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Comovement of exchange rates: A wavelet analysis

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Abstract

In this paper we investigate the behaviour of exchange rates in the Central and Eastern European countries. The results strongly indicate that interactions between exchange rates have different characteristics at different timescales. Our results show that CEE exchange rates are nearly perfectly integrated in the short and medium run, since the returns obtained in any of the CEE foreign exchange market can almost be explained by the overall performance in the other CEE markets. The discrepancies between CEE exchange rates are small, but increase within three to six months and that means in the long run the integration of foreign exchange markets is weak.

Keywords: Exchange rate; Co-movements; Wavelet analysis

JEL: F31, C10, C51

1. Introduction

The introduction of the Euro in January 1, 1999 was undoubtedly one of the most important events that stimulated the regional integration in European Union. Due to the continuous enlarging of the euro area with new members that will subsequently adopt the common currency, the non-euro foreign exchange markets in Central and Eastern European countries (CEEC) became interdependent. They face similar behaviours, even though sometimes only one or two countries are affected by internal or external shocks.

In this paper we use the wavelet methodology to investigate the co-movement of exchange rates from CEEC in the time – frequency space and provide new insights on the exchange rate co-movements in selected CEEC, given the status of the Euro as anchor currency in this region.

This research is relevant in a wider context of exchange rates prediction literature. In their seminal paper, Meese and Rogoff (1983) found that the best exchange rate forecasting model is the “random walk”, that is it generates better forecasts that economic models. Since then the efforts of academia were oriented to identify new models, predictors, estimation methods, data horizons and data frequency to improve the exchange rates prediction. It seems that the forecasts' quality depends on the authors choices on the items listed above. In a comprehensive survey of the literature Rossi (2013) found some evidence that linear models with a small number of estimated parameters that use Taylor rule or net foreign assets as predictors may offer better exchange rate forecasts. However the literature has not found yet an clear evidence on the exchange rates predictability, on the most appropriate predictors and on the stability of exchange rate predictions (Kim and Ryu, 2013). This motivates academics to find an alternative to the "traditional" exchange rate forecasting approaches. The time series co-movement literature may offer new insights on this topic.

The existence of exchange rates co-movement would suggest that news originating in a specific market is not country-specific and idiosyncratic, but efficiently transmitted to other foreign markets (Bekiros and Marcellino, 2013). The analysis of such interdependencies and volatility spillovers in exchange rates, and their evolution over time, is thus of great importance influencing the decisions of central bank interventions, international trade, risk management and portfolio diversification (Antonakakis, 2012).

Even though the adopted exchange rate policies may be different, the world financial integration and capital mobility are expected to increase the interdependence of the national markets. This effect is deepened by the regional integration, as the European one, which amplifies these processes. Moreover, quite homogeneous groups of countries show common behaviours, often not as consequences of significant changes in fundamentals. Authorities will thus lose full control over the national policies, as the instruments they use are less efficient under these conditions. If we refer to "imposible trinity" theory, the consequences of the capital mobility in the CEE region are that national authorities apparently have only two possibilities to choose: monetary policy autonomy with floating exchange rates or exchange rate stability with no-autonomy. However, as Frankel et al (2004) noticed, the monetary policy autonomy may not be a valid possibility when national monetary authorities voluntarily follow the same monetary rules and/or countries share a high degree of business cycles synchronization. This is often the case in EU country members and especially in the CEEC. The empirical evidence confirms that flexible exchange rate regimes in CEEC may not necessarily be accompanied by the monetary autonomy (Căpraru and Ihnatov, 2012). In this context, the expected behavior of the exchange rates in the region is the co-movement.

The countries in our sample are Czech Republic, Hungary, Lithuania, Latvia, Poland and Romania. We eliminated Estonia, Slovenia and Slovakia because they adopted the euro during the analyzed period, while Bulgaria operated a currency board and had an invariant exchange rate. During the investigated period, the countries in our sample adopted exchange rate arrangements with different degrees of flexibility, according to the IMF's Annual Report on Exchange Arrangements and Exchange Restrictions. The group is thus partially homogenous. Latvia and Lithuania adopted very rigid regimes. Most of the time, Latvia employed a conventional fixed peg, while Lithuania operated a currency board, with two short spells of horizontal band arrangement. The lack of exchange rate volatility in the Lithuanian case or the reduced volatility of the Latvian lat exchange rate will probably show scarce or no evidence of co-movement with other currencies in the region. Czech Republic, Poland and Romania operated regimes with a large flexibility – managed or independent floating with some short spells of crawling band (in the case of Poland and Romania). We expect in these cases clear evidence of exchange rate co-movement given the regional integration and the interdependencies that these countries face.

Another country in the sample, Hungary, operated rigid regimes until 2007, ranging from a crawling band to a more restrictive horizontal band regime and switched to independent floating or managed floating regimes after 2008, with the beginning of the international financial crisis. In the latter period we expect an increased co-movement of the Hungarian foreign exchange market with other flexible regime countries. The major international financial crisis may amplify the co-movement of the exchange rates as the portofolio investors treat CEEC countries as a whole.

