The influence of the international oil prices on the real effective exchange rate in Romania in a wavelet transform framework

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ABSTRACT

The purpose of this paper is to assess the empirical influence of oil prices on the real effective exchange rate in Romania in a wavelet transform framework. More precisely, we investigate to what extent oil prices impact the real effective exchange rate in an Eastern European transition country, characterised by a low level of retail fuel prices and by an important growth rate of these prices as compared to the other EU countries. For this purpose we use a discrete wavelet transform approach and scale-by-scale Granger causality tests. We find that oil prices have a strong influence on the real effective exchange rate in the short run, but also for long time horizons. These results are important considering the fact that, in a classical Granger causality linear framework for the entire sample, we find that oil prices have no influence on the real effective exchange rate. The findings remain robust when resampling the initial 1986–2009 period, or when we use an alternative continuous wavelet transform. In addition, we discover that mainly the positive shocks associated with an increase in oil prices have an impact upon the real effective exchange rate movements in the short and long runs.

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1. Introduction

Oil prices have important implications both on the real economy and on financial markets. During the last decades, large increases in oil prices have been considered responsible for economic recessions, high inflation, trade deficits, high uncertainty and low values for stocks and bonds (Chaudhuri and Daniel, 1998). At the same time, the price of the crude oil has been shown to be a key factor in explaining movements of foreign exchange rates, particularly those measured against the US dollar (Huang and Tseng, 2010). Several representative studies in this area include those of Amano and van Norden (1998), Chen and Chen (2007), Bénassy-Quéré et al. (2007) and Lizardo and Mollick (2010). On the one hand, according to these studies, increasing oil prices favour the appreciation of the currencies of oil-exporting countries relative to those of oil-importing ones (see Ding and Vo, 2012). On the other hand, some recent studies have provided indirect evidence that exchange rates, particularly the US dollar exchange rates, have a significant influence on oil prices. This relationship is also of great interest for oil-exporting countries.

However, even if the oil prices are regarded as an important determinant of the real effective exchange rate (REER), the literature mostly concentrates on industrialised countries, leaving small open economies outside the analysis (Özale and Pekkurnaz, 2010). No research has been done on the particular case of Eastern European transition countries. Their efforts of integration into the EU resulted in a high volatility of the exchange rate due to capital account liberalisation. International oil prices played a role in this respect.

Because the oil prices–exchange rate relationship is usually analysed from both aforementioned perspectives, the empirical literature appeals to vector auto-regression, cointegration and to the Granger causality method. The empirical results show a double causality, one-way causality or no causality between oil prices and REER. Nevertheless, all these techniques can be successfully employed with a stationary time-series condition, but neither the oil prices nor the exchange rate proves to be stationary. The non-stationarity of the series requires special treatment (i.e., differentiating, cointegration, etc.).
Wavelet Transform (DWT) framework, which allows us to avoid the non-stationarity problems of the time-series. We use the wavelet time-scale decomposition and the Maximal Overlap Discrete Wavelet Transform (MODWT) to decompose the time-series into different frequencies.

Second, we study the particular case of an Eastern European transition country, namely Romania. Romania is characterised by a very low level of retail fuel prices and by an important growth rate of these prices in the last years, as compared to the other EU countries. In analysing the particular case of a small economy like Romania, we focus on the one-way causality between oil prices and REER, as it is hard to consider that the exchange rate fluctuations of a small economy would influence the international oil prices.

Third, we test for the robustness of our results using a different methodology, namely the Continuous Wavelet Transform (CWT). The robustness is obtained also by the resampling of the initial data series. In order to see to what extent we can generalise our results for the Eastern European countries, we perform the same analysis for the Czech Republic.

Forth, we analyse how frequency movements of oil price affect the frequency movements of the Romanian REER, performing conventional Granger causality tests. Consequently, we test whether short and/or medium and/or long run oil price movements affect short and/or medium and/or long run REER movements. We compare the results of these tests with a traditional VAR analysis and a classical one-shot Granger causality test in order to emphasise the contribution of the new methodology.

Finally, we extract from the oil-price series the positive and negative shocks associated, respectively, with an increase or a decrease in oil prices over the last period—based on Hamilton’s (2003) approach. This technique gives us the possibility to assess which kind of oil-price shocks play the major role in the REER movements. At the same time, we assess the asymmetric causality between the oil price and REER using the Hatemi-J’s (2012) technique, in order to test for the robustness of our results.

The remainder of the paper is as follows. Section 2 describes the relationship between oil prices and exchange rate, presenting a short overview of the literature. Section 3 presents a brief note on the wavelet approach. Section 4 is dedicated to the empirical findings and Section 5 concludes.

2. Oil prices–exchange rate relationship

2.1. Short overview of the literature

The impact of oil prices on the macroeconomic indicators has received a great deal of attention since the 1970s with the appearance of oil shocks (Iwayemi and Fowowene, 2011). Large fluctuations in demand and supply and also speculative factors have resulted in an exponential rise in oil prices, especially in the last decade. As a consequence, the research on the topic has blossomed and many studies have attempted to draw the causal link between oil prices and macroeconomic fundamentals. Along this line, some researchers have investigated the relationships between oil prices and stock prices (Arouri, 2011; Bashier et al., 2012), between oil prices and economic growth (Elia and Magnussen, 2000; Fuderer, 1996; Kilian, 2009; Prasad et al., 2007), between oil prices and industrial production (Tiwari, 2012), between oil prices and trade balance (Hassan and Zaman, 2012) or between oil prices and inflation rates (Chen, 2009).

The link between oil prices and the exchange rate is important to be analysed as the exchange rate stands for the primary channel through which an oil-price shock is transmitted to the real economy and financial markets. The role of oil prices in explaining exchange rate movements was emphasised early in the literature by Golub (1983) and Krugman (1983), and more recently by Reboredo (2012) and Turhan et al. (2013). In a few words, their analytical studies argue that an oil-exporting (oil-importing) country may experience exchange rate appreciation (depreciation) when oil prices rise and depreciation (appreciation) when oil prices fall.

The transmission mechanisms through which oil prices influence the exchange rate include both supply and demand channels (Oriavwote and Eriemo, 2012). On the supply side, oil prices are associated with the basic input in production and consequently, an increase in oil price leads to a rise in the cost of production, resulting in a reduction of the consumption capacity. This will shrink the demand for non-tradable goods that triggers a fall in their prices. Consequently, the real exchange rate depreciates. The reasoning is similar for the demand channel and it highlights the influence of oil prices on the exchange rate (Wang and Wu, 2012). Relevant papers in this line cover those of Amano and van Norden (1998), Chen and Chen (2007), Bénassy-Quéré et al. (2007) and Lizardo and Mollick (2010).

The relationship between oil prices and the exchange rate can be also analysed from the perspective of the exchange rate impact on oil prices. In this case, the US dollar represents a particular case study. Since the US dollar is the major invoicing currency of international crude-oil markets, the fluctuations in the US dollar exchange rate is believed to underlie the volatility of crude oil prices (Benhmad, 2012). Conversely, the crude oil-importing countries will be adversely affected by an overvalued US dollar (Reboredo, 2012). Other studies, including those of Sadorsky (2000) and Akram (2009), show that a weaker dollar leads to higher oil prices.

However, these studies, which research the effect of oil prices upon exchange rate fluctuations and vice versa, mostly concentrate on industrialised countries, leaving aside analysis of small open economies (Özlale and Pekkurnaz, 2010). Among the very few studies that approach inclusion of small open economies, the findings differ to a significant extent, depending on whether the small open economy is an oil-exporter or oil-importer (Dawson, 2007; Ghosh, 2011; Hassan and Zahid, 2011; Huang and Guo, 2007; Narayan et al., 2008; Oriavwote and Eriemo, 2012; Selmi et al., 2012).

Moreover, many of these studies analyse the linear relationship between oil prices and exchange rate, employing classical econometric methodologies such as linear regression, vector auto-regression, cointegration and Granger causality, reaching different econometric results. Using a VAR model, Dawson (2007) and Oriavwote and Eriemo (2012) find that oil prices significantly affect the exchange rate in the Dominican Republic and Nigeria respectively. A similar result is reported by Hassan and Zahid (2011), who discover, using a VECM analysis, that real oil price exercises a significant positive effect on the real exchange rate in the long run in Nigeria. Huang and Guo (2007) and Narayan et al. (2008) show that oil-price shocks generate an appreciation of China’s and Fiji’s currency, while Ghosh (2011) proves that an increase in the oil-price return leads to the depreciation of the Indian currency. Using a GARCH analysis, Selmi et al. (2012) report a negative influence of the real price of oil on the variability of real exchange rate for an oil-importing economy (Morocco) and for a small oil-exporting country (Tunisia).

