Oil price, exchange rate and consumer price co-movement: A continuous-wavelet analysis

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Oil Price, Exchange Rate and Consumer Price Co-movement: A Continuous-wavelet Analysis

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Abstract

Using the cross-wavelet coherency, partial-wavelet coherency and wavelet phase-difference, this paper investigates the time-frequency co-movement among crude oil price, Rwandan Franc/USD exchange rate and consumer price index. The time-frequency analysis unveils the strong dependency between oil prices and exchange rate; the two series are in phase at a short cycle of three to four months. This co-movement intesnfied and expanded to intermediate scales of four to sixteen months beginning late 2007, the onset of global financial crisis. There is evidence that oil prices might have significantly contributed to the depreciation of the Rwandan Franc that depreciated by 446% in only 21 years. This effect varies in time and frequency. Our findings suggest that there is no singificant time-frequency relationship between, on one side oil prices and consumer prices, and exchange rate and consumer prices on the other side. This implies that oil prices are not inflationary, which provides greater freedom for pursuing an independent monetary policy, and makes it easier for the Central Bank to possibly implement inflation targeting in the future. However, fiscal and monetary authorities need to devise policies to attenuate the effect of oil shocks on macroeconomic stability, including the effect of continuous depreciation of the Rwandan Francs on the balance of trade, and on external debt servicing since debt is denominated in foreign currencies.

Key words: Consumer prices, continuous wavelet, exchange rate, oil price, time-frequency analysis, wavelet coherency

JEL: C22; E31; E32; F31; F41; Q43

1. Introduction

The increasing volatility in oil prices has fueled a lot more interest in understanding the relationship between oil prices and the macroeconomy. Understanding the role played by oil prices is paramount, especially for developing and oil-importing countries. One of the challenges that developing countries face is the incessant deterioration of the terms of trade coupled with the depreciation of currencies. The relationship between the deterioration of the terms of trade and exchange rates in developing countries has been linked to the exchange rate regime. The deterioration of the terms of trade, as pointed out by Broda (2004), leads to a small and slow depreciation of exchange rates in developing countries with a currency peg but a large and immediate real exchange rate depreciation in country where the exchange rate is floating. There has been numerous studies that have investigated the sources of fluctuations in exchange rates. Traditionally, it was believed that exchange rates are affected solely by monetary shocks. However, as argued by Clarida and Gali (1994), Lastrapes (1992) and Chaudhuri and Daniel (1998), real shocks can account for an important share in the variance of exchange rate. Oil prices have been cited as a non-monetary source of exchange rate fluctuations. As pointed out by Krugman (1983), for an oil-importing country, a rise in the price of oil worsens the balance of payments and eventually lead to currency depreciation, while it generates the current account surplus for oil exporters. In order to improve competitiveness, the home country would have to raise the nominal exchange rate, which would eventually lead to further depreciation (Chen and Chen, 2007).

A plethora of studies have investigated the effect of oil prices on the macroeconomy of oil-exporting countries, but little is known about the same effect in landlocked imports-dependent countries like Rwanda. The Rwandan economy heavily depends on imported products in general and on imported oil in particular. Rwanda has no access to the sea, which may multiply the effect of oil prices on prices of imported products through transport costs. Figure 1 shows the widening overtime of the gap between imports and exports. It can be observed how the value of imports of energy products has been increasing. There are different plausible causes of the situation in Figure 1, one potential channel is the increase in oil prices that worsens the terms of trade and eventually accelerates the depreciation of the Rwandan Franc.

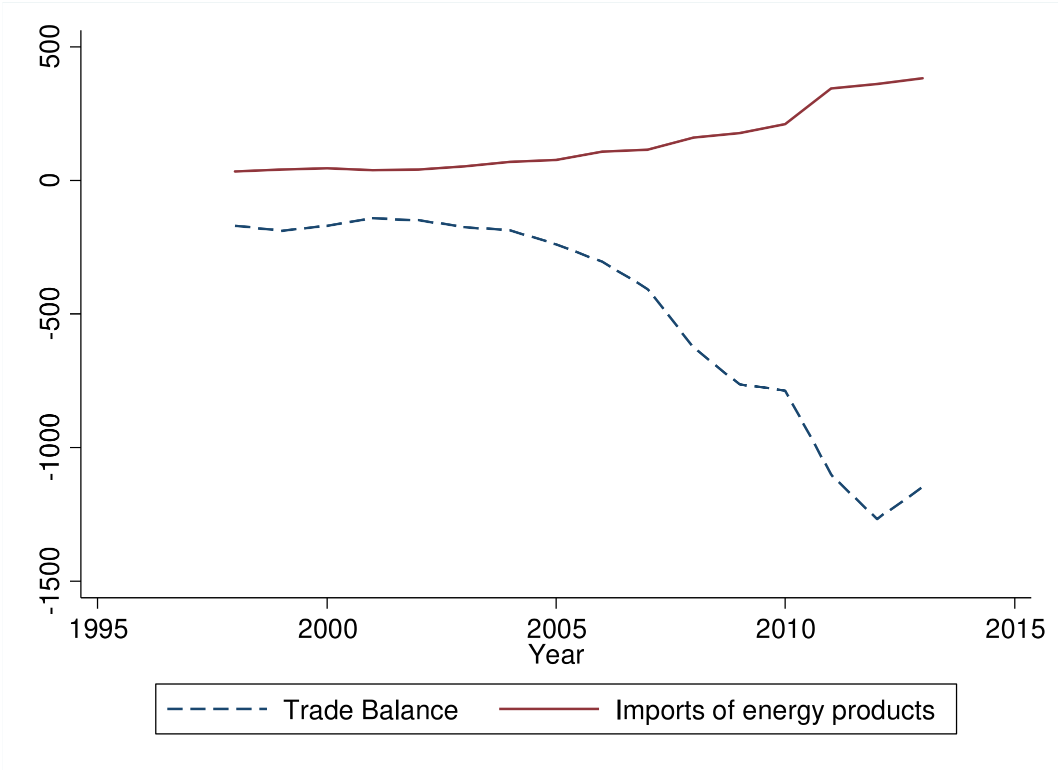


Fig.1 Balance of trade and imports of energy products, in millions USD

Source: National Bank of Rwanda

The period depicted in Figure 1 has been marked by high rates of economic growth mainly due to post-war reconstruction that might have put pressure on the imports of energy products. The lack of direct sea-access coupled with soaring and volatile oil prices have reduced the competitiveness of exported products, which have to be road-transported to the port before being shipped to their destination, adding a margin to their prices. As argued by Amjadi and Yeats (1995), the incidence of transport costs fall heavily on the landlocked African countries since they have to adjust their selling price to world prices. Limao and Venables (2001) and Irwin and Terviö (2002) point out that landlocked countries trade on average 30% less than coastal countries.