On the other hand, the crisis that started in 2008 revealed how important is that authorities have a multitude of policy instruments to react, including the exchange rates. While before the crisis the CEEC countries were developing converging policies towards a common goal – the adoption of euro –, after 2008 the perspectives changed. National authorities realized that the flexible exchange rates may be used as a shock absorber in a policy mix, that is CEEC will lose a valuable policy lever with the adoption of the euro. This situation practically posponed the deadline for the euro adoption in a series of CEE countries, i.e. Czech Republic, Poland or Romania. Even though there is a common behavior, that is a co-movement of the exchange rates in these countries, the exchange rate remains sufficiently flexible to allow smoother adjustments when included in a policy mix. This may explain why Hungarian authorities have chosen to move from a quite rigid to a more flexible regime after the crisis started.

On the base of current discussion, the co-movement of the exchange rates in CEEC may not be an immutable process. The research on regional integration of financial markets and especially on co-movements of exchange rate series is very large. An ample literature has emerged in this field especially in the framework of the Asian crisis of the late 1990s and in the framework of European monetary integration. The results influenced the central banks policies, the management of financial investments and the international trade.

A plethora of research activity has emerged on the exchange rate co-movements. Conventionally, the study of exchange rates returns co-movement has been undertaken through the cross-correlation analysis (see e.g. Komarkova and Komarek, 2007, Wang and Xie, 2013). Later on more sophisticated methods like Dynamic Conditional Correlation model (Antonakakis, 2012), cross-sample entropy method (Liu et al., 2010), cross-spectral methodology (Orlov, 2009), residual cross-correlation approach (Inagaki, 2007), vector autoregressive modeling (Nikkinen et al., 2006), multifrequency volatility decomposition (Calvet et al., 2004) or wavelet analysis (Gençay et al., 2001; Nikkinen et al., 2010; Bekiros and Marcellino, 2013) were used to analyze and forecast the co-movement of exchange rates.

Since seminal work of Grossmann and Morlet (1984) wavelet methodology has been introduced in the literature as an alternative for analyzing nonstationary data with irregularities. The wavelet multi-scale decomposition, allowing for simultaneous analysis in the time and frequency domain, is a valuable means of exploring the complex dynamics of financial time series (Bekiros and Marcellino, 2013). By our knowledge, there are very few papers that investigated the exchange rate co-movements in the CEE region (see e.g. Komarkova and Komarek, 2007; Stavarek, 2009).

The previous papers on this topic used conventional methodologies (i.e. correlation analysis, panel models, GARCH models or state-space models). But, given the high noise level in financial time series, conventional models may provide us with a distorted picture of economic relationships, tending to reflect average behavior over the states of the economy, rather than their distinctive features.

We contribute to the literature by using the wavelet-based measure of co-movement that allows one to assess the extent to which two variables move together over time and across frequencies within an unified framework. In this way, it is possible to capture the time and frequency varying features of co-movement within a unified framework that constitutes a refinement to previous approaches (Rua, 2010). In the second part we employ two statistical tools recently developed by Fernández-Macho (2012) – the wavelet multiple correlation and the wavelet multiple cross-correlation – to investigate the behavior of exchange rates in the CEE region.

The main advantage of wavelet analysis is the ability to decompose the data into several time scales and ability to handle non-stationary data and localization in time. Finally the short-run and long-run relationship is clearly established through wavelet time scales, it provides us a holistic picture on the entire relationship (Durai and Bhaduri, 2009). In fact, wavelets are considered as a powerful mathematical tool for signal processing which can provide more insights to co-movement among financial variables via a decomposition of the time series into their time scale component. Particularly, the decomposition into sub-time series and the localization of the interdependence between time series are the two most widely considered area of the wavelet approach in finance. (Aloui and Hkiri, 2014).

Our results strongly indicate that interactions between exchange rates have different characteristics at different timescales and suggest that the synchronization of exchange rates among the CEEC has always been high at high frequencies. Also, the results show that CEE exchange rates are nearly perfectly integrated in the short and medium run, since the returns obtained in any of the CEE foreign exchange market can almost be explained by the overall performance in the other CEE markets. The discrepancies between CEE exchange rates are small, but increase within three to six months and that means in the long run the integration of foreign exchange markets is weak.

The rest of the study is structured as follows. Section 2 reviews the main literature on exchange rate co-movements. Section 3 describes the methodology used to investigate the on the exchange rate co-movements in Central and Eastern Europe countries. Section 4 discusses the data used and empirical results. In Section 5 we present the results using alternative methods and Section 5 concludes.

2. Literature review

The literature on foreign exchange markets integration is ample (Gómez-González and García-Suaza, 2012). One stand focuses on the co-movement of major currencies of the world. Calvet et al. (2004) use the multifrequency volatility decomposition and find strong patterns in volatility co-movement between major currencies against the US Dollar exchange rate series in the period between 1973 and 2003. Inagaky (2007) finds a unidirectional volatility spillover from the euro to the British pound (against US dollar), by investigating the period between 1999 to 2004 with the residual CCF method. Nikkinen et al. (2006) using the VAR methodology gets a similar conclusion, that market expectations of future exchange rate volatilities are closely linked among major European currencies (euro, British pound and Swiss franc) in the analyzed period (2001-2003). Drozdz et al. (2007) study the cross correlations in changes of the daily foreign exchange rates within the basket of 60 currencies on a period between 1998 and 2005. Their result is heterogonous, but the mechanism of correlations has some common elements for all the currencies on daily time scale. However, the changes in value of a peripheral currency do not affect the important world currencies, but in the case of strong economic ties between two countries their currencies are expected to behave in a similar way. More recently, Cristescu et al. (2012) propose a new method - parameter motivated sliding window correlation analysis – which they apply to 1999-2011 daily GBP, JPY, SGD, KRW, RON and INR exchange rate series against US dollar. Their results show a correlation between the developed countries currencies, as well as anti-correlation between advanced countries and the less developed countries currencies, but a clear distinction can be made between the pre- and post-crisis periods.