Table 1 reports the results of the empirical relationship between oil prices and exchange rate for the selected studies. In classical approaches that study the relationship between oil prices and the exchange rate, the condition of stationarity for time-series is not systematically fulfilled. If the variables are non-stationary, the results of a standard regression analysis are largely invalid (Kisswani and Nusair, 2013). A solution to avoid the problem related to the time-series non-stationarity is the wavelet transform. The main advantage of the wavelet analysis is represented by its ability to decompose macroeconomic time-series into a set of time-scale components, each describing the time development of the signal at a particular observation scale.

Several applications of wavelet analysis to economics and finance have been documented in the recent literature (Gallegati et al., 2011; In and Kim, 2006; Jammazi, 2012; Naccache, 2011; Nachane and Dubey, 2011). To the best of our knowledge, only Benhmad (2012)
### Table 1
Comparison of studies analysing the oil prices–exchange rate relationship.

<table>
<thead>
<tr>
<th>Study</th>
<th>Country</th>
<th>Period</th>
<th>Methodology</th>
<th>Results</th>
</tr>
</thead>
<tbody>
<tr>
<td>Amano and van Norden (1998)</td>
<td>Germany, Japan and the United States</td>
<td>1973M1–1993M6</td>
<td>LS estimator, cointegration, Granger causality</td>
<td>Strong evidence of cointegration between the oil price and the real effective exchange rate for Germany and Japan, but not for the United States. However, Johansen–Juselius tests find evidence consistent with cointegration for all three currencies.</td>
</tr>
<tr>
<td>Huang and Tseng (2010)</td>
<td>United States</td>
<td>1983M6–2008M3</td>
<td>Two-step regression approach, VEC</td>
<td>Real oil prices may have been the dominant source of real exchange rate movements.</td>
</tr>
<tr>
<td>Nijkhi (2011)</td>
<td>Seven OPEC members</td>
<td>2000M1–2007M12</td>
<td>Panel cointegration tests, Granger causality</td>
<td></td>
</tr>
<tr>
<td>Iwayeni and Fowowe (2011)</td>
<td>Nigeria</td>
<td>1985Q1–2007Q4</td>
<td>VAR, Granger causality</td>
<td></td>
</tr>
<tr>
<td>Ding and Vo (2012)</td>
<td>United States</td>
<td>2004M7:28–2009M9:28</td>
<td>Bivariate model of VAR, bivariate GARCH(1,1), structural breaks</td>
<td>During turbulent time, there is bidirectional volatility interaction between oil market and the foreign exchange market.</td>
</tr>
<tr>
<td>Oriavwote and Erieme (2012)</td>
<td>Nigeria</td>
<td>1980–2010</td>
<td>VAR, Johansen cointegration test</td>
<td>Whether for an oil-importing or oil-exporting economy, the real price of oil is negatively and significantly related to the variability of the real exchange rate. Long run equilibrium relationship between the real oil price and the REER. A rise in oil price leads to a significant appreciation in emerging economies’ currencies against the US dollar. Strong bidirectional causal relationship between the real oil price and the real dollar exchange rate for large time horizons. Evidence of causality between oil price and the real effective exchange rate of the Indian currency, at higher time-scales only.</td>
</tr>
<tr>
<td>Turhan et al. (2013)</td>
<td>Thirteen emerging countries</td>
<td>2003M1:03–2010M6:02</td>
<td>VAR models, Granger causality</td>
<td></td>
</tr>
<tr>
<td>Tiwari et al. (2013)</td>
<td>India</td>
<td>1993M4–2010M12</td>
<td>Wavelet approach, linear and nonlinear Granger causality</td>
<td></td>
</tr>
</tbody>
</table>

Source: Authors’ compilation.
and Tiwari et al. (2013) explore the oil prices–US dollar real exchange rate relationship, in a wavelet framework and apply nonlinear causality tests. Benhmad (2012) discovers that the linear and nonlinear causal relationships between the real oil price and the US dollar real effective exchange rate vary over frequency bands, as they depend on the timescales. The author reports a strong bidirectional causal relationship for large time horizons (low frequencies). A similar result is obtained by Tiwari et al. (2013), who find bidirectional causal relationships between the oil price and the REER of the Indian rupee at higher timescales. None of the above-mentioned studies analyse the relationship between the oil price and the REER in the case of an Eastern European transition country.

2.2. The particular case of Romania

Romania was one of the important players on the regional, and even international, oil market in the 1970s. At present, only a part of the fuel demand in Romania is ensured by the internal production. Besides other transition countries, Romania currently can be considered an oil-importing country, as fuel imports largely exceed exports (Fig. 1).

![Fig. 1. Fuel exports and imports, cumulated for the period 1995–2012.](source: UNCTAD database)

![Fig. 2. The level and the growth rate of diesel and gasoline prices in the EU countries.](source: European Commission Oil Bulletins of 19th January 2009 and 19th November 2012)
However, Romania presents several particularities regarding the level and the dynamics of the retail prices.\textsuperscript{1} According to the European Commission Oil Bulletin, in November 2012, the lowest level of gasoline and diesel prices among the EU countries was recorded in Romania (Fig. 2a). As compared to January 2009, Romania registered some of the highest increases in fuel prices for the gasoline, ranking behind Greece, with an increase of 76%, and behind Poland, Hungary and Cyprus for diesel prices, with an increase of 62% over the interval 2009–2012 (Fig. 2b). As the level of gasoline and diesel is reduced, Romania still has enough space for the rise of retail oil prices and this could be a sign of potential fluctuations of the exchange rate.

3. A brief note on the wavelet approach

Traditional mathematical methods, such as the Fourier transform, examine the periodicity of phenomena by assuming that they are stationary in time. One of the main limitations of the Fourier transform is thus related to the assumption that analysed time-series are periodic and that the frequencies do not evolve in time.\textsuperscript{2} Consequently, the time dimension is lost in frequency-domain analysis.

The wavelet approach was proposed in order to fix several introduced limitations of the Fourier transform.\textsuperscript{3} The wavelet transform routinely allows adjustments to the high or low frequencies, with a short window for high frequencies, and a long window for low frequencies. Yet, wavelets reveal mathematical functions that transform the data into a mathematically equivalent representation, and split the data into different frequency components, with a resolution adapted to its scale. The main goal of the wavelet approach is to represent a function of time $X(t)$ as a linear superposition of wavelets (Gallegati et al., 2011). They are considered by Nachane and Dubey (2011) as essential functions, with narrow support, i.e., rapidly converging to zero as $t$ becomes large.

Applying a wavelet analysis has several salient features (In and Kim, 2006). First, the main advantage of using wavelet analysis is the ability to decompose the data into several time-scales. Second, the wavelet covariance decomposes the covariance between two stochastic processes over different time-scales (a wavelet covariance in a particular time-scale indicates the contribution to the covariance between two stochastic variables). This allows for better estimating the causality relationship between variables. As a consequence, the wavelet filters deal with the time-varying characteristics of the most real-world time-series, avoiding the assumption of stationarity. The wavelet transform represents an ideal tool for studying non-stationary time-series, as it is an opportune analysis of many variables at the same time. In addition, it uses a limited number of observations since most economic and financial time-series register complicated patterns over time (e.g., trends, accentuated changes, and volatility clustering). In this context, the traditional spectral tools may miss the frequency components, because they could be non-stationary, as they may appear, disappear, and then reappear over time.

\textsuperscript{1} Retail oil prices are highly correlated with international oil prices. An increase in international prices is perceived nearly instantaneously as an increase in retail prices (see Clerides, 2010).

\textsuperscript{2} More detailed explanations are also offered in Ramsey and Lampart (1998a, 1998b) and Kim and In (2003).

\textsuperscript{3} The Fourier approach is characteristic for stationary time-series and entails several drawbacks since most economic and financial time-series register complicated patterns over time (e.g., trends, accentuated changes, and volatility clustering). In this context, the traditional spectral tools may miss the frequency components, because they could be non-stationary, as they may appear, disappear, and then reappear over time.