The non-access to the sea affects imports as well. Compared to coastal countries, landlocked countries pay more and wait longer. Moreover, the dependence on the transit countries adds more transaction costs, plus delays and negative externalities whenever there is political instability or uncertainty in transit countries, for example the 2007-08 post-election violence in Kenya when roads that connect Kenya to neighboring countries were blocked and truck and rail lines vandalized, which had repercussions on the economies of neighboring countries that rely on Kenya’s Mombasa port.

Considering the mentioned challenges, the objective of this study is to examine the relationship between oil prices and exchange rate, and possible pass-through to consumer prices. The approach followed supersedes several previous studies that have investigated the same co-movement in the time domain. Our approach combine both the time and the frequency domains, which helps to capture the effect of oil price shocks across time and at different time scales. The rest of the paper is organized as follows. Section 2 discusses the existing literature. Continuous wavelet analysis is amply described in Section 3. Findings are presented and discussed in the fourth section. Section 6 concludes.

2. Theoretical and empirical background

2.1.Oil prices and exchange rate co-movement

Krugman (1983) proposes a theoretical framework to explain the effect of oil prices on exchange rate through the balance of payments. For an oil-importing country, a rise in the price of oil worsens the balance of payments and eventually lead to currency depreciation, while it generates current account surplus for oil exporters. By the same token, Golub (1983) argues that oil price increase raises the current account surplus of oil exporters and the current account deficit of oil importing countries (wealth redistribution), eventually reducing expenditure on oil and leading to the depreciation of currencies of oil-importing countries.

The link between oil price and exchange rate can be explained using the law of one price (LoP). The LOP or the absolute version of the PPP stipulates that, converted in the same currency, a good must sell for the same price in all locations. Thus, for any good j, in this case oil,

$$P_j = E.P_j^* \tag{1}$$

Where P_j is the price of oil in domestic currency; P_j^* is the price in foreign currency, and E is the nominal exchange rate.

Applying log transformation to equation (1), one gets

$$p_j = e + p_j^* \tag{2}$$

Where small letters stand for the variables in logarithm. As pointed out by Reboredo and Rivera-Castro (2013), equation (2) can be used to explain the effect of USD exchange rate on oil prices. The appreciation of the Home country’s currency (a reduction in e) reduces the oil price (since $p_j - e = p_j^*$) for foreigners relative to their commodities priced in foreign currencies, increasing thereby the purchasing power and oil demand of foreign consumers; thus pushing up the price of oil. In reality, however, the LOP is less likely to hold. As Rogoff (1996) points out, prices differ in different locations due to transportation costs, tariffs, and other nontariff barriers. This argument very much hold for a landlocked country. The transport of oil using oil whose price has increased, leads to higher wedge in prices between landlocked and those that have access to the sea. High transport costs (since the arbitrageur would need oil to transport oil) make even arbitrage less likely even when the LOP does not hold.

Generalizing equation (2) to any good, following Chen and Chen (2007) and Reboredo and Rivera-Castro (2013), and taking a log-linear approximation of the home and foreign country consumer price indexes given by

$$p = \left(1-\omega\right) p^T + \omega p^N \tag{3}$$

$$p^* = \left(1-\omega^*\right) p^{T^*} + \omega^* p^{N^*} \tag{4}$$

Where p^T and p^N are the price of traded and nontraded goods, respectively. The star ($*$) shows foreign country. ω is the expenditure share of nontraded goods. The nominal exchange rate e can be expressed as

$$e = \left(p^N - p^{N^*}\right) + \left(1-\omega^*\right)\left(p^{T^*} - p^{N^*}\right) - \left(1-\omega\right)\left(p^T - p^N\right) \tag{5}$$

Equation (5) tells us that, assuming $\omega \simeq \omega^*$, for a home country that is dependent on imported oil, an increase in oil price increases the relative prices of traded goods in the home country more proportionally than in the foreign country, thereby increasing e. This depreciation would be intensified for a landlocked country that imports the totality of oil necessary to run its economy.

Empirically, several studies have investigated the nexus between global oil prices and exchange rates. These studies can be categorized according to the econometric methodology they apply. The first category, that constitutes the majority, has investigated this link in a time domain. A bulk of studies in this category have applied cointegration and Granger causality. However, their findings differ according to the direction of the causality that they find. For example Chen and Chen, (2007), Lizardo and Mollick (2010), Camarero and Tamarit (2002) and Amano and van Norden (1998), employing cointegration and Granger causality, argue that global oil prices can explain the long-run fluctuations in exchange rates, while other studies suggest that exchange rates can explain movements in oil prices (see for example Pindyck and Rotemberg (1990); Sadorsky, 2000; Yousefi and Wirjanto, 2004; Zhang et al., 2008).

Beckmann, Berger and Czudaj (2015) use daily data to analyze the co-movements between oil prices and exchange rates before and after the financial crisis for different oil exporting and importing countries. They conclude that the intensity of the relationship between oil prices and exchange rates has increased over time, and the dependency between the two series became more dynamic after the onset of financial crisis. Moreover, the increase in oil prices led to the depreciation of currencies of oil importers and to the appreciation of oil exporters with, however, a different dependency structure. These results are similar to what has been found by Reboredo (2012) who suggests that there are different types of causality for different currencies with an increasing intensity of the relationship between oil prices and dollar exchange rates after the onset of the global financial and economic crisis.