On the other hand, Gençay et al. (2001) use a powerful econometric approach - wavelet multi-scaling – and find out that DEM and JPY against USD rate volatilities followed different scaling laws at different horizons between 1986 to 1996. Using a similar process signalling approach (wavelet cross-correlation techniques), Nikkinen et al. (2010) investigates the cross-dynamics of exchange rate expectations over different time-scales. The evidence shows that market expectations are closely related among the three major exchange rates, namely JPY/USD, EUR/USD and GBP/USD. Significant lead-lag relationships between the expected exchange rate probability densities were discovered. Bekiros and Marcellino (2013) use, from the same range of methods, wavelet multiresolution analysis of EUR/USD, GBP/USD and USD/JPY series for the period between 1999 and 2010. They discovered that the interactions between currency markets have different characteristics at different timescales. The evidence shows that the lead-lag pattern changes over time and there is not a “global causal behaviour” of exchange rate series.

At European level, Kearney and Patton (2005) investigate the exchange rate volatility transmission in the period before the introduction of the Euro between the major European currencies (German mark, French franc, Italian lira and the ECU). The results showed volatility transmission evidence and indicated the German mark as a “leader” currency. Boero et al. (2011) investigate the bivariate dependence structure of the DEM (EUR), GBP, CHF and JPY against the US dollar, both before and after the introduction of the euro. They found, in the post-euro period, a higher integration of British pound and euro compared to the period before. Otherwise, co-movements of the euro and the franc remain stable over time. Antonakakis (2012) employs the DCC model to investigate the return co-movements and volatility spillovers between major exchange rates before and after the introduction of euro (1986-2012). He discovers significant return co-movements and volatility spillovers, but their extent is, on average, higher in pre-euro period.

A large strand of the exchange rates literature emerged after the Asian crisis in the 1990 and focuses on that region. Tai (2007) employs a ICAPM model using an asymmetric multivariate GARCH(1,1)-in-Mean approach on six Asian countries. He finds a strong positive impact of return shocks originating from the domestic foreign exchange market during the crisis. Orlov (2009) examines the co-movements of exchange rates before and during a financial crisis (1996-1998) on nine exchange rate series from Asian countries. He uses the cross-spectral methodology and finds out that the Asian crisis manifested itself in greater co-movements particularly along the high-frequency components. Liu et al. (2010) assess the degree of asynchrony of every two exchange rate returns time series by the cross-sample entropy method. They discover a weaker correlation between exchange rates after the Asian currency crisis, especially for Singapore, Thailand and Taiwan, and explain it by the policies change. Feng et al. (2010) use the random matrix theory to investigate the exchange rate co-movements in the ASEAN+6 countries before the Asian crisis, as well as before and after the China exchange rate reform. They discover both a weaker correlation between Asian currencies and the US Dollar after the Asian crisis, and increased intra-Asian interactions. This trend amplified after the Chinese currency reform in 2005. Wang and Xie (2013) use cross-correlation techniques and identify significant cross-correlations in Chinese yuan exchange rate against US dollar, euro, Japanese yen and Korean won.

By our knowledge, there are few papers that investigated the exchange rate dynamics and determinants and their co-movements in the CEE region (Dufrenot ands Égert, 2005; Dreger and Fidrmuc, 2011). Komarkova and Komarek (2007) found out, by using standard and rolling correlation analysis, state-space model and panel regression analysis, that between 2004 and 2007 the mutual relationship of the Czech, Hungarian, Polish and Slovak currencies relative to the euro increased significantly. In a more recent paper, Stavarek (2009) uses daily returns correlation analysis and implied GARCH volatility analysis to investigate the convergence of some selected CEE currencies (Czech koruna, Hungarian forint, Polish zloty, Romanian leu, Slovak koruna) with euro. He concludes that the most remarkable process of convergence was recorded during the pre-EU accession period. After 2004 the convergence of the exchange rate series decreased, except for the Polish zlot. He explains that the underlying shocks are still not symmetric and supports the decisions of postponing the euro adoption in Czech Republic, Poland and Hungary.

3. Methodology

Wavelet transforms perform a time-frequency analysis of signals and hence are able to estimate the spectral characteristics of signals as a function of time. Consequently, this can provide not only the time-varying power spectrum but also the phase spectrum needed for computation of coherence.

Compared to the Fourier transform, that does not allow for any time dependence of the signal and therefore cannot provide any information about the time evolution of its spectral characteristics, the main advantage of the wavelet transform is that it makes possible a representation of the signal in both time and frequency (Caraiani, 2012).

Torrence and Compo (1998) developed the approaches to estimating the cross-wavelet power, the cross-wavelet coherency, and the phase difference which can be interpreted as local variance, covariance and the time lag in the time-frequency space respectively. The term “phase” implies the position in the pseudo-cycle of the series as a function of frequency. Consequently, the phase difference gives us information “on the delay, or synchronization, between oscillations of the two time series” (Aguiar-Conraria et al., 2008, p. 2867).