The wavelet approach was proposed in order to fix several introduced limitations of the Fourier transform. The wavelet transform becomes:

$$
\begin{align*}
t(t) &= \sum_{k} s_{jk} \varphi_{jk}(t) + \sum_{k} d_{jk} \psi_{jk}(t) \\
&+ \sum_{k} d_{j-1,k} \psi_{j-1,k}(t) + \cdots + \sum_{k} d_{1,k} \psi_{1,k}(t) \\
&= \sum_{k} s_{jk} \varphi_{jk}(t) + \sum_{k} d_{jk} \psi_{jk}(t) + \sum_{k} d_{1,k} \psi_{1,k}(t)
\end{align*}
$$

(1)

where: $J$ represents the number of multi-resolution levels, and $k$ describes the ranges from 1 to the number of coefficients in each level. The coefficients $s_{jk}$, $d_{jk}$, $\cdots$, $d_{1,k}$ are the wavelet transform coefficients, while $\varphi_{jk}(t)$ and $\psi_{jk}(t)$ illustrate the approximating wavelet functions. The wavelet transforms become:

$$
\begin{align*}
s_{jk} &= \int \varphi_{jk}(t)f(t)dt \\
d_{jk} &= \int \psi_{jk}(t)f(t)dt. \text{ for } j = 1, 2, \ldots, J
\end{align*}
$$

(2)

(3)

where: $J$ describes the maximum integer such that $2^J$ has a value less than the number of observations.

The coefficients, $d_{jk}$, $\cdots$, $d_{1,k}$ reveal an increasing finer scale deviation from the smooth trend. $s_{jk}$ is the smooth coefficient which captures the trend. As a consequence, the initial $f(t)$ series under wavelet approximation can be expressed as follows:

$$
\begin{align*}
f(t) &= S_{1,k}(t) + D_{jk}(t) + D_{j-1,k}(t) + \cdots + D_{1,k}(t)
\end{align*}
$$

(4)

where: $S_{jk}$ indicates the smooth signal and $D_{jk}$, $D_{j-1,k}$, $D_{j-2,k}$, $\ldots$, $D_{1,k}$ indicate detailed ones.

These smooth and detailed signals can be written as follows:

$$
\begin{align*}
S_{jk} &= \sum_{k} s_{jk} \varphi_{jk}(t), D_{jk} = \sum_{k} d_{jk} \psi_{jk}(t), \text{ and } D_{1,k} \\
&= \sum_{k} d_{1,k} \psi_{1,k}(t), j = 1, 2, \ldots, J = 1.
\end{align*}
$$

(5)

The $S_{jk}$, $D_{jk}$, $D_{j-1,k}$, $D_{j-2,k}$, $\ldots$, $D_{1,k}$ are listed in increasing order of the finer scale components.

In economic research, the discrete wavelet transform is the commonly used approach due to its advantages related to data decomposition of many variables at the same time. In addition, it uses a limited number of translated and dilated versions of the mother wavelet and does not generate redundant information (Benhmad, 2012). Therefore, we consider DWT as the appropriate approach for our study.

The DWT involves a modification of a time-series into segments of time domain named “scales” or frequency “bands”, which represent the progressivity of the frequency fluctuations (i.e., the shortest scale illustrates progressively high frequency fluctuations, while the largest scale illustrates progressively low ones). The DWT description and its developments regarding the maximal overlap (MODWT) can be found in Tiwari et al. (2013) and are presented in Appendix A.

Another family of wavelets – the continuous wavelet transform – is also used in recent studies in economics (see Appendix B for a description of the methodology and its developments, which are described by Grinsted et al., 2004). The CWT developments, as the cross-wavelet transform (XWT), the wavelet coherence (WTC) and the cross-wavelet phase angle, help us to analyse not only the common power of the series, the relative phase in time-frequency space, and the simple cause-effect relationship, but also the phase-differences between components. The CWT is computationally complex and contains a high amount of redundant information. However, it can be considered as complementary to the DWT and can be seen as a robustness analysis.
implemented and Romania moved toward a managed
1990 up to 1991, Romania had in place a conventional
rates were devalued (International Currency Analysis, Inc., 1987).

a period of appreciation, on 1st March 1986, the two exchange

T h e i m p a c t o f o i l p r i c e s o n t h e e x c h a n g e r a t e i s l a r g e l y

4.2. Wavelet decomposition based on DWT

In the recent econometric literature there are many papers that try
to capture both the short and long run dynamics between oil prices
and exchange rate. However, perhaps many periods, and not just two,
can represent the appropriate time-scales in this particular analysis
(Gallegati et al., 2011). The theory of signal can be thus employed. It is
obvious in certain fields such as telecommunications or meteorology,
but, surprisingly, to a lower extent in economics (Naccache, 2011).

Consequently, to study the relationship between real oil prices and
Romania’s REER, we employ the methodology described in the previous
section. Wavelets, as opposed to time- and frequency-domain analyses,
consider non-stationarity as an intrinsic property of the data rather than
a problem to be solved by the pre-processing of the data. Figs. 4 and 5
illustrate the multi-resolution analysis (MRA) of order \( j = 6 \) for the
oil prices and exchange rate by applying the MODWT based upon the
Daubechies’ (1992) least asymmetric (LA) wavelet filter LA(8).\(^6\)
In each figure we plot the orthogonal components \( (D1, ..., D6) \) that rep-
resent different frequency components of the original series in details,
and a smoothed component \( (S6) \).

Our choice of a filter length \( L = 8 \) responds to the reasonable
strategy that suggests using, in empirical studies, the smallest \( L \) that gives
reasonable results.\(^7\) We use reflecting boundary conditions, whereas
each time-series beyond its boundaries is assumed to be a symmetric
reflection of itself, to lessen the impact of circular filtering (Percival
and Walden, 2000).

MODWT plots for oil prices, and especially for the REER, show
that there is a great peak in the original series at the beginning
of 1990, which is captured in D1–D3 components. These shocks get
smaller as the time-scale increases, meaning that the short term shocks
do not affect the long run movements of the oil price and REER,
respectively.

After the decomposition of both variables, it is also relevant to study
the relative importance of the short, medium and long term dynamics.
Here we use the energy of both variables wavelet decomposition,
\( E \), the energy of each scale, to measure the relative importance
of the short, medium and long run. The energy is analogous to the variance
at each detail level, and it is given as percentage of the overall energy.
Hence, we examine the percentage of variance that each scale is explain-
ing. Percival and Walden (2000) describe that the DWT has the
ability to decompose the energy in a time-series across scales, and
Percival and Mofjeld (1997) prove that the MODWT is also an energy-
preserving transform (i.e., the variance of the time-series is preserved
in the variance of the coefficients from the MODWT). Hence, a time-
series \( x(t) \), with wavelet coefficients for scale \( j \), \( w_j(t) \), and scaling coef-
cients \( v_j(t) \), from a MODWT, has the following energy decomposition:

\[
\sum_{t=1}^{N} x^2(t) = \sum_{j=1}^{J} \sum_{t=1}^{N} w_j^2(t) + \sum_{j=1}^{J} v_j^2(t)
\]  

where: \( N \) is the number of observations used in the calculation.\(^8\)

\(^6\) The Daubechies’ (1992) least asymmetric wavelet filter LA is a widely used wavelet,
because it provides the most accurate time-alignment between wavelet coefficients at
various scales and the original time-series, and it is applicable to a wide variety of data
types.

\(^7\) Given that the maximum decomposition level \( j \) is given by \( \log_2(N) \), we apply the
MODWT up to a level \( j = 6 \). Shorter widths can introduce undesirable artefacts while
wider widths, even if better matching the characteristic feature of the time-series, can re-
sult in a decrease in the degree of localisation of wavelet coefficients.

\(^8\) An unbiased estimator of the energy is calculated with the coefficients unaffected by
the boundary, so \( N \) is not always equal to \( T \). \( N \) depends on the basis and the number of
scales used.
Fig. 4. MODWT decomposition of the real oil price on $J = 6$ wavelet levels.