Very recently, Pershin, Molero and De Gracia (2016) employ a Vector AutoRegressive (VAR) model to investigate the impact of oil prices on the exchange rates and short term interbank interest rates in Botswana, Kenya and Tanzania. Their results suggest that an oil price shock leads to the appreciation of local currencies in the short-run. Moreover, they point out that the relevance of oil prices as an explanatory variable of exchange rates increased after the 2008 financial crisis.

Besides the unidirectional effect, there are studies that have found evidence of biderictional causality (for example Kisswani, 2016), while others have found weak or no co-movement at all (Huang and Guo, 2007; Chen, Rogoff, and Rossi, 2010; Czudaj and Beckmann, 2013).

The second category of studies, which is more relevant for the present study, has investigated oil prices and exchange rate co-movement using wavelets. In this category, most of the studies have applied discrete wavelet transform in a multiscale analysis. Tiwari et al (2012) use a battery of non-linear causality tests in a multiscale analysis. Their findings suggest that there are linear and nonlinear causal relationships between oil price and real effective exchange rate of Indian rupee at higher scales. Similarly, Reboredo and Rivera-Castro (2013) investigate the relationship between oil prices and US dollar exchange rates using wavelet multi-resolution analysis for a diverse group of countries including developed and emerging economies, net oil-exporting and oil-importing. They find evidence of contagion and negative dependence after the onset of the crisis but not before the crisis. Overall, this category of studies seem to suggest that the co-movement between oil prices and exchange rate has changed overtime, therefore justifying the relevance of continuous wavelets.

2.2.Exchange rate pass-through to consumer prices

The collapse of the Bretton Woods system in the early 1970s led countries to switch from fixed to floating exchange rates. The fear and uncertainty of floating has fueled research to understand how much of exchange rate fluctuation is actually passed on to other prices. Traditionally the interest has been to assess the pass-through from exchange rate to import prices. Since the introduction of inflation targeting in the 1990s, there has been more interest in understanding the exchange rate pass-through (ERPT) to consumer prices. As pointed out by Choudhri and Hakura (2006), a low ERPT provides greater freedom for pursuing an independent monetary policy and to make it easier to implement inflation targeting. Taylor (2000) proposes a microeconomic model of firm behavior based on staggered price setting and monopolistic competition. The model indicates that the extent to which a firm matches an increase in costs or prices by increasing its own price depends on how persistent the increase is expected to be. High-inflation countries tend to have more persistent costs, and thus higher ERPT to domestic prices.

Choudhri and Hakura (2006) extend Taylor's model of ERPT to incorporate imperfect competition and price inertia in a framework of staggered price adjustment framework. They argue that the change in exchange rate is initially passed-through to a fraction of goods whose prices are being reset; expectations play a crucial role since firms take into account the influence of the exchange rate on the expected values of future costs and prices. Since the effect of monetary shocks tends to be more persistent and is likely to be reflected in exchange rate changes to a larger degree, the ERPT is therefore larger in high inflation regimes.

Devereux and Yetman (2010) develops a simple theoretical model that can be used to account for the determinants of ERPT to consumer prices. In their model, sticky prices represent a key determinant of ERPT. They claim that a slow adjustment in price explains low ERPT, and that ERPT is increasing in average inflation, but, unlike previous theoretical models, at a declining rate.

Empirically, the theoretically-predicted low ERPT has been investigated. Calvo and Reinhart (2002) find that, compared to developed countries, the ERPT is much higher especially in countries with high inflation episodes. Similarly, Ito and Sato (2008) examine the pass-through effects of exchange rate changes on the domestic prices in the East Asian economies. Their findings suggest that the ERPT to Consumer Price was generally low. Several other studies investigated the ERPT to domestic prices (Antzoulatos and Yang, 1996; Goldberg and Knetter, 1997; Nidhaleddine and Waël, 2016, to name but a few).

The discussed literature provides evidence in the time-domain. Using wavelets, it is possible to observe the dynamics both in time and frequency of the co-movement between exchange rate and consumer prices, which is the contribution of this paper.

3. Wavelet analysis

Measuring the co-movement among economic variables is a longtime practice in the econometrics literature. Traditionally, co-movements have been analyzed in the time domain. However, the time-domain analysis is not able to capture those features that vary across not only time but also across frequencies. It is in this context that the Fourier Transform (FT) has been developed as a tool for frequency-domain analysis. However, the FT is appropriate only if the time series are periodic and the frequencies do not change over time; it is appropriate for stationary time series. Moreover, the FT is able to keep only the information on frequencies, but the time information is lost. And because of this loss of information, it is impossible to distinguish transient relations or to identify structural changes (Aguiar-Conraria and Soares, 2011).

Since the seminal work of Nelson and Plosser (1982), it has been an empirical regularity that economic time series in general are not stationary and thus the FT is not suitable for econometric analysis. As a remedy to the shortcomings of the FT, wavelet analysis has been developed. Unlike Fourier analysis, wavelet analysis helps to estimate the spectral characteristics of the time series as a function of time, giving information on change over time of periodic components of the time series. The wavelet transform (WT) is able to perform natural local analysis of the time series by stretching into a long function and compressing into a short function to measure the low frequency movements and the high frequency movements, respectively (Aguiar-Conraria and Soares, 2011).