According to frequency and time spaces, the Continuous Wavelet Transform (CWT) $W_t^u(\tau)$ of a time series x_t at time n and scale τ with uniform time steps, the Morlet wavelet[1] equation (1) can be rewritten in the following expression:

$$W_m^x(s) = \frac{\delta t}{\sqrt{s}} \sum_{n=0}^{N-1} x_n \cdot \psi^*\left((m-n)\frac{\delta t}{s}\right), \quad m = 1,2,\ldots,N-1 \tag{1}$$

where, the wavelet power $\left|W_t^u(\tau)\right|^2$ is defined as the local phase. The Cone of Influence (COI) is important to introduce a as edge effects. The Monte-Carlo simulation process is used in this paper that is explained by Torrence and Compo (1998). We computed the wavelet power spectrum[2] using the similar procedure used by Torrence and Compo (1998). The description of CWT, Cross Wavelet Transform (XWT) and Wavelet Coherency (WTC) presented is introduced from Grinsted et al. (2004).

The two financial time series such as the change in trade balance and the change in real oil price, u_t and v_t, with the wavelet transformation W^u and W^v, the XWT is defined as $W^{uv} = W^u W^{v*}$, where W^{v*} denotes complex conjugate of W^v. However, following Aguiar-Conraria and Soares (2011) WTC, instead of the XWT is preferable, since "(1) the wavelet coherency has the advantage of being normalized by the power spectrum of the two time-series, and (2) that the wavelets cross spectrum can show strong peaks even for the realization of independent processes suggesting the possibility of spurious significance tests".

According to Torrence and Compo (1998), theoretical distribution of the cross wavelet power of two time series P_k^u and P_k^v with background power spectra can be defined as:

$$D\left(\frac{W_t^u(\tau)W_t^{v*}(\tau)}{\sigma_u \sigma_v} < p\right) = \frac{z_\omega(p)}{\omega}\sqrt{P_k^u P_k^v} \tag{2}$$

The confidence level $z_\omega(p)$ explained the square root of the product of two χ^2 distributions. Using the similar description of the XWT, the WTC (Torrence and Webster, 1999) between the change in oil price and the change in trade balance can be defined as:

$$R_t^2(\tau_S) = \frac{\left|\varepsilon(\tau_s^{-1}W_t^{uv}(\tau_s))\right|^2}{\varepsilon\left|(\tau_S^{-1}W_t^{uv}(\tau_S))\right| \cdot \varepsilon\left|(\tau_S^{-1}W_t^{uv}(\tau_S))\right|} \tag{3}$$

where ε is considered as a smoothing operator (Rua and Nunes, 2009). In equation 3, the numerator is the absolute value squared of the smoothed cross-wavelet spectrum and denominator represents the smoothed wavelet power spectra (Torrence and Webster, 1999; Rua and Nunes, 2009). The value of the wavelet squared coherency $R_t^2(\tau_S)$ gives a quantity between 0 and unity. In other words WTC can be defined as the ratio of the cross-spectrum to

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[1] $\psi_\theta(\mu) = \pi^{-1/4} e^{i\omega_a \mu} e^{-\frac{1}{2}\mu^2}$, where ω_a and μ are dimensionless frequency spaces and time scales. Morlet wavelet with frequency parameter, $\omega_a = 6$.

[2] $D\left(\frac{\left|W_t^u(\tau)\right|^2}{\sigma_u^2} < p\right) = \frac{1}{2} P_k \chi_\nu^2(p)$, where ν is equal to 1 and 2 for real and complex wavelets respectively.

the product of the spectrum of each series, and can be thought of as the local correlation, both in time and frequency, between two time series. Thus, wavelet coherency near one shows a high similarity between the time series, while coherency near zero show no relationship. This present study will focus on the WTC, instead of the XWT pursuing the application by Aguiar-Conraria and Soares (2011). In this study, we follow Torrence and Compo (1998) for identifying the COI region and phase relationship.

Further we define the phase difference as follows, which shows any lag or lead relationships between components,

$$\phi_{u,v} = \tan^{-1}\frac{I\{W_n^{uv}\}}{R\{W_n^{uv}\}}, \phi_{u,v} \in [-\pi, \pi] \tag{4}$$

where, I and R are the imaginary and real parts, respectively, of the smooth power spectrum. A phase difference of zero indicates that the time series move together (analogous to positive covariance) at the specified frequency; if $\phi_{u,v} \in [0, \pi/2]$, the series move in-phase, with the time-series *v* leading *u*; if $\phi_{u,v} \in [-\pi/2, 0]$, the series move in-phase, with the time-series *u* leading *v*. We have an anti-phase relation if we have a phase difference of π (or $-\pi$). If $\phi_{u,v} \in [\pi/2, \pi]$, there is anti-phase relation with *u* leading *v* and if $\phi_{u,v} \in [-\pi, -\pi/2]$, there is anti-phase relation with *v* leading *u*.