Fig. 5. MODWT decomposition of the REER on $J = 6$ wavelet levels.
This allows us to separate the contribution of energy in the time-series due to changes at a given scale. Table 2 presents the energy of each scale (as percentage of the overall energy) for the two variables under consideration, i.e., oil price and REER. In Table 2, in order to get an unbiased estimator, the coefficients affected by the boundaries were not accounted for. Notice here that only six scales were used (the seventh scale is included in the smooth). This is done to disregard as few of the boundary observations as possible, in order not to lose too much information. The Daubechies’ (1992) filter (LA) was used for Table 2, given that it is less affected by the boundaries.

The first column of Table 2 presents the wavelet scales, and the second and third columns, respectively, present the energy distribution of the oil price and REER corresponding to the wavelet scales. We discuss energy distribution in four major periods, namely: short run (D1 + D2), medium run (D3 + D4), long run (D5 + D6) and very long run (S6). For both series, the short run dominates all other periods/frequencies, explaining most of the variance (63.63% and 82.85%, respectively). This highlights the issue that high frequency variations and seasonal components are very important for both oil price and REER.

Fig. 6 presents a box plot for each of the series to show the crystal energy distribution, as presented in Table 2. The crystal energy distribution is obtained based on the MODWT technique and shows that crystals D1, D2 and D3 contain most of the series’ energy. Each scale crystal is used afterwards as a basis for decomposing the variance of a given series into variances and covariances at different scales.

Of great interest is the analysis of the association between these two series. For this purpose, we proceed to a separation of the effects across time-scales and frequency bands, using a wavelet covariance analysis. Fig. 7a describes the MODWT based wavelet covariance of the real oil price and REER which shows how the two series are associated with one another. According to these results, the wavelet covariance slowly fluctuates in the analysed period, with a flattening tendency for the long run interval. It is also evident that covariance is positive only at the 3rd level of decomposition and for all other cases it is negative. It clearly indicates a business-cycle type situation. Notice that a positive covariance explains that an increase in oil price is associated with a real depreciation of the currency (increase in REER). A negative covariance (our situation) shows an association between an increase in oil price and a real appreciation of the national currency. This association is strong in the short run (high frequencies), but especially in the long run (low frequencies).

Although there is an increasing association between oil price and REER, it is difficult to compare the wavelet scales because of the different variability they exhibit. In this case, dividing by the variance of each series is a natural way to standardise the covariance, thereby overcoming this influence and making it possible to compare the magnitude of the association across scales. Therefore, the wavelet correlation should be constructed to examine the magnitude of the association of each series.

Wavelet correlation between oil price and REER is presented in Fig. 7b. This figure shows that there is significant difference between the short run and the medium and long runs. In the short run (1st–4th scale), we have no clear evidence of positive or negative correlation, whereas in the medium and long runs, the correlation is negative. However, there is a general tendency of the correlation coefficients to move downwards with scales.

Further, we use the wavelet cross-correlation, as shown in Fig. 8, to test the causal relationship between oil price and REER. We are particularly interested in the one-way causality between oil price and REER. Even if the empirical results show, for some frequencies, a bidirectional causality, it is hard to consider that Romania’s REER influences international oil prices.

The wavelet cross-correlation examines the lead–lag relationship between oil price and REER in various time-scales. More specifically, Fig. 8 illustrates the wavelet cross-correlation between oil prices at time t and REER at time t − k, at the six levels of decomposition. As can be seen, the short and medium term fluctuations of both variables are less correlated than those in the long term, so the magnitude of the cross-correlation is close to zero by increasing the frequency band. These findings show that at the shortest scales, i.e., 1st and 2nd scales, the magnitude of the association between the two variables is generally reduced at all leads and lags, indicating that the oil price and the REER in this period were independent. However, for the last levels, the relationship between these variables has significant events. At the 6th level, the only significant events that we can find happen on the left side of the graph, which means that only the oil price is leading the REER. Moreover, the correlation of these significant events is negative. The fact that we observe a negative correlation between the oil price and the REER at large time-scales (over 64 month time periods) makes plausible sense in that Romania, being a small economy, is affected by oil shocks rather than influencing in its turn the international oil prices.

This conventional approach for identifying the information flow, however, involves the finding of whether a peak in the correlation exists at some non-zero lag. Hence, it could be inferred that the leading variable “causes” or transmits information to the lagged variable. However, using such an approach to deduce causation, or even a direction of information flow, can be quite misleading. The cross-correlation, for example, is a symmetric measure and therefore, may not be suitable for identifying the lead–lag relationships in systems with feedback. Granger causality testing provides a much more stringent criterion for causation (or information flow) than simply observing high correlation with some lead–lag relationship. At the same time, the results presented above require several robustness checks.

4.3. Robustness checks

4.3.1. Resampling approach

As the Romanian financial system has undergone important reforms at the beginning of 1990s, we resample our data series for the period 1992–2009, and we perform a similar DWT analysis. We compare the new results with the previous ones, assessing the energy decomposition, the wavelet covariance and correlation and the cross-wavelet correlation (the results are reported in Appendix C).

The energy decomposition shows that the short run (D1 + D2 + D3) dominates the long run (D4 + D5 + D6), as in the original MODWT decomposition, for the period 1986–2009. The short run explains 78% of the variance in case of the oil price and 86% in case of REER. Consequently,

Table 2

<table>
<thead>
<tr>
<th>Wavelet scales</th>
<th>Oil price (%)</th>
<th>REER (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>D1 (2–4 month cycles)</td>
<td>36.34</td>
<td>51.66</td>
</tr>
<tr>
<td>D2 (4–8 month cycles)</td>
<td>27.29</td>
<td>31.19</td>
</tr>
<tr>
<td>D3 (8–16 month cycles)</td>
<td>18.17</td>
<td>11.94</td>
</tr>
<tr>
<td>D4 (16–32 month cycles)</td>
<td>9.69</td>
<td>2.48</td>
</tr>
<tr>
<td>D5 (32–64 month cycles)</td>
<td>6.05</td>
<td>1.54</td>
</tr>
<tr>
<td>D6 (64–128 month cycles)</td>
<td>1.60</td>
<td>0.52</td>
</tr>
<tr>
<td>S6 (above 128 month cycles)</td>
<td>0.83</td>
<td>0.63</td>
</tr>
</tbody>
</table>

1 These periods can be associated with short, medium or long term objectives of the monetary authorities (see Aguiar-Conraria et al., 2008 for a discussion).

2 The detail crystals have a zero mean by construction and the energy distribution of the detail crystals amounts to a various decomposition of the series by frequency band.

3 A wavelet covariance in a particular time-scale indicates the contribution to the covariance between two series.
the high frequency variations characterise both the oil price and the REER, pointing out similarities between series in the short run.

When analysing the wavelet covariance, we can see that the results are quite similar with the exception of the 3rd level of decomposition. The covariance is negative for the period 1992–2009 for all the frequencies, which shows opposite behaviour between the two series. An increase in oil price is associated with a decrease of REER and thus with the real currency appreciation (similar results are reported by Huang and Guo, 2007 and by Narayan et al., 2008). At the same time, a fall in international oil prices is accompanied by a real depreciation of the currency. However, the correlation is negative at all frequencies, including the short run, and remains strong at low frequencies, which confirms the dependence of the two series for the long run. The wavelet cross-correlation offers clues about the lead–lag relationship between oil price and REER, and shows that the causality is stronger at the 5th and 6th levels of decomposition.

Because the robustness of the results is not very strong regarding the wavelet correlation (for the original series we had a positive correlation at the 3rd level of decomposition), we decide to perform a second robustness check using the same DWT methodology, analysing the situation of another transition country, namely the Czech Republic. At present, according to the IMF classification, the Czech Republic has in place a managed floating exchange rate regime, as does Romania. The exchange rate regime in place is important in analysing a particular case, because the transmission and the absorption of the oil-price shocks are different depending on the strategy and objectives of the monetary authorities. Therefore, the results should be interpreted with caution, as, during the analysed period, the two countries had in place different exchange rate regimes, which were replaced at different moments in time.

The results for the Czech Republic covering the period 1992–2009 are reported in Appendix D. We observe that the short run energy distribution is dominant in this case too and represents 78% for the oil price and 74% for the REER. Consequently, the short term movements characterise both variables. The wavelet covariance is positive at very short term (D1) and becomes negative afterwards. These findings prove an opposite movement of the series, associating the increase of oil prices with the real appreciation of the currency. The wavelet correlation shows, as in Romania’s case, a difference between the short and long runs. The correlation is positive at D1 and becomes then negative, being stronger at low frequencies. We observe a very strong negative correlation at the 16-month cycle and a decrease of the correlation toward the 32-month cycle (contrary to our findings in the case of Romania for that level of decomposition). The wavelet cross-correlation shows short run similarities regarding the oil-price impact on the REER in Romania and the Czech Republic. However, in case of the Czech Republic, in the long run, the oil price is lagging.