It is worth mentioning however, that the application of wavelets in economics is very recent and has been mainly dominated by the use of the discrete wavelet transform (DWT), especially the maximum overlap discrete wavelet transform (MODWT). Crowley (2007) provides a survey of these studies. The DWT however, has not been very convincing. As pointed out by Aguiar-Conraria, Azevedo and Soares (2008), it is not easy to justify the difference between the DWT and the traditional practice of using the band-pass filtering methods. To overcome this critique, a method that is able to study the interaction between time series overtime and at different frequencies is needed. To assess the co-movement among oil prices, exchange rate and consumer prices , three continuous wavelet tools, as proposed by Hudgins et al. (1993) and Torrence and Compo (1998), are applied: the cross-wavelet transform, the cross-wavelet coherency, and the wavelet phase-difference. The wavelet power spectrum describes the evolution of the variance of a time-series at the different frequencies, the wavelet coherency can be seen as a localized correlation coefficient in the time–frequency space. The phase-difference gives information on the delay between the oscillations of two time-series (Aguiar-Conraria and Soares, 2011).

3.1.The continuous wavelet transform (CWT)

The CWT decomposes the time series in terms of elementary functions $\psi_{\tau,s(t)}$ derived by translation and dilation from the time-localized mother wavelet. τ is the translation parameter controlling for the location of the wavelet, and s is the dilation or scaling parameter that controlls for the width of the wavelet.

From the mother wavelet ψ, a family of "wavelet daughters" $\psi_{\tau,s}$ is obtained by scaling and translating ψ:

$$\psi_{\tau,s(t)} = \frac{1}{\sqrt{|s|}}\psi\left(\frac{t-\tau}{s}\right), \quad \mathrm{s}, \tau \in \mathbb{R},\ \mathrm{s} \neq 0 \tag{6}$$

Where the normalization factor $\frac{1}{\sqrt{|s|}}$ ensures that the wavelet transforms are comparable across time and frequencies.

The CWT of a time series $x(t) \in L^2(\mathbb{R})$ is given by:

$$W_x(\tau,s) = \int_{-\infty}^{+\infty} x(t)\psi^*_{\tau,s(t)}(t)\,dt = \frac{1}{\sqrt{s}}\int_{-\infty}^{+\infty} x(t)\psi^*\left(\frac{t-\tau}{s}\right)dt \tag{7}$$

Where $*$ denotes the complex conjugate.

After the transformation the process can be reversed to recover the original series $x(t)$ using the inverse wavelet transform by integrating over all scales and time positions through the following parseval-type relation:

$$x(t)=\frac{2}{C_\psi}\int_{-\infty}^{+\infty}\int_{-\infty}^{+\infty}\psi_{\tau,s}(t)W_x(\tau,s)\frac{d\tau ds}{s^2} \quad (8)$$

Where C_ψ is admissibility constant[1]

3.2.Morlet wavelet

To perform a wavelet transform, one needs a mother wavelet. There are currently three choices: Morlet, Paul, and DOG (Derivative of Gaussian, whose imaginary part, unlike others, is zero). Throughout this paper the Morlet wavelet is chosen. The Morlet wavelet is defined as

$$\psi_{\omega_0}(t)=\pi^{\frac{-1}{4}}e^{i\omega_0 t}e^{\frac{-t^2}{2}} \quad (9)$$

There are four properties that make the Morlet wavelet the most popular of the complex valued wavelets (see Aguiar-Conraria and Soares, 2011). Among others, the fact that the peak frequency, the energy frequency and the central instantaneous frequency of the Morlet wavelet are all equal (equal to ω_0) facilitate the conversion from scales to frequencies. It has been shown through Monte Carlo simulation that when $\omega_0=6$, $f=\frac{6}{2\pi s}\approx\frac{1}{s}$ and the Heisenberg box reaches its lower bound. The Morlet wavelet has an optimal joint time-frequency concentration in the Heisenberg sense.

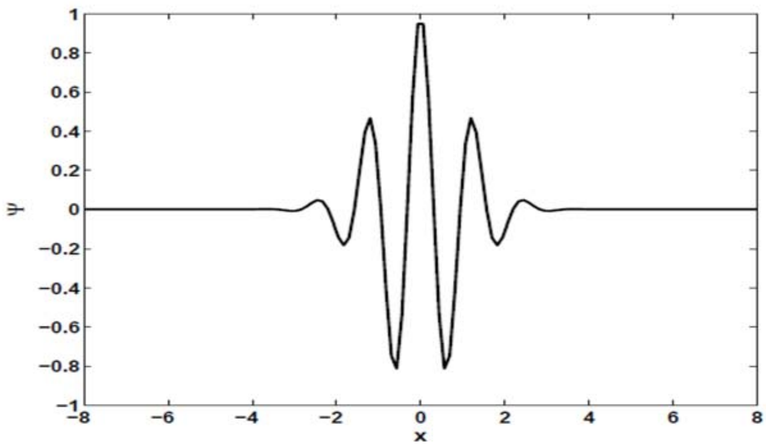


Fig.2 Morlet wavelet

[1] This is guaranteed by the admissibility condition imposed on mother wavelet that

$$0<C_\psi:=\int_{-\infty}^{+\infty}\frac{|\Psi(\omega)|}{|\omega|}d\omega<\infty$$

3.3. Wavelet power spectrum

The wavelet power spectrum (WPS) also called *wavelet periodogram* measures the relative contribution to the variance of the time series. It depicts the local variance of the time series, and it is defined as:

$$(WPS)_x(\tau,s)=\left|W_x(\tau,s)\right|^2 \tag{10}$$

Which can be averaged over time to obtain the *global wavelet power spectrum* given by:

$$(GWPS)_x(s)=\int_{-\infty}^{+\infty}\left|W_x(\tau,s)\right|^2 d\tau \tag{11}$$

To recover the total variance of the series, the WPS is integrated across τ and s:

$$\sigma_x^2=\frac{1}{C_\psi}\int_{-\infty}^{+\infty}\int_{-\infty}^{+\infty}\left|W_x(\tau,s)\right|^2\frac{d\tau ds}{s^2} \tag{12}$$

