchange rate movements in the Central and Eastern European region over the past 10 years. The overall picture is that we find the existence of bidirectional volatility spillovers between the selected countries in the CEE region. More precisely, cross-market connectedness in the CEE region is time-varying and has become stronger over time, with large increases in the level of shock spillover effects after the European stock collapse in 2015 towards the end of our sample, in comparison with the beginning of the research period. Finally, the Czech Republic has not only significant spillover with markets of close geographical proximity, but also has a dramatic influence on the rest of the foreign exchange markets. The total spillover remained very high during the 2010–2012 and 2015–2017 periods, despite the noteworthy fluctuations in other periods, while the lowest volatility index was for 2014.

Figure 9. Total return spillovers to forecast horizon
Source: author.
These empirical results are useful for portfolio managers, policy makers and speculative traders in terms of developing exploitable strategies, providing them with knowledge of transmission mechanisms of the volatility of foreign exchange markets in the CEE region. It might be beneficial to distribute assets in a financial portfolio, especially after greater financial integration.

REFERENCES


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