4.3.2. CWT approach

The DWT combines time and frequency analysis, but it is not easy to interpret. In this case, the frequency information has different resolutions at every stage. Continuous analysis is often easier to interpret, since its redundancy tends to reinforce the traits and makes all information more visible. Therefore, we use CWT to prove the robustness of the DWT outcome and to facilitate the interpretation of our findings. We perform the analysis in case of Romania for the period 1986–2009, and we interpret the results using the power spectrum of each series (Fig. 9), cross-wavelet power spectrum (Fig. 10a) and coherence (Fig. 10b) of the two series.

The wavelet power spectrum shows the co-movement of the two series, represented in a contour plot with three dimensions: time, frequency (period) and colour code. Fig. 9 clearly indicates that the different time-series have different characteristics in the time-frequency domain. In the case of REER, we observe a strong variance for the small and medium scale at the beginning of 1990s. However, after 2000, the variance was quite stable. This suggests that the exchange rate regime and the monetary policy strategy performed well. In the case of the oil price, we observe a strong variance in 1990–1992, 1999 and 2001, at short and medium scales, but also a considerable variance between 1995 and 2002 at high scales. A common pattern of the two series can be observed at the 8–16 month cycle for the period 1990–1992.

As the similarities between the portrayed patterns in the analysed period are low between the two series (except for 1990–1992 at high frequencies and for 1995–1999 at low frequencies), we proceed to further investigations. On the one hand, the cross-wavelet transform exposes the common power (features) of the series and the relative phase in time-frequency space. On the other hand, the wavelet coherence method allows us to estimate the presence of a simple cause–effect relationship between the phenomena recorded in the time-series. Finally, the cone of influence (COI) tests for phase differences between the components of the two time-series (i.e., the series are in an anti-phase position or not).

If we look to the 2–4 month and 4–8 month cycles (short run), we observe that the arrows are mainly oriented to the left during the entire period. As in the DWT framework, we see that the two variables are out-of-phase (an increase in oil price causes a decrease of the REER and thus a real appreciation of the currency), but it is not very clear which variable is leading. This evidence is strong in the period 1990–1992, and the oil price is lagging. In the long run, for the period 1995–1999, the arrows show also an anti-phase relationship but it is not clear if the oil price is leading or lagging.

It is worth mentioning that the XWT describes the common power of two series without normalisation to a single-wavelet power spectrum. Therefore, if one of the spectra is local and the second one illustrates strong peaks, those peaks in the cross spectrum can be produced even if they have no association with any relationship between the series. The wavelet coherence solves this drawback and allows us to use, at the same time, the wavelet cross-spectrum in order to estimate the phase spectrum.

Looking at the WTC, some different patterns emerge. First, in the short run (2–8 month cycle), we observe several different situations. In 1988, we see an anti-phase case, where the oil price is leading (has a causal influence on the REER). In 1994, the two series are out-of-phase, but in this case the oil price is lagging. No economic explanation can be found here as the REER of Romania cannot influence
international oil prices. In 1994–1995, the anti-phase relationship manifests, but it is not clear which variable is leading or lagging. While in 2004–2005 we have an opposite movement and the oil price is lagging, for 2006 we observe a phase situation and the oil price is leading. This means that for the 2005–2006 time-interval, an increase in oil price causes an appreciation of the currency.

In the medium run (8–16 month horizon), the results are much clearer. In 1990–1993, the variables are in-phase and the oil price is lagging. In 1996–1997 and 2001–2002, strong evidence appears regarding the anti-phase relationship between the two variables where the oil price is leading (an increase in oil price causes currency real appreciation). In the long run (16–24 month cycle), the variables are in-phase and the oil price is leading, while for the 24–48 month cycle, an anti-phase relationship is observed, where the oil price is lagging. To resume our findings based on the CWT, we can state that in the short run (high frequencies), the variables are usually in an anti-phase position (as in the DWT analysis), but the oil price causes the REER only in some periods during the 1990s. In the medium run, there is clear

**Fig. 7.** Wavelet covariance and correlation between oil price and REER.

**Fig. 8.** Wavelet cross-correlation between oil price and REER.

Notes: (i) The first variable is the oil price and the second is the REER; (ii) Level 1, 2, 3, 4, 5, and 6, respectively, denotes 2, 4, 8, 16, 32, and 64-month periods; (iii) Upper and lower red lines represent upper and lower confidence interval at 95% level.
evidence that the oil price influences the REER. In the long run, there is an anti-phase situation where the oil price is lagging. At the same time, we observe a phase situation in the period 1994–1998, where the oil price is leading. However, the causality relationship is not continuous and varies across frequencies. Therefore, in order to obtain more information about the causality between the variables, in the next section we combine the DWT with the traditional Granger causality analysis, at different scales.

4.4. Granger causality results

Testing the influence of the oil price on the REER at various time-scales using Granger causality yields similar results. Our findings, presented in Table 3, indicate the variability of causal relations across frequency ranges and time-scales.

Testing the causality at different cross-frequencies, we are able to see if high, medium or low frequencies in oil price Granger cause high, medium or low frequencies of the REER series. Additional information is thus obtained, as in not all cases a certain frequency band characterising the oil price determines a similar cycle in the REER (i.e., medium frequencies in oil price can Granger cause medium frequencies in the REER). Consequently, structural changes in one variable can produce short run fluctuations in the other variables and vice versa.

The empirical results of the Granger causality tests clearly show that, in a classical Granger causality framework, for the raw series expressed in logarithmic difference, no influence of the real oil prices growth

Table 3, indicate the variability of causal relations across frequency ranges and time-scales.

The colour code for power ranges from blue (low power) to red (high power).

Fig. 9. Continuous wavelet power spectra of the oil price and the REER.

Note: The thick black contour designates the 5% significance level against the red noise. The cone of influence, which indicates the region affected by edge effects, is also shown with a light black line. The phase differences between the two series are indicated by arrows. Arrows pointing to the right mean that the variables are in-phase, to the right and up mean that the oil price is leading (the oil price causes the REER), and to the right and down mean that the oil price is lagging. Arrows pointing to the left mean that the variables are out-of-phase, to the left and up mean that the oil price is lagging and to the left and down mean that the oil price is leading. The in-phase condition indicates that variables will have a cyclical effect on each other, and the out-of-phase or anti-phase condition shows that the variables will have an anti-cyclical effect on each other.

Fig. 10. Cross-wavelet power spectrum and wavelet coherence of the oil price and the REER.
on the REER fluctuation can be found (similar results are reported by Tiwari et al., 2013, in case of the REER of the Indian rupee). When we pass to the spectral-density approach, the Granger causality from the return-series of the oil price to the REER appears different for different frequency bands. We can thus observe the interest assigned to the wavelet transform as compared to a classical VAR analysis for studying the oil price influence on the REER.

The data presented above show that for the medium run (D3 + D4), the results are puzzling. But, if we consider only two categories of frequencies, namely the short run (D1 + D2 + D3) and the long run (D4 + D5 + D6), our results are quite compact. In the short run, there is strong evidence that the return-series of the oil price causes the REER movement in Romania. Causality tests also indicate that for the time-interval of the 8–16 month cycle, this influence is very important. In the long run, the causality manifests only at the D5 level of decomposition (32–64 month cycle). Otherwise said, in a managed floating regime, the Romanian authorities should be concerned both with recent fluctuations in the oil price, and also with long run fluctuations (32–64 month cycle), as both categories of movements influence the REER.

More details are provided by the band-by-band causality tests. If the oil price at D1 affects the REER only in very short run and the oil price at D2 influences the REER at (D1 + D2), we see that the oil price at D3 (8–16 months) affects the entire short-term REER movement (D1 + D2 + D3). We conclude then, saying that the real oil-price series associated with different frequency decompositions, negative shocks, and we test for the Granger causality using the same cross-frequency approach.