3.4. The cross-wavelet spectrum and the cross-wavelet power

First introduced by Hudgins, Friehe and Mayer (1993), the cross-wavelet spectrum the covariance between two series in the time-frequency space. The cross-wavelet spectrum of $x(t)$ and $y(t)$ is defined as

$$W_{xy}(\tau,s)=W_x(\tau,s)W_y^*(\tau,s) \tag{13}$$

Where W_x and W_y are the respective wavelet transforms. From the cross-wavelet spectrum, Croux, Forni and Reichlin (2001) suggest a counterpart to the usual coefficient of correlation in the time domain defined as

$$\rho_{xy}(\tau,s)=\frac{\Re\left(W_{xy}(\tau,s)\right)}{\sqrt{\left|W_x(\tau,s)\right|^2\left|W_y(\tau,s)\right|^2}} \tag{14}$$

Where the cross-wavelet spectrum is decomposed into real and imaginary parts, and $\Re$ denotes the real part that measures the contemporaneous variance. $\rho_{xy}(\tau,s)$ ranges between -1 and 1 and helps to quantify the co-movement in the time-frequency space and assess over which periods of time and frequencies is the co-movement higher (Rua, 2010).

The cross-wavelet power indicate areas where the time series have a high common power. It is defined as

$$\left(XWP\right)_{xy} = \left|W_{xy}\right| \tag{15}$$

3.5. Cross-wavelet coherency (WTC)

Unlike the wavelet power, the wavelet coherency is able to detect regions in time-frequency space where the two series co-move. The series do not necessarily need to have a high common power. The wavelet coherency is the ratio of cross-spectrum to the product of the spectrum of each series. It can be interpreted as the local correlation between the two wavelet transforms. It is defined as

$$R_{xy} = \frac{\left|S\left(W_{xy}\right)\right|}{\left[S\left(\left|W_x\right|^2\right)S\left(\left|W_y\right|^2\right)\right]^{\frac{1}{2}}} \tag{16}$$

With $0 \le R_{xy} \le 1$. S is the smoothing operator in both time and scale.

3.6. Partial wavelet coherency

Partial wavelet coherency is used to analyze the association between two series accounting for the interactions with other series. It is a simple generalization of the corresponding concept of partial correlation in the time-domain, or (Fourier) partial coherency in the frequency domain, onto the time-frequency plane (Priestley, 1992; Aguiar-Conraria and Soares, 2014). It is defined by

$$r_{xy.z} = \left|\frac{\zeta_{xy} - \zeta_{xz}\zeta_{yz}}{\sqrt{\left(1-R_{xz}^2\right)\left(1-R_{yz}^2\right)}}\right| \tag{17}$$

Where R_{xy} is defined by equation (16), and ζ_{xy} is the complex wavelet coherency defined by

$$\zeta_{xy} = \frac{S\left(W_{xy}\right)}{\left[S\left(\left|W_x\right|^2\right)S\left(\left|W_y\right|^2\right)\right]^{\frac{1}{2}}} \tag{18}$$

3.7. Wavelet phase difference

It is important to know the delays of cycles of the studied series. The wavelet phase difference serves this purpose. The phase difference is an angle given by:

$$\phi_{xy} = \tan^{-1}\frac{\Im\left(W_{xy}\right)}{\Re\left(W_{xy}\right)} \qquad (19)$$

Where $\phi_{xy} = \phi_x - \phi_y$, with $\phi_{xy} \in (-\pi, \pi)$; and $\Im$ and $\Re$ are the imaginary and real parts, respectively. $\phi_{xy} = 0$ indicates that the time series have a positive covariance (move together) at a given frequency; $\phi_{xy} \in \left(0, \frac{\pi}{2}\right)$ indicates that the series move in phase with x leading y; $\phi_{xy} \in \left(-\frac{\pi}{2}, 0\right)$ indicates that y is leading; an anti-phase relation (negative covariance) is indicated by a phase difference of π or $-\pi$, and y is leading if $\phi_{xy} \in \left(\frac{\pi}{2}, \pi\right)$ while x is leading if $\phi_{xy} \in \left(-\pi, \frac{-\pi}{2}\right)$.

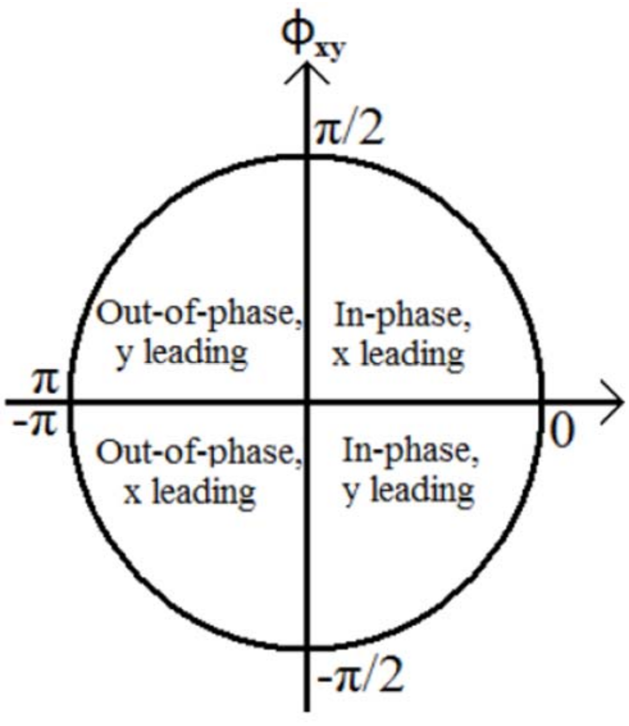


Fig.3 Phase-difference cycle

4. Data and empirical findings

Figure 4 shows the time series plots of oil price, exchange rate and consumer price. The high volatility in oil price can be observed in Panel (a). The Oil price peaked in July, 2008 amid the global financial crisis. After this record peak, however, oil price plummeted at the end of 2008. There is a sharp rebound, but plummets again in mid-2014.