4. Data and Empirical Results

The data comprise six time series of daily closing exchange rates denoted relative to the Euro, namely Czech koruna (CZK), Hungarian forint (HUF), Lithuanian litas (LTL), Latvian lats (LVL), Polish zloty (PLN) and Romanian leu (RON). All series were then transformed into daily returns by taking the first difference of the logarithms series. The data span a time period from January 5, 1999, namely from the introduction of the Euro, to February 1, 2013 (3610 observations). During the investigated period, the countries in our sample adopted exchange rate arrangements with different degrees of flexibility, according to the IMF’s Annual Report on Exchange Arrangements and Exchange Restrictions. Czech Republic, Poland and Romania operated regimes with a large flexibility, ranging from crawling band to independent floating. Hungary operated rigid regimes until 2007, ranging from a crawling band to a more restrictive horizontal band regime and switched to independent floating or managed floating regimes after 2008, with the beginning of the international financial crisis. On the other hand, Latvia and Lithuania adopted very rigid regimes: most of the time, Latvia employed a conventional fixed peg, while Lithuania operated a currency board, with two short spells of horizontal band arrangement. However the EUR as an anchor currency for the LTL was introduced only in February 2002, while previously it pegged to the USD. Similarly, the LVL switched form SDR to EUR as anchor at the beginning of 2005. The inclusion of these two currencies in our analysis is thus supported by the following arguments. Firstly, we needed to account the period before the policy change and after 1999. Secondly, all the countries in the sample were converging their policies, at least before the recent international financial crisis, due to the European integration and later the Euro adoption objective. Thus periods of relative stability of exchange rates, and consequently of low volatility may appear as a co-movement effect between the currencies with flexible and rigid exchange rate regimes. Selected descriptive statistics of daily returns for all exchange rates are presented in Table 1.

INSERT HERE TABLE 1

The Jarque-Bera statistic for all returns implies non-normality while kurtosis statistics shows that all return series are leptokurtic, with significantly fatter tails and higher peaks. Based on the Ljung-Box Q-statistic, return series present serial dependence. Table 1 also reports significant sample cross-correlations for currency from CEEC, especially between LTL and LVL, indicating a high interrelationship between the two markets. However, since linear correlations cannot be expected to fully capture the linear/nonlinear linkages in a reliable way, these results should be interpreted with caution.

INSERT HERE FIGURE 1

From Figure 1 we find that there are clearly common features in the wavelet power of four time series (CZK, HUF, PLN and RON) such as 1~6 month's scale (band) that corresponds to the period around 2008 - 2009. This is the international financial crisis period that generated high uncertainty in all the emerging regions, including the CEE. The large capital outflows from the region affected both countries with deep structural misbalances (i.e Romania) and countries with sound policies in the period before the crisis (i.e. Poland, Czech Republic). Despite the differences in macroeconomic fundamentals of these countries, the fluctuations of the CEEC exchange rates show a common behavior during the crisis period. LTL and LVL series also have high power in the 1~3 month's scale (band) that corresponds to 1999-2001, and for both series the power is above the 5% significance level. The low power after 2002 in the case of LTL and after 2005 in the case of LVL is explained by the change of the anchor currency to EUR, respectively from USD and SDR. The different features of the wavelet power of LTL and LVL during the international financial crisis, compared to other four series, show that the exchange rate couldn't act as an adjustment mechanism, and consequently the shocks were absorbed by other macroeconomic variables (i.e. in the case of Latvia, the GDP decreased in 2009 with about 18% and in the case of Lithuania with about 15%).

However, the similarity between the portrayed patterns in these periods is not very much clear, but it allows us to do further analysis in terms of WTC and explore the co-movement of exchange rates between the countries.

INSERT HERE FIGURE 2

The results WTC for all possible exchange rate pairs are presented in Fig. 2. The wavelet-based measure of co-movement is presented through a contour plot as there are three dimensions involved. The horizontal axis refers to time while the vertical axis refers to frequency. To ease interpretation, the frequency is converted to time units. The colour scale is for the wavelet-based measure whereas red corresponds to an increasing value and mimics the height in a surfaceplot. Hence, by inspecting the contour plot one can identify both frequency bands (in the vertical axis) and time intervals (in the horizontal axis) where the series move together and assess if the strength of the co-movement changes across frequencies and over time.

From the analysis of the results several interesting findings emerge. In general, there is a high degree of co-movement at higher frequencies, i.e. short-term fluctuations, among the exchange rates of Central and Eastern European countries, especially in the case of HUF, PLN and CZK. The above findings suggest that the synchronization of exchange rates among the CEE countries has always been high at high frequencies. One should notice the lack of co-movement of the Latvian lat after January 1st, 2005 when Latvian authorities decided to peg the lat to euro. On May 2005 the Latvian currency has been formally included in the Exchange Rate Mechanism II, which implies a currency band of ±15% around a central rate. However the Latvian authorities declared that they would maintain the LAT/EUR exchange rate at the central rate with a fluctuation band of ±1%. Thus, the change of the exchange rate policy was reflected on the results of the co-movement analysis.

All these results highlight the usefulness of the proposed wavelet-based measure of co-movement. In fact, the degree of co-movement can change across frequencies and over time and being able to capture such evolving features is crucial for a richer co-movement assessment.

5. Further analysis

In this section we employ two statistical tools recently developed by Fernández-Macho (2012) – the wavelet multiple correlation and the wavelet multiple cross-correlation – to investigate the behavior of exchange rates in the CEE region. The proposed methodology could be useful over the conventional methods at least in three directions: overall correlation within the multivariate set of different time scales in exchange rates can be viewed just in two plots of wavelet multiple correlation and wavelet multiple cross correlation; this method provides protection against spurious correlation obtained from the pair wise correlations within the multivariate set of exchange rates; and finally, the proposed method is useful in providing the protection against type 1 errors.