4.5. The Granger causality between positive and negative price oil shocks and the REER

4.5.1. Hamilton’s methodology

Starting with Mork (1989) and Hamilton (1996, 2003) and continuing with Cong et al. (2008) and Babatunde et al. (2013), the researchers were interested in estimating the different effects of the positive and negative oil-price shocks on the economic variables. In his seminal work, Mork (1989) argues that, for measuring how an increase in the price of oil is likely to influence the economic variables, it seems more appropriate to compare the current price of oil with where it has been over the previous months rather than with the previous month alone. In the same spirit, Hamilton (2003) proposes using the difference between the log oil price in month t and its maximum value over the previous n months in order to identify the shocks. Even if Hamilton’s methodology became a reference in the field, it covers only the positive shock in oil price, associated with a sudden increase of the price.

Using Hamilton (2003) as starting point, the studies of Cong et al. (2008) and Babatunde et al. (2013) identify both the positive and negative oil-price shocks and their different implications on the macroeconomic variables. Adopting the same approach, we transform each oil-price series associated with different frequency decompositions, into two different series characterising the positive and negative shocks, respectively. If the oil price in month t is higher that its level over the past 12 months, then a positive shock occurs. It is equal to the difference between the level of the price in t and its maximum value in the previous 12 months. The same reasoning is applied for the negative shocks, according to the following two formulae:

\[
oil^+ = IF(oilt - \text{MAX}(oilt_{t-1} : oilt_{t-12}), 0)
\]

\[
oil^- = IF(oilt - \text{MIN}(oilt_{t-1} : oilt_{t-12}), 0)
\]

This rolling approach helps us to identify positive and negative shocks, both in normal and high volatility periods. On the contrary, if the new price level is reported to all previous observations (as in Cong et al., 2008), we will have an association between positive shocks and high volatility periods and between negative shocks and low volatility periods.

The causality between the positive shocks in oil price and the REER is reported in Table 4. The results are similar to those reported in Table 3, stating the fact that the positive shocks of the oil-price returns influence the REER movements in the short run.

Positive shocks in the oil price at the 4–8 month and 8–16 month frequencies Granger cause the REER in the short run. This observation is consistent with the results generated by the CWT and shows that positive shocks at high frequencies Granger cause high frequencies

<table>
<thead>
<tr>
<th>Oil price</th>
<th>Time domain</th>
<th>Frequency bands (months)</th>
</tr>
</thead>
<tbody>
<tr>
<td>H0: Oil price does not cause REER (p-values)</td>
<td>Raw series</td>
<td>0.2991</td>
</tr>
</tbody>
</table>

Note: p-values for the F-test show the rejection of null hypothesis of no causality (i.e., if p-values < 0.10, we accept the causality at 10% significance level).
movements of the REER. In addition, we see that at the D5 level of decomposition, the causality manifests for the 16–32 and 64–128 month cycles of the REER. However, a slight difference appears regarding the very long run frequencies. Apparently, the positive shocks of oil prices affect economic growth in Turkey.

Using the Hatemi-J’s approach, we look for the asymmetric causality between the positive components of the two series and between the negative components of the two series. Apart from Hamilton’s technique, this methodology assumes the decomposition of the two series into positive and negative components. We then perform a crossing analysis to verify causality effects between positive components of the oil price and negative components of the REER, and also between negative components of the oil price and positive components of the REER, at different frequencies. Hence, we report four categories of results. The critical values of the tests are generated based on 10,000 bootstrap simulations.

Table 6 presents the results for the asymmetric causality between positive components of the two series.

We observe an asymmetric causality between the positive components of the two series in the very short run (D1 level of decomposition) and in the long run (D6 level). The positive components of the oil-price series cause the positive components of the REER series especially at the 3rd and the 5th levels of decomposition, as in the previous case (Hamilton’s approach).

The results show that the 8–16 month cycle in the positive components of oil price influence the positive components of the REER in the short run, thus proving the complementarity of the methodologies. At the same time, we observe a causality effect at the D6 level of decomposition, and also in the very long run.

The asymmetric causality between the negative components of the two series, in the time-frequency domain, is reported in Table 7. We discover that the 8–16 month cycle in the oil price causes a 4–8 month cycle in the negative components of the REER. The results are similar to those reported in Table 5 above. However, for the long run, the causality between the negative components of the two series seems more important (see the D6 level of decomposition).

Nevertheless, as stated in Section 4.4, the increase of the oil price is not associated in all cases with an appreciation of the domestic currency. Because the results obtained based on the CWT show that in many cases the two variables are in an anti-phase position with oil prices leading.

### Table 5

Results of the Granger causality tests (negative shocks).

<table>
<thead>
<tr>
<th>Oil</th>
<th>Time domain</th>
<th>Frequency bands (months)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>REER</td>
<td>D1</td>
</tr>
<tr>
<td>Raw series</td>
<td>2–4 M</td>
<td>4–8 M</td>
</tr>
<tr>
<td>D1</td>
<td>0.9638</td>
<td>0.9991</td>
</tr>
<tr>
<td>D2</td>
<td>0.7244</td>
<td>0.6059</td>
</tr>
<tr>
<td>D3</td>
<td>0.2513</td>
<td>0.1087</td>
</tr>
<tr>
<td>D4</td>
<td>0.6601</td>
<td>0.6408</td>
</tr>
<tr>
<td>D5</td>
<td>0.0003</td>
<td>0.1229</td>
</tr>
<tr>
<td>D6</td>
<td>0.9196</td>
<td>0.7061</td>
</tr>
<tr>
<td>S6</td>
<td>0.9999</td>
<td>0.9597</td>
</tr>
</tbody>
</table>

Note: p-values for the F-test show the rejection of null hypothesis of no causality (i.e., if p-values < 0.10, we accept the causality at 10% significance level).
we want to see if positive and the negative components of oil price also influence the negative and, respectively, the positive components of the REER.

In Table 8, we report the results of the asymmetric causality tests between the positive components of the oil price and the negative components of the REER. Not surprisingly, we find a causality relationship between positive shocks in the oil price and negative shocks in the REER, at the same level of decomposition (in the short run), as in Table 6. Consequently, the 8–16 month cycle of positive oil-price shocks (D3) cause either positive or negative shocks in the REER at the 2–4 and 4–8 month cycles. Similar observations are valid for the long run (D5 + D6). These results do not supply additional evidence on the appreciation or depreciation of the domestic currency. However, we can state that positive oil-price shocks, not only in the short run, but also in the long run, cause positive or/and negative shocks in the REER in the short run, and respectively, in the long run.

In respect of the relationship between negative shocks in the oil price and positive shocks in the REER (Table 9), we observe a causal influence from the 3rd level of decomposition of the oil price to the 2nd level of decomposition of the REER (similar results are reported in Table 7). In the case of the long run, the causality relationship is very pronounced, but less compact.

### 4.6. Policy implications

Remember that Romania presents the lowest level of retail fuel prices in the EU and it experienced one of the highest increases of the fuel prices over the last years as compared to other European countries. At the same time, the real exchange rate volatility for the domestic currency in the last years cannot be neglected. In this context, the influence of the oil price on the exchange rate movements, highlighted by our results, has several potential policy implications.

Currently, Romania is one of the candidates for the Eurozone. Against this background, the exchange rate stability is a must. According to the empirical evidence, the international oil price causes the REER in the short, as well as in the long run. In this context, particular attention must be paid by the National Bank of Romania to the international oil price in its attempt to preserve the stability of the exchange rate. The oil price must become one of the key economic indicators in the monetary policy decisions of the National Bank of Romania, as it influences not only the short term objectives, but also the strategic exchange rate objectives. Increasing consideration should be assigned to positive shocks, as these price movements have a stronger influence on the REER, both in the short and long runs.

At the same time, in order to fulfil the Maastricht criteria, the Romanian “leu” must join the ERM II (exchange rate mechanism) for at least two years. Consequently, the choice of the equilibrium exchange rate has to be made taking into account the future influences of the international oil price. Specifically, the evidence for the tail dependence in the short and long runs increases the efforts of the monetary authorities to stabilise the exchange rate. Our results are very important in this context. Although we look to positive or negative shocks in the oil price, these shocks will cause positive or negative movements in the REER, in the short and long runs. As a currency in ERM II is allowed to float within a range of ±15% with respect to a central rate against the euro, either the positive or negative shocks caused by the international oil price may determine the failure of this objective.

