



Decomposing time–frequency relationship between producer price and consumer price indices in Romania through wavelet analysis

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ARTICLE INFO

Article history:

Accepted 29 November 2012

JEL classification:

C10
C82
E32
E47
E52
E60

Keywords:

Producer Price Index
Consumer Price Index
Time-frequency analysis
Non-stationary time-series
Wavelets

ABSTRACT

This study analyses Granger-causality between the return series of CPI and PPI (i.e., inflation measured by CPI and PPI) for Romania, by using monthly data covering the period of 1991m1 to 2011m11. To analyse the issue in depth, this study decomposes the time–frequency relationship between CPI- and PPI-based inflation through a continuous wavelet approach. Our results provide strong evidence that there are cyclical effects from variables (as variables are observed in phase), while anti-cyclical effects are not observed.

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1. Introduction

In this study we analyse the relationship between Producer Price (PPI) and Consumer Price (CPI) indices in Romania using the Wavelet Transform Method (also referred to as the Wavelet Analysis Method) in order to assess the causality between CPI and PPI. The relationship between CPI and PPI is very important for the measurement of inflation, for the analysis of the process of inflation within an economy, and for the efforts of the monetary authorities to minimise the uncertainty introduced by price instability into economic analysis and any decision-making process.

To forecast inflation and manage inflation expectations, and to achieve (implicit) inflation targets, policymakers need to better understand what types of factors influence the inflation process (Mihailov et al., 2011). Having an adequate inflation target is essential for good monetary policymaking in cases where a country decides on a flexible exchange rate regime (Ghatak and Moore, 2011). Also, the setting of

the inflation target is found to have an important international dimension because higher world inflation is positively correlated with inflation targets (Horváth and Matějů, 2011). Analysis of inflation in Romania is perhaps more important than in other countries, considering the fact that the year 1989 marked the beginning of the transition of Romanian economy from a centralised economy, where most consumer prices were fixed, to a market economic system. The transition proved to be much more complicated than initially thought, entailing reforms in the political, economic, financial, banking and social areas (Cerna et al., 2004) and, unfortunately, has been marked by high and volatile inflation rates.

In Romania, as with many other European countries' national or central banks, the primary objective of the National Bank of Romania (NBR) is to ensure and maintain price stability, and the main tasks of the NBR are to define and implement the monetary policy. Furthermore, without prejudice to its primary objective, the NBR supports the general economic policy of the government.

Monetary policy choices have been rooted in an understanding of inflation as an excess aggregate demand phenomenon. The policy framework has changed throughout transition, from broad money targeting (1990–1996) to high-powered money targeting (1997–2005), and then to inflation targeting (Gabor, 2008). During the first years of the

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transition period, the NBR used, as an operational objective of monetary policy, a broad monetary aggregate (M2) and, from the second half of 1993, after having created the basis for exerting indirect control over the money supply, the NBR attempted to directly control the base money (M0). The period until 1998 was marked by the pre-eminence of exchange rate stabilisation over monetary targeting considerations, but starting from 1999 until 2005, the NBR's monetary targeting strategy used M0 as the operational objective and M2 as the intermediate objective (Sánchez, 2011). Between 1994 and 2005, Romania had no official commitment to a monetary policy strategy (Frömmel et al., 2011), and the pursuit of a monetary targeting strategy by the NBR was justified because the attempts at using the exchange rate as an anti-inflationary anchor failed, while, to this end, the interest rate was not taken into consideration (Popa et al., 2002). In order to achieve its primary objective, the NBR continued to improve its discretionary monetary policy, and in 2005 announced the transition to inflation targeting, although many deviations from the inflation-targeting principles could be noted (Nenovsky and Villieu, 2011).

This monetary policy strategy is a CPI-based inflation target and was adopted after completing a preparatory process that involved bringing the annual inflation rate to single-digit levels, earning and strengthening central bank credibility, and getting a better insight into macroeconomic behaviour patterns and economic mechanisms in order to identify and enhance the effectiveness of monetary policy transmission channels (Popa, 2005). By adopting inflation targeting, the central bank more clearly assumed the task of consistently pursuing the fulfilment of its fundamental objective, its accountability for achieving the inflation target being more clearly expressed (NBR, 2005).