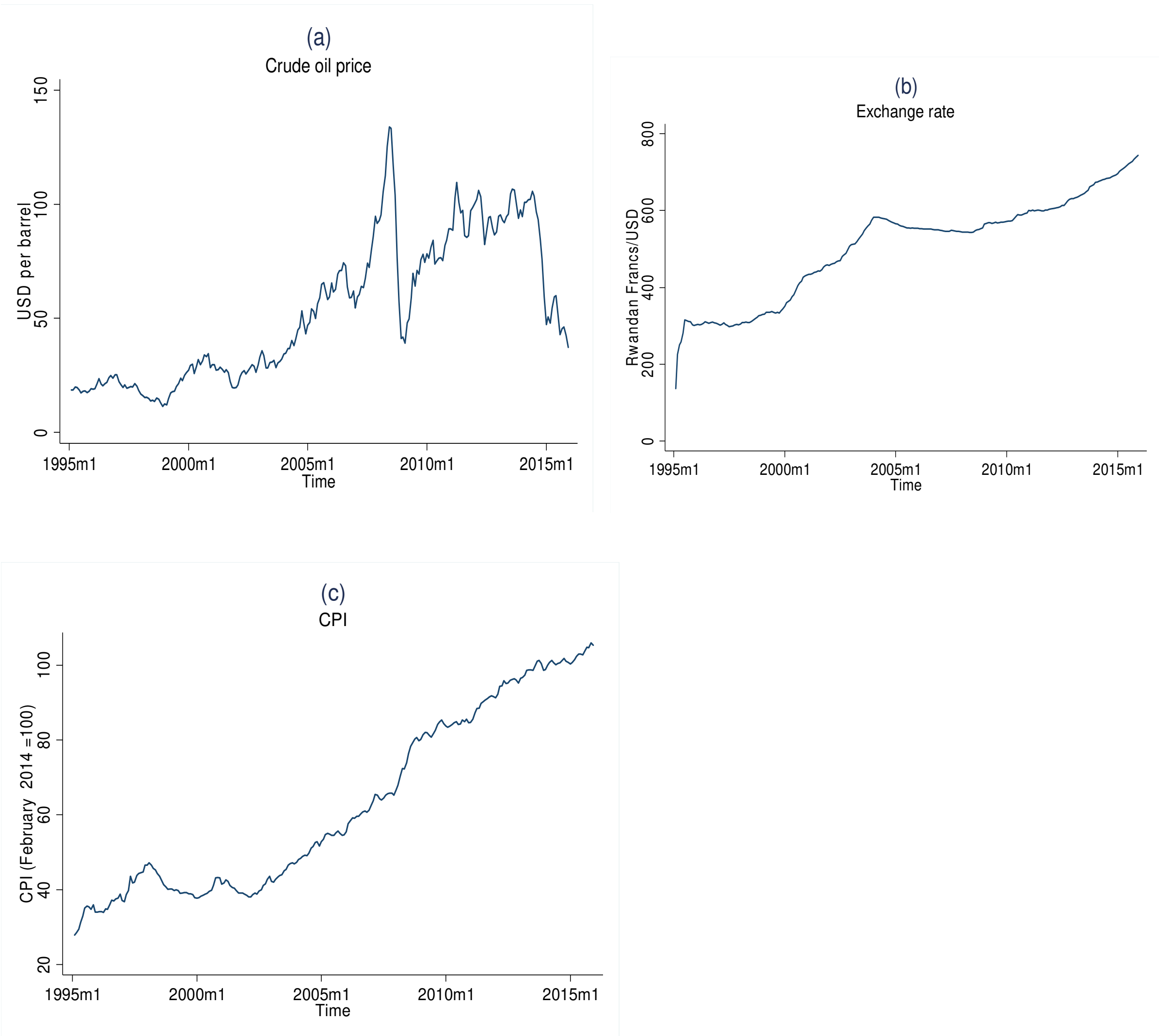


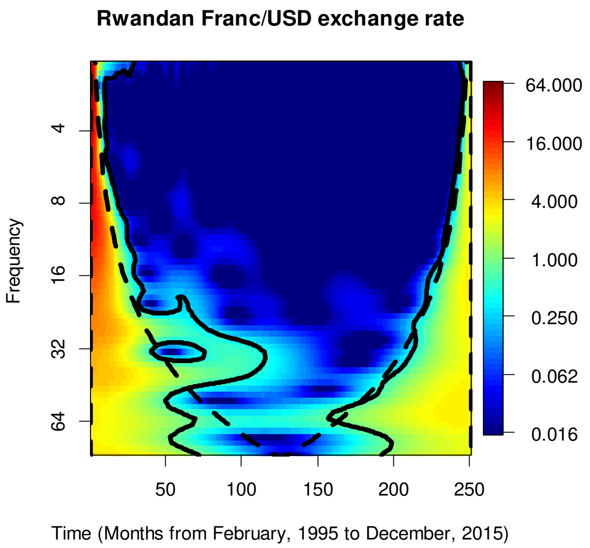
Fig.4 Time series plots of oil price, exchange rate and consumer price

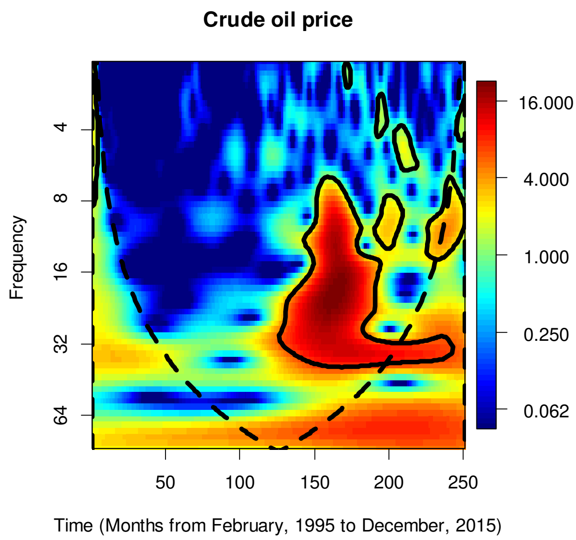
Source: Exchange rate and CPI data are obtained from the National Bank of Rwanda. Data on crude oil price are obtained from the Energy Information Administration (EIA).