The international oil price and the REER co-movements have also implications for investors and for exporting companies, as their revenues are influenced by the exchange rate fluctuations. Therefore, from the risk management perspective, awareness should be raised on the short and long run positive shocks in the international oil price, especially on those shocks at the D3 and D5 decomposition levels, which influence the REER fluctuations.

### Table 6

Results of the Hatemi-J asymmetric causality between positive components of the two series.

<table>
<thead>
<tr>
<th>Oil price</th>
<th>Time domain</th>
<th>Frequency bands (months)</th>
</tr>
</thead>
<tbody>
<tr>
<td>REER</td>
<td>D1 2–4 M</td>
<td>0.16</td>
</tr>
<tr>
<td></td>
<td>D2 4–8 M</td>
<td>0.07</td>
</tr>
<tr>
<td></td>
<td>D3 8–16 M</td>
<td>0.27</td>
</tr>
<tr>
<td></td>
<td>D4 16–32 M</td>
<td>0.57</td>
</tr>
<tr>
<td></td>
<td>D5 32–64 M</td>
<td>2.52</td>
</tr>
<tr>
<td></td>
<td>D6 64–128 M</td>
<td>0.86</td>
</tr>
<tr>
<td></td>
<td>S6 (&gt;128 M)</td>
<td>9.64**</td>
</tr>
<tr>
<td>Raw series</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Note: The data reflects the W-statistic.

* ** *** shows the acceptance of the causal relationship at 10%, 5% and 1% significance levels respectively.
Using the DWT, we find a strong influence of the oil price on the real effective exchange rate in the short run, as well as in the long run. More precisely, our results of energy distribution show that, both for the oil-price returns in positive and negative frequencies, explaining most of the variance. Nevertheless, for large time horizons, the negative correlation between the series grows more important. The wavelet cross-correlation which examines the lead–lag relationship between the oil price and the REER in various time-scales shows that the oil price leads the REER and this relationship is stronger in the long run.

Two supplementary batteries of tests confirm the robustness of our results. First, we use a resampling approach and we check for the stability of this relationship after the beginning of the 1990s, a period characterised by important monetary reforms in Romania. The resampling approach confirmed the initial findings. In addition, we test the same relationship for the Czech Republic, a transition country which has in place the same managed floating exchange rate regime. The results present several similarities, except for the long run, but they must be interpreted with caution and cannot be generalised. Second, we employ a complementary CVT, which allows us to observe common movements in the two series, causality relationships and month-cycle correlations. The results obtained based on the CVT confirm the DWT findings and bring forward additional evidence. First of all, an anti-phase relationship is documented between the two variables in most of the cases, which means that an increase of the oil price is associated with a real appreciation of the Romanian "leu". However, there are also periods where the two variables are in-phase at different frequency bands. In most of the cases, the oil price is leading the REER.

In order to see if the causality relationship varies across frequencies, we have performed scale-by-scale Granger causality tests. In the classical VAR and one-shot Granger causality approach, no causality can be found between these two variables. The Granger causality tests across frequencies confirm the fact that, in the short run (D1, D2, D3), but also in the long run (D5), there is strong evidence that the international oil price causes the REER in Romania.

We have further developed our analysis by decomposing the time-frequency bands for the oil-price returns in positive and negative shocks, following Hamilton's approach. Performing the same Granger causality test across frequency bands, we have discovered that the positive shocks associated with an increase in the oil price have a more powerful impact on the REER movements in the short run than the negative shocks. We have also observed that in the long run, both the positive and negative shocks in oil price returns cause REER fluctuations in Romania. In order to check for the robustness of these results, we have used a second approach which allows for assessing the

### Table 8

<table>
<thead>
<tr>
<th>Oil price</th>
<th>Time domain</th>
<th>Frequency bands (months)</th>
</tr>
</thead>
<tbody>
<tr>
<td>REER</td>
<td>Raw series</td>
<td>D1 2-4 M</td>
</tr>
<tr>
<td></td>
<td></td>
<td>0.41</td>
</tr>
<tr>
<td></td>
<td>D1</td>
<td>1.04</td>
</tr>
<tr>
<td></td>
<td>D2</td>
<td>0.32</td>
</tr>
<tr>
<td></td>
<td>D3</td>
<td>0.42</td>
</tr>
<tr>
<td></td>
<td>D4</td>
<td>3.06</td>
</tr>
<tr>
<td></td>
<td>D5</td>
<td>1.77</td>
</tr>
<tr>
<td></td>
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</tr>
<tr>
<td></td>
<td>S6</td>
<td>6.49</td>
</tr>
</tbody>
</table>

Note: The data reflects the W-statistic.
* shows the acceptance of the causal relationship at 10%, ** at 5% and *** at 1% significance levels respectively.

### Table 9

<table>
<thead>
<tr>
<th>Oil price</th>
<th>Time domain</th>
<th>Frequency bands (months)</th>
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<tbody>
<tr>
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<td>D2</td>
<td>0.83</td>
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<td>10.31***</td>
</tr>
<tr>
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<td>D4</td>
<td>2.29</td>
</tr>
<tr>
<td></td>
<td>D5</td>
<td>1.72</td>
</tr>
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<td></td>
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<tr>
<td></td>
<td>S6</td>
<td>0.14</td>
</tr>
</tbody>
</table>

Note: The data reflects the W-statistic.
* shows the acceptance of the causal relationship at 10%, ** at 5% and *** at 1% significance levels respectively.
asymmetric causality between the two series. The Hatemi-j’s methodology reveals the same results in the case of positive and negative cumulative shocks. In both cases, the 8–16 month cycle in the oil price causes a 4–8 month cycle in the REER. However, despite these additional results, we cannot state if the positive shocks in the oil price determine a currency appreciation or depreciation, as both results are valid according to the Hatemi-j’s methodology.

Our main findings have some important policy implications. The National Bank of Romania must pay particular attention to the international oil price when establishing the equilibrium exchange rate for joining the ERM II. Additionally, taking into account the fact that the level of the retail oil prices in Romania is reduced and that there still remains enough room for further increases, the REER becomes more sensitive to international oil prices. Consequently, the monetary authorities could be required to undertake considerable efforts in their attempt to stabilise the exchange rate and to pay particular attention to shocks in oil prices when defining short and long term exchange rate objectives.

Acknowledgements

The authors would like to thank the two anonymous referees for their valuable comments and suggestions on this paper. The authors are fully responsible for any remaining shortcomings.

Appendix A. Discrete wavelet transform

The discrete wavelet transform (DWT)

Daubechies’ (1992) wavelet filter coefficients are \( h_l = (h_{1,0}, \ldots, h_{1, t}, t = 1, \ldots, 0, \ldots, 0) \), which compactly supports the Daubechies’ wavelet unit scale, and is zero-padded to length \( N \).

By this definition, we consider \( h_{1,j} = 0 \) for \( l > L \). Moreover, the wavelet filter must satisfy three properties, as follows:

\[
\sum_{l=0}^{L-1} h_{1,l} = 0; \quad \sum_{l=0}^{L-1} h_{1,l}^2 = 1; \quad \sum_{l=0}^{L-1} h_{1,l+2n} = 0 \quad \text{for all non-zero integers } n
\]

Based on these conditions, the wavelet filter must sum to zero (have zero mean), must have unit energy and must be orthogonal to its even shifts.

Consider \( g_l = (g_{1,0}, \ldots, g_{1, L-1}, 0, \ldots, 0) \) as being the zero-padded scaling filter coefficients, which are defined through \( g_{1,l} = (-1)^{1-l} h_{1,l+1}, \ldots, \) and let \( x_0, \ldots, x_{N-1} \) be a time-series. For scales with \( N \gg L \), where \( L = \left(2^j - 1\right)\left(L - 1\right) + 1 \), in order to obtain the wavelet coefficients, the time-series can be filtered using \( h_l \):

\[
W_{j,l} = 2^{j/2} \tilde{W}_{j/2, l-1}; \quad \left[\left(l-2\right) - \left(1 - \frac{1}{2}\right)\right] \leq t \leq \left[\frac{N}{2^{j-1}}\right],
\]

where:

\[
\tilde{W}_{j,l} = \sum_{l=0}^{L-1} h_{1,l} x_{t-l}, \quad t = L - 1, \ldots, N - 1
\]

The \( \tilde{W}_{j,l} \) coefficients, associated with changes on a scale of length \( \tau_j = 2^j \), are obtained by sub-sampling every 2\( \text{th} \) of the \( W_{j,l} \) coefficients.