Although Romania has made substantial progress in lowering inflation over time, inflation continues to be an issue of key policy concern. This is due to the persistent character of inflation rates and to the remaining risks of inflationary spikes. Given the moderate and persistent character of inflation, it is particularly important to better understand the extent to which inflation is a demand-driven phenomenon so that the policies aimed at limiting discretionary demand can be used to bring down inflation and stabilise the economy. On the other hand, it is also important to find out the role that supply-side of economy has in maintaining inflation at a moderate level.

Theoretical literature suggests that movements (shocks) in producer prices should affect, through the production chain, consumer prices. This is a standard supply-side or cost-push explanation of changes in consumer prices. Based on this point of view, changes in producer prices at earlier stages of production should pass through to producer prices at later stages of production and, ultimately, to consumer prices (Clark, 1995). Following these presumptions, information on producer prices should offer valuable predictive power about consumer prices and could therefore be useful for central banks in identifying cost-push shocks and improving forecasts of consumer-price inflation (Caporale et al., 2002).

Colclough and Lange (1982) argue that an alternative view of the causal relationship between CPI and PPI that stresses the demand side seems equally plausible and they provide evidence of a bidirectional relationship between CPI and PPI. According to this view, changes in the demand for final consumer goods exert an influence on input prices through the impact of changes in the prices of consumer goods on the derived demands for inputs. Also, Jones (1986) suggests that a valid theoretical explanation of the relationship between CPI and PPI must include both demand-pull and cost-push aspects of aggregate price determination, and recommends that for the bivariate model consisting of the CPI and the PPI, the simultaneous equation approach is the appropriate method for estimation. Also, Caporale et al. (2002) reported bivariate causality between PPI and CPI.

The literature on the dynamic relationship between CPI and PPI shows that PPI could be used as a short-term indicator of inflationary

trends. Furlong and Ingenito (1996) reveal that PPI represents a strong and statistically robust leading indicator of inflation, especially during the period with unstable and high CPI or with significant increase of PPI. Cushing and McGarvey (1990) re-evaluate the theoretical and empirical debate surrounding the bivariate time-series relationship between wholesale and consumer price inflation. They argue that the existence of a one-sided Granger causal relationship running from PPI to CPI cannot be taken as evidence of either markup pricing or cost-push inflation, and find that wholesale price shocks had little or no permanent effect on consumer price inflation.

Mehra (1991) shows that long-run movements in the rate of growth in CPI and production costs are correlated over time, but the presence of this correlation appears to be due to Granger-causality running from inflation to wage growth, not from wage growth to the rate of inflation. Blomberg and Harris (1995) analyse the short- and long-run relationships between production and consumer prices, and show that PPI inflation did have predictive power in explaining CPI inflation. They also present evidence that commodities have either lost that power or, in some cases, are sending perversely negative signals. Also, Hess and Schweitzer (2000) show that there is little systematic evidence that production costs, especially wages, are helpful for predicting inflation. In fact, the authors show that there is more evidence that inflation helps predict wages.

In a recent study, using frequency domain approach, Tiwari (2012a) explores the Granger-causality between the producers' and the consumers' price in the case of Australia.¹ The dataset covers the period 1969q3–2010q4. According to the author, the consumers' price Granger-causes producers' price at an intermediate level of frequencies, providing evidence of medium-run cycles. Otherwise, the producers' price does not Granger-cause consumers' price at any level of frequencies. Using the same methodology, Tiwari (2012b) conducts another analysis focused on India. The main outputs reveal that "CPI Granger-cause WPI (whole sale price index) at a lower, intermediate as well as higher level of frequencies reflecting very long-run, intermediate as well as short-run cycles." WPI Granger-causes CPI at intermediate frequencies, reflecting significant intermediate cycles. Finally, Shahbaz et al. (2012) treat the causality between WPI and CPI in the case of Pakistan, from 1961 to 2010. The frequency-domain approach demonstrates the unidirectional causal relationship from CPI to WPI, which varies across frequencies. Moreover, "CPI Granger-causes WPI at lower, medium as well as higher level of frequencies reflecting long-run, medium and short-run cycles."