Exchange rate and consumer prices in Panel (b) and (c) exhibit a common steady upward trend. From February, 1995 to December, 2015, in only 21 years the Rwandan Franc depreciated by 446%. During the same period, consumer prices rose by 279%, but unlike the exchange rate, there is a sharp increase in the slope from late-2007 which can be linked to the onset of the financial crisis.

Figure 5 plots the same series, but in the time-frequency domain. The wavelet power spectrum (WPS) of each series is plotted. The WPS measures the relative contribution of each at each time and each scale to the variance of the time series. It depicts the local variance of the time series. Looking at exchange rate, the wavelet power is very lower for the time under study and at all frequencies. The same pattern is observed for CPI. The time-frequency representation of these two series gives similar information as the time series plot in Figure 4; the two series are less volatile over time; there are no important periods or frequencies that contribute more to their variation.

The wavelet power spectrum for oil price shows that the variance was very high and significant at cycles of 8 months to 16 months between mid-2007 and beginning-2010. From mid-2005 to 2010, the variance was very high at cycle frequencies of 16 months to approximately 3 years. From 2010 and afterwards, the volatility decreased at higher frequencies (lower scales), but remained important at lower frequencies of 2.5 to 3 years.





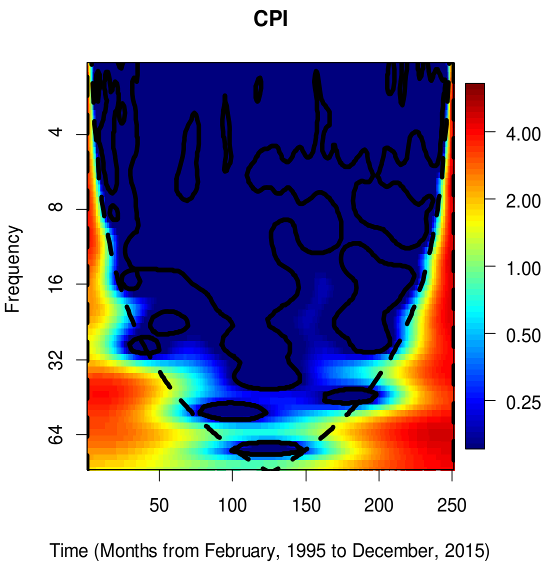


Fig.5 Wavelet power spectrum of oil price, exchange rate and CPI

Note: The power ranges from blue (low power) to red (high power). The thick black contour designates the 5% significance level against red noise. The cone of influence (COI) where edge effects might distort the picture is shown as a discontinued thick black line which is estimated byMonte Carlo simulations with 10000 replicates using phase randomized surrogate series. The Y axis is in months, the frequencies decrease with months.

Volatility increased after 2005 and continued in the aftermath of the financial crisis at a scale of 8 to 32 months. Since 2011 volatility reduces at lower scales, but still significant at a scale around 32 months.