Two main drawbacks characterise the orthogonal discrete wavelet transform (DWT): the dyadic length requirement (i.e., a sample size divisible by 2\( j \)), and the wavelet and scaling coefficients, which are not shift-invariant as a result of their sensitivity to circular shifts (there is a decimation operation).

Maximal overlap DWT (MODWT)

A non-orthogonal variant of DWT is an alternative to DWT, talking here about the maximal overlap DWT (MODWT), which is opposite to DWT. In this situation, the MODWT does not decimate the coefficients, the number of scaling and wavelet coefficients at every level of transform being the same as the number of sample observations. Even if the MODWT loses the orthogonality and efficiency in computation, this approach does not have limitation in any sample size and it is shift-invariant. Wavelet coefficients, \( \tilde{W}_{j,l} \) and scaling coefficients \( \tilde{V}_{j,l} \) at levels \( j = 1, \ldots, J \), are:

\[
\tilde{W}_{j,l} = \sum_{l=0}^{L-1} g_{1,l} \tilde{W}_{j-1,l-1} \text{ mod } N \quad \text{and} \quad \tilde{V}_{j,l} = \sum_{l=0}^{L-1} h_{1,l} \tilde{V}_{j-1,l-1} \text{ mod } N.
\]

The wavelet and scaling filters, \( g_{1,l}, h_{1,l} \), are rescaled as \( \tilde{g}_{1,l} = g_{1,l}/2^{j/2}, \tilde{h}_{1,l} = h_{1,l}/2^{j/2} \).

The differences between generalised averages of the scale data \( \tau = 2^{j-1} \) are non-decimated wavelet coefficients. The MODWT presents several advantages as compared to DWT: MODWT can handle any sample size, it is translation-invariant, and can provide an increase in resolution at coarser scales. In the wavelet correlation analysis, we also note that the MODWT offers a larger sample size and produces a more asymptotically efficient wavelet covariance estimator than the DWT.

Appendix B. Continuous wavelet transform

The continuous wavelet transform (CWT)

In both the frequency and time-scales, the wavelet is a function with a zero mean. A wavelet include both a time \( (dt) \) and a frequency \( (do or \text{ the bandwidth}) \) dimension. We define a limit to the smallness of the uncertainty product \( dt \cdot doa \). According to the specification of a particular wavelet, the Morlet wavelet is defined as:

\[
\psi_0(\omega) = C^{-1/4} e^{in_0 \omega} e^{-\omega^2}
\]

where: \( \omega_0 \) is a dimensionless frequency and \( \alpha \) is a dimensionless time.

The Morlet wavelet (with \( \omega_0 = 6 \)) is a good choice in economic data analysis because it provides a satisfactory balance between time and frequency localisation. We therefore restrict our further treatment to this wavelet. The idea behind the CWT is to apply the wavelet to the time-series as a band pass filter. The wavelet is stretched in time by varying its scale \( (s) \) such that \( \alpha = s \cdot \tau \) and normalising it to unit energy. For the Morlet wavelet (with \( \omega_0 = 6 \)), the Fourier period \( (\lambda_{int}) \) is nearly equal to the scale \( (\lambda_{int} = 1.03s) \). The CWT of a time-series \( a_t, t = 1, \ldots, N, N \) with uniform time-steps \( dt \) is defined as the convolution of \( x_n \) with the scaled and normalised wavelet.

\[
W_t(s) = \sum_{n=-\infty}^{\infty} x_n \psi_0 \left[ \frac{t-n}{s} \right]
\]

We define the wavelet power as \( |W_t(s)|^2 \). The complex argument of \( W_t(s) \) is interpreted as the local phase. The CWT contains edge artefacts because the wavelet is not completely localised in time. The cone of influence (COI) overcomes this limitation. It can be associated with the white-noise and red-noise wavelet power spectra, from which the corresponding distribution for the local wavelet power spectrum at each time \( n \) and scale \( s \) is derived under the null, is as follows:

\[
D \left( \frac{|W_t(s)|^2}{\sigma^2_s} < p \right) = \frac{1}{2} P_s X_t^2 \left( p \right)
\]

where: \( \nu \) is equal to 1 for real and 2 for complex wavelets.
The cross-wavelet transform (XWT)

The cross-wavelet transform of two time-series $a_t$ and $b_t$ is defined as $W_{ab} = W_x W_y^*$, where $W_x$ and $W_y$ are the wavelet transforms of $x$ and $y$, respectively, and $*$ denotes complex conjugation. The cross-wavelet power is defined as $|W_{ab}|^2$. The complex argument $\arg W_{ab}$ is interpreted as the local relative phase between $a_t$ and $b_t$ in time-frequency space. The theoretical distribution of the cross-wavelet power of two time-series with background power spectra $P_x$ and $P_y$, is given in Torrence and Compo (1998) as:

$$D \left( \frac{|W_{ab}(s)|^2}{\sigma_x \sigma_y} \right) < p = \frac{Z(p)}{\sqrt{\frac{\pi}{2}}}$$

where: $Z(p)$ is the confidence level associated with the probability $p$ for a pdf defined by the square root of the product of $\chi^2$ distributions.

On the one hand, the wavelet power spectrum depicts the variance of a time-series with occurrences of large variance indicating large power. On the other hand, the cross-wavelet power of two time-series depicts the covariance between these time-series at each frequency.

The wavelet coherence (WTC)

The wavelet coherence is defined as the ratio of the cross-spectrum to the product of the spectrum of each series and is treated as the local correlation both in time and frequency between two time-series. At the same time, the wavelet coherence is defined as the ratio of the cross-spectrum to the product of the spectrum of each series (Aguiar-Conraria et al., 2008). Following Torrence and Webster (1999), we define the WTC of two time-series as:

$$R^2_t(s) = \frac{\left| S \left( s^{-1} W_{ab}^*(s) \right) \right|^2}{\left| S \left( s^{-1} |W_x(s)|^2 \right) \right| \left| S \left( s^{-1} |W_y(s)|^2 \right) \right|}$$

where: $S$ is a smoothing operator.

The cross wavelet phase angle

We estimate the mean and confidence interval of the phase difference, in order to see if the series are in-phase or out-of-phase. Consequently, we use the circular mean of the phase over regions with statistical significance greater than 5% (i.e. outside the COI), to quantify the phase relationship. The circular mean of a set of angles ($a_t$, $t = 1, ..., n$) is:

$$a_m = \arg (A, B), \text{ with } A = \sum_{t=1}^{n} \cos (a_t) \text{ and } B = \sum_{t=1}^{n} \sin (a_t)$$

In order to calculate the confidence interval of the mean angle, we define the circular standard deviation as:\n
$$s = \sqrt{2 \ln(R/t)}$$


The circular standard deviation is analogous to the linear standard deviation and varies from zero to infinity. At the same time, the phase angle is quantified as a number of months.

Monte Carlo simulation methods are used to obtain the statistical significance level of the wavelet coherence. We generate a large ensemble of surrogate data set pairs with the same AR(1) coefficients as the input datasets and we compute the wavelet coherence for each pair.


Energy decomposition

<table>
<thead>
<tr>
<th>Wavelet scales</th>
<th>Oil price</th>
<th>REER</th>
</tr>
</thead>
<tbody>
<tr>
<td>D1 (2–4 Month Cycles)</td>
<td>35.72%</td>
<td>27.59%</td>
</tr>
<tr>
<td>D2 (4–8 Month Cycles)</td>
<td>24.31%</td>
<td>29.06%</td>
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<tr>
<td>D3 (8–16 Month Cycles)</td>
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<td>29.37%</td>
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<tr>
<td>D4 (16–32 Month Cycles)</td>
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<tr>
<td>S6 (Above 128 Month Cycles)</td>
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<td>1.34%</td>
</tr>
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</table>

Wavelet covariance and correlation

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13 The number of angles used in the calculation can be set arbitrarily high, simply by increasing the scale resolution.

Energy decomposition

<table>
<thead>
<tr>
<th>Wavelet scales</th>
<th>Oil price</th>
<th>REER</th>
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</thead>
<tbody>
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<tr>
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Wavelet covariance and correlation

Wavelet cross-correlation
Appendix E. Supplementary data

Supplementary data to this article can be found online at http://dx.doi.org/10.1016/j.eneco.2013.08.016.

References