In order to calculate the wavelet multiple correlations we begin by decomposing the time series of exchange rates returns into different time scales using Maximal Overlap Discrete Wavelet Transform (MODWT). We choose the Maximal Overlap Discrete Wavelet Transform (MODWT) over the more conventional orthogonal DWT because, by giving up orthogonality, the MODWT gains attributes that are far more desirable in economic applications. For example, the MODWT can handle input data of any length, not just powers of two; it is translation invariant – that is, a shift in the time series results in an equivalent shift in the transform; it has also increased resolution at lower scales since it oversamples data (meaning that more information is captured at each scale); the choice of a particular wavelet filter is not so crucial if MODWT is used and, finally, excepting the last few coefficients, the MODWT is not affected by the arrival of new information. The decomposition is carried out by using MODWT with Daubechies least asymmetric (LA) wavelet filter of length 8.

INSERT HERE TABLE 2

Given the sample of 3609 observations and maximum decomposition possibility of [log2(T)], we could have decomposed all the exchange rates return series into eleven details and one smooth component. However, for higher level decompositions, feasible wavelet coefficients get smaller, thus we choose to decompose the time series of exchange rate returns into six details ($w_{i1},...w_{i6}$) and one v_{i6} smooth component. The corresponding time dynamics of each wavelet coefficient is given in Table 2.

INSERT HERE TABLE 3

Wavelet multiple contemporaneous correlations with upper and lower bound of 95% confidence intervals obtained from all the exchange rates returns are shown in Table 3 and its plots are shown in Figure 3.

INSERT HERE FIGURE 3

It can be seen that multiple correlations are high at all the time scales[3]. In particular correlation at the highest frequency (Intraweek) is 0.92 and 0.926 for weekly. The highest level of correlation is recorded for monthly scale (0.932), but decrease for lower frequencies and reaching 0.90 at lowest frequency. The discrepancies between CEE exchange rates are small, and even though they increase within three to six months, the correlations are statistically the same across scales. Since the returns obtained in any of the CEE foreign exchange market can almost be explained by the overall performance in the other CEE markets, this means that CEE exchange rates are nearly perfectly integrated with the same degree of integration across scales.

INSERT HERE FIGURE 4

In Figure 4 we present the wavelet multiple cross-correlations for the different wavelet scales with leads and lags up to one month using Daubechies least asymmetric (LA) wavelet filter of length 8, (with Poland acting as potential leader/follower at scales D1, D2 and D4 and Czech Republic acting as potential leader/follower at scales D3, D5 and D6 respectively). The country that maximises the multiple correlations against the linear combination of other countries is shown in the upper left corner of Figure 4. We find that multiple cross correlation gets stronger with lower frequencies but gets weaker with successive lags. It is interesting to

[3] Results however should be interpreted with caution. Confidence intervals are based on Fisher's result for usual bivariate correlation. We rely on simulation exercises carried in Fernandez-Macho (2012), which show that this could also be applicable for multivariate correlation.

see that at the higher frequencies w_{i1} and w_{i2}, Poland maximises the multiple correlation against the linear combination of other countries, whereas at other lower frequencies Czech Republic maximises the multiple correlation against the linear combination of other countries. This indicates that Poland has a potential to lead or lag other markets at higher frequencies (w_{i1} and w_{i2}) but at lower frequencies Czech Republic has the potential to lead or lag other markets. Nevertheless, given the symmetry (zero skewness) in Figure 4, there is no clear evidence of lead-lag potential of two countries. Overall we find strong linkages in the CEE foreign exchange market returns, especially at lower frequencies.

The results may be explained by the fact that both Czech Republic, but especially Poland are benchmark countries in the CEE, starting from the transition period to market economy, continuing with the European integration process and with the behaviour during the recent international financial crisis. They had the fastest advance of the reforms in order to implement the market economy. During the last quarter of century, Poland and Czech Republic were examples of sound policies that brought them in 2009 and 2006 respectively in the high-income countries group, according to the World Bank classification[4]. In 2012, Poland reported a GDP per capita of 10584.8 USD, while the Czech Republic reported 14235.02, being the most developed country in the region. Even though Hungary, Latvia and Lithuania had GDP per capita values between 8400 and 10100 USD (Romania about 5800 USD), Poland remains a benchmark as the greatest country in the region with a population of about 38.5 million people, compared to Romania (about 20 million), Hungary (about 10 million) etc. Moreover, due to the sound macroeconomic policies Poland was the only country registering a positive growth during 2009, when the international financial crisis hit the CEE. These are only few macro indicators that illustrate the position of Poland and Czech Republic in the region and explain the leading role of their currencies.

6. Conclusions

Wavelet methodology could become a valuable means of exploring and forecasting the complex dynamics of exchange rate series, as it allows for temporal and frequency analysis at the same time. The aim of the paper was to investigate the co-movement of exchange rates from CEEC in the time–frequency space because the detailed knowledge of the nature of interdependency between the exchange rates and the degree of their integration at different timescales will help practitioners and policymakers to take the right decisions. The results strongly indicate that interactions between exchange rates have different characteristics at different timescales and suggest that the synchronization of exchange rates among the CEE countries has always been high at high frequencies.