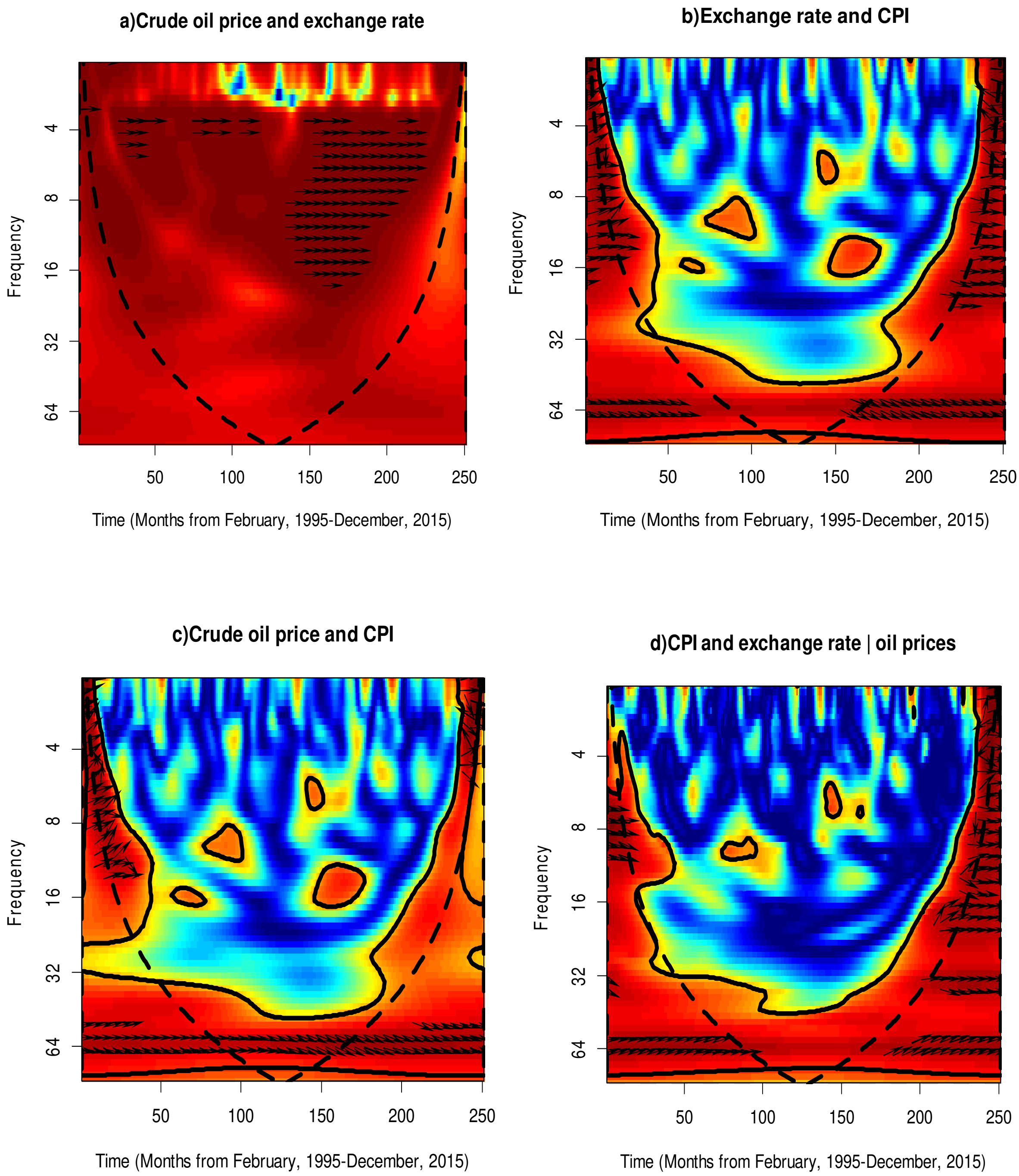


Fig. 6 Cross-wavelet coherency, partial-wavelet coherency and wavelet-phase difference among oil price, CPI and exchange rate

Note: The cross-wavelet power spectrum is computed[2] applying the Morlet wavelet. The power ranges from blue (low power) to red (high power). The thick black contour designates the 5% significance

[2] The computations are done with the package biwavelet version 0.17.10. Unlike older versions (older than 0.14), this most recent version computes and plots the bias-corrected wavelet and cross-wavelet power spectrum using

level against red noise. The cone of influence (COI) where edge effects might distort the picture is shown as a discontinued thick black line which is estimated by Monte Carlo simulations with 10000 replicates using phase randomized surrogate series. The phase difference between the two series is indicated by arrows. A phase difference of zero indicates that the time series move together (analogous to positive covariance). Arrows pointing to the right (left) indicate that the time series are in-phase (anti-phase), i.e. positively (negatively) correlated. Arrow pointing up means that the first time series leads the second; arrow pointing down indicates that the second time series is leading. The Y axis is in months, the frequencies decrease with months.

Panel (a) in Figure 6 depicts the wavelet coherency between oil prices and the Rwandan Franc/USD nominal exchange rate. The co-movemet between the two series is very powerful and significant for the whole considered time. Most importatnly, exchange rate and oil price are in phase (positive covariance) between 1999 early 2001 at the finest scale (high frequency) of around 3 to 6 months. Between late 2001 to mid-2005 the two series are in phase at a smaller scale of approximately 3 to 4 months. The co-movement intensifies and expands to intermediate scales of 4 to 16 months beginning late 2007, the onset of global financial crisis, the period marked by volatile global oil prices as depicted in Figure 4.

Panel (b) depicts the wavelet coherency between exchange rate and consumer price. There is little interdependence during the period 2001 and 20013 and during 2007-2009, the period of the financial crisis at a scale of 8 to 16 months. overall, however, there is less power; the relationship between the two is weak; the two series are not in phase excpet outside the cone of influence (discontinued black line) and outside the 5% significance (the thick black contour). This finding gives more insights on the exchange rate disconnect. However, it's not suprising since recent studies have found the (ERPT) very low.

To investigate the effect oil prices may have on the co-movement between echange rate and consumer prices, Panel (d) depicts the wavelet coherence between exchange rate and consumer price by partialling out the effect of oil price. The picture does not significantly differ from panel (b). It can be visibly seen that the cross-wavelet power is very low; the two series are not

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the methods suggested by Liu et al. (2007) and Veleda et al. (2012). This correction was suggested because the traditional approach as suggested by Torrence and Compo (1998) was found to reduce power at lower frequencies.

in phase, except the ruled-out region that is affected by edge effects. This finding is corroborated in Panel (c) which clearly shows very low power between the two wavelet spectrums. There is no significant co-movement between oil prices and consumer prices, even after controlling for the effect of oil prices.

5. Conclusion

This study has applied three continuous wavelet tools to investigate the time-frequency co-movement among crude oil price, exchange rate and consumer price level for a landlocked, oil-dependent and oil-importing country. The wavelet spectrum showed that the 2007-2008 financial crisis increased volatility in oil prices and has remained very important afterwards at higher scale (lower frequency). The same wavelet-spectrum analysis revealed the low volatility in Rwandan Franc exchange rate and consumer prices.

The cross-wavelet coherency and the wavelet-phase difference revealed the strength and significance of the time-frequency relationship between global oil price and the Rwandan Franc exchange rate. The wavelet power is high for the whole considered time. The covariance between the two series is positive (the rise in oil prices is associated with the depreciation of the Rwandan Franc) at higher frequencies, and intensified and expanded to intermediate scales during the onset of the financial crisis, the period marked by high volatility in global oil prices. The co-movement between global oil and exchange rate explains the role played by global oil price fluctuations in exacerbating Rwanda's balance of payments. These findings are in line with the theoretical argument by Krugman (1983), Golub (1983), and later by Chen and Chen (2007), that the worsening of terms of trade obliges the country to raise the nominal exchange rate, which leads to even further depreciation.

These wavelet tools reavealed that the time-frequency relationship between exchange rate and consumer prices on one hand and between oil prices and consumer prices on the other hand is not singificant, and there is no indication of the effect of the global financial crisis as it is the case for oil prices and exchange rate co-movement. This gives more evidence of the exchange rate disconnect. One tentative explanation to why the international oil price shocks are not passed through to consumer prices can be that Rwanda has been subsidizing energy products, mainly oil; the internal oil market is very much regulated which limits the pricing power of oil retailers, and restricts entry to big companies to take advantage of the economies of scale that reduce the cost of supply. Although there is no evidence of the pass-through of oil prices shocks to consumer prices, however, considering the continuous deterioration of the balance of payments caused mainly by the gap between imports and exports that has been widening overtime, coupled with the servicing of debt which is denominated in foreign currency, fiscal and monetary authorities need to devise policies to attenuate the effect, through exchange rate, of oil price shocks.

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