Our results have two important policy implications. On one hand, the exchange rates movements on short and medium run (Intraweek to Monthly scales) are not driven by the general economic situation of a CEEC country. This implies for managed exchange rates that authorities' interventions might be very costly if one tries to stabilise or impose a tough control on the exchange rates. The eventual exchange rate objectives should be followed on

[4] http://go.worldbank.org/L547EEP5C0

quarterly or half-year basis. On the other hand, the lack of foreign exchange market integration on a longer run in some CEEC suggest that they are not prepared to adopt euro and thus to sacrifice an important macroeconomic instrument: the exchange rate. This explains the hesitation of some countries as Czech Republic, Poland or Romania to set an exact date of euro adoption.

In the CEE region one distinguishes two leader-countries: Poland and Czech Republic. The evidence of their potential leader/follower position at different scales one somehow expected: they are the most developed countries in the region and their authorities actions influence the markets' behaviour in the region.

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Table 1 Descriptive statistics

	R_CZK	R_HUF	R_LTL	R_LVL	R_PLN	R_RON
Mean	-8.71E-05	4.17E-05	-8.64E-05	1.36E-05	7.25E-06	0.000334
Median	-0.000123	-3.94E-05	0.000000	0.000000	-0.000245	2.45E-05
Maximum	0.031650	0.050693	0.043048	0.032814	0.041636	0.112335
Minimum	-0.032745	-0.033885	-0.020909	-0.020597	-0.036798	-0.098731
Std. Dev.	0.004019	0.005854	0.003386	0.003038	0.006657	0.006265
Skewness	0.261449	0.774244	0.956542	0.460553	0.453046	1.183643
Kurtosis	9.143283	12.15297	21.28757	12.05181	7.659921	53.18134
Jarque-Bera	5716.258*	12958.52*	50841.03*	12448.59*	3388.832*	379512.1*
Ljung-Box Q-statistic	15.445	30.219*	70.454*	64.678*	43.551*	119.58*
Observations	3609	3609	3609	3609	3609	3609
Return correlation matrix	R_CZK	R_HUF	R_LTL	R_LVL	R_PLN	R_RON
R_CZK	1					
R_HUF	0.4005	1				
R_LTL	0.0930	0.0676	1			
R_LVL	0.0971	0.0556	0.77841	1		
R_PLN	0.4106	0.5554	0.3092	0.3092	1	
R_RON	0.1337	0.2064	0.5186	0.5166	0.3201	1

Table 2: Time interpretation of different frequencies

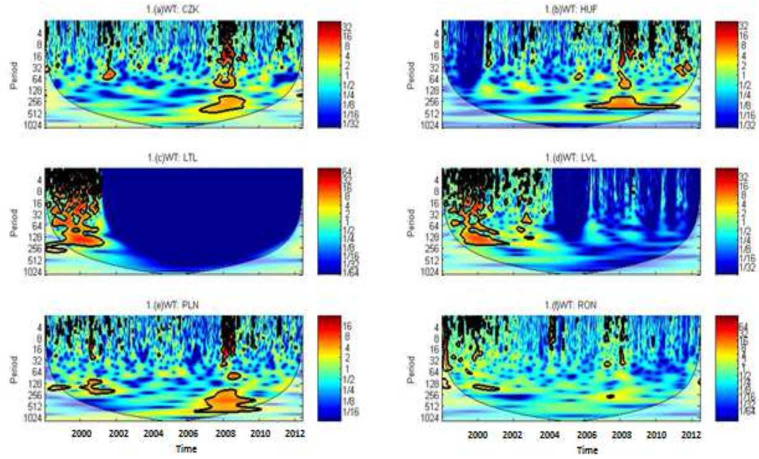
w_{i1}	2 ~ 4 days	Intraweek scale
w_{i2}	4 ~ 8 days	Weekly scale
w_{i3}	8 ~ 16 days	Fortnightly scale
w_{i4}	16 ~ 32 days	Monthly scale
w_{i5}	32 ~ 64 days	Monthly to quarterly scales
w_{i6}	64 ~ 128 days	Quarterly to biannual scale

Table 3: Wavelet multiple correlation among CEE exchange rates returns using Daubechies least asymmetric (LA) wavelet filter of length 8.

Scales	***L***	***Cor***	***U***
w_{i1}	0.912	0.920	0.928
w_{i2}	0.916	0.926	0.935
w_{i3}	0.901	0.917	0.930
w_{i4}	0.913	0.932	0.947
w_{i5}	0.883	0.918	0.943
w_{i6}	0.836	0.900	0.940

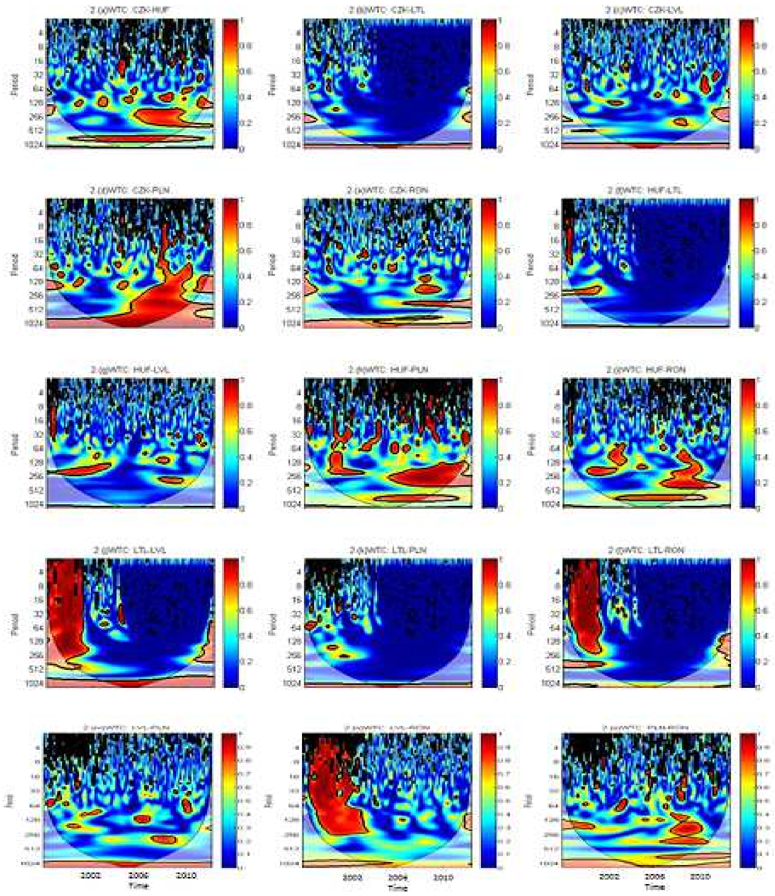
Cor = Correlation Coefficient., **L** = Lower bound of 95% confidence Interval., **U=** Upper bound of 95% confidence Interval.

Figure 1: Wavelet power spectrum analysis



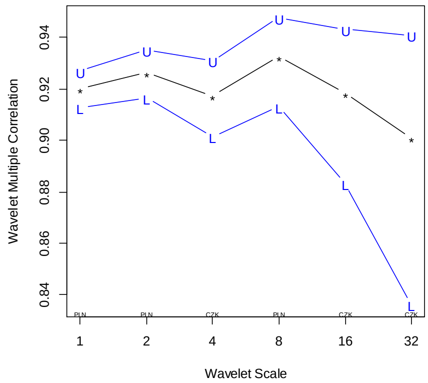
Note: The continuous wavelet power spectrum of all exchange rate series are shown here. The thick black contour designates the 5% significance level against red noise and the cone of influence (COI) where edge effects might distort the picture is shown as a lighter shade. The color code for power ranges from blue (low power) to red (high power). Y-axis measures frequencies or scale and X-axis represent the time period studied. Periods which are mentioned in the y-axis corresponds to 2^j, where j is scale. Thus period up to 4 represents 2^2 which is equal to 1-2 scale and horizon of 2 to 4 days. Similarly, from 4 to 8, we have horizons from $2^2 – 2^3$, thus scale 2-3 gives the information about horizon from 4 to 8 days etc.

Figure 2: Wavelet coherency analysis



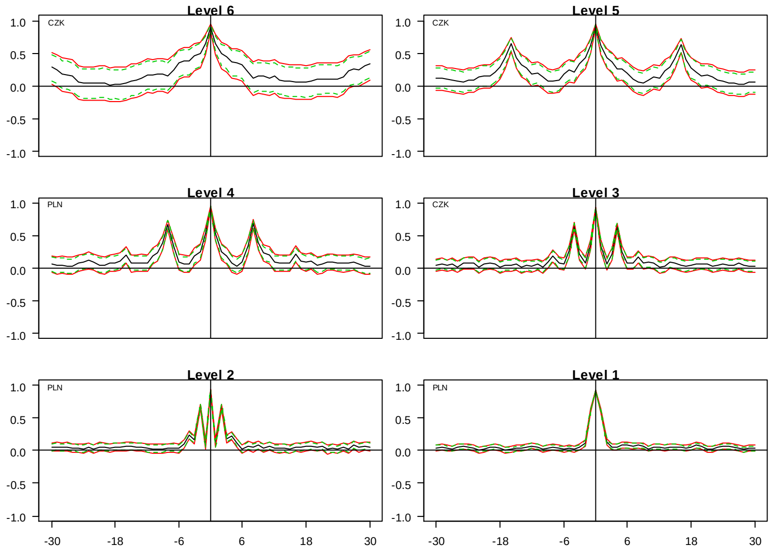
Note: The thick black contour designates the 5% significance level against red noise which is estimated from Monte Carlo simulations using phase randomized surrogate series. The cone of influence, which indicates the region affected by edge effects, is also shown with a light black line. The color code for coherency ranges from blue (low coherency-close to zero) to red (high coherency-close to one). Periods which are mentioned in the y-axis corresponds to 2^j, where j is scale. Thus period up to 4 represents 2^2 which is equal to 1-2 scale and horizon of 2 to 4 days. Similarly, from 4 to 8, we have horizons from $2^2 – 2^3$, thus scale 2-3 gives the information about horizon from 4 to 8 days etc.

Figure 3. Wavelet multiple correlations for the CEE exchange rates returns



Note: The coloured lines correspond to the upper and lower bounds of the 95% confidence interval.

Figure 4. Wavelet multiple cross-correlations for the CEE exchange rates



Note: The coloured lines correspond to the upper and lower bounds of the 95% confidence interval. The wavelet multiple cross-correlations graphs for the CEE exchange rates are at different time scales using Daubechies least asymmetric (LA) wavelet filter of length 8 with Poland acting as potential leader/follower at scales D1, D2 and D4 and Czech Republic acting as potential leader/follower at scales D3, D5 and D6 respectively.