Based on this literature framework, the aim of this paper is to examine the relationship between PPI and CPI in Romania, using monthly data from 1991m1 to 2011m11. In order to analyse the relationship between Producer Price and Consumer Price Indices at different time scales, we use the wavelets analysis method. All data are obtained from an International Monetary Fund (IMF) CD ROM (2012) of IFS (International Financial Statistics). The results provide strong evidence of cyclical effects from variables, while the anti-cyclical effects are not observed. This paper extends the literature in the field, improving on the studies of Tiwari (2012a,b) and Shahbaz et al. (2012). In this way, using the wavelet method, the objective of our investigation is twofold: (i) to demonstrate if there is anti-cyclical relationship, and (ii) to show in which year these cyclical and anti-cyclical relationships are observed.

This paper is organised as follows. Section 2 presents the wavelet analysis method adopted, while Section 3 describes data and reveals empirical findings on the relationship between Producer Price and Consumer Price Indices at different time scales. The paper concludes in Section 4.

¹ To the best of our knowledge Tiwari (2012a) is the first study to analyse the Granger-causality in the frequency-domain approach.

2. Methodology

2.1. The continuous wavelet transform (CWT)²

Wavelet transforms perform a time-frequency analysis of signals and hence are able to estimate the spectral characteristics of signals as a function of time. Consequently, this can provide not only the time-varying power spectrum but also the phase spectrum needed for computation of coherence. Specifically, a wavelet is a function with a zero mean and it is localised in both frequency and time. We can characterise a wavelet by how localised it is in time (Δt) and frequency (Δf or the bandwidth). The classical version of the Heisenberg uncertainty principle tells us that there is always a trade-off between localisation in time and frequency, and hence, Δt and Δf should be properly defined. The Morlet wavelet provides a balance between localisation of time and frequency (Grinsted et al., 2004), and therefore it allows for a good identification and isolation of periodic signals. The Morlet wavelet yields a complex transform (being a complex wavelet) with information on both amplitude and phase, which is essential for studying synchronisms between different time-series. Therefore, in this study we used the Morlet wavelet as the basis function for wavelet transform (Percival and Walden, 2000). In its simplified version, the Morlet wavelet is defined as:

$$\phi_{\eta}(t) = \pi^{-1/4} e^{i\eta t} e^{-\frac{1}{2}t^2}, \tag{1}$$

where $i = \sqrt{-1}$.

The relationship between scale (s) and frequency (f) is simply $f = \mu_f/s \approx 1/s$ which indicates that the wavelet scale is inversely related to the frequency. Here, μ_f is the frequency centre of the Fourier transform of (ϕ) , $\Phi(f)$. The central frequency of a wavelet determines the waveforms, where, for the Morlet wavelet, the central frequency was chosen to be equal to six ($\eta = 6$), providing a good balance between time and frequency localisation. For this central frequency the Fourier frequency period ($1/f$) is almost equal to scale. A good balance between time and frequency localisation is needed because, if we construct wavelets over short-time scales, it will tend to isolate sharply, and lend high frequency volatility in the time-series. The advantage of the short-time scales is that it will have good time resolution, but the disadvantage is that it will have a poor scale (frequency) resolution. Similarly, if we construct wavelets for relatively long-scale it will tend to capture low frequency volatility and will have relatively poor time resolution but good scale (frequency) resolution.

The literature discusses two classes of wavelet transforms: first is the discrete wavelet transforms (DWT), quite often used in the empirical research work, and second is the continuous wavelet transforms (CWT). However, the CWT is better for feature-extraction purposes, whereas the DWT is a compact version of the data and is particularly useful for noise reduction and data compression. The CWT, with respect to the ‘mother wavelet’ (ϕ) , is a function $W_X(s, \tau)$ that provides wavelet coefficients, defined as:

$$W_X(s, \tau) = \int_{-\infty}^{+\infty} x(t) (1/\sqrt{s}) \phi^* \left(1 - \tau / s \right) dt, \tag{2}$$

where $*$ denotes the complex conjugate form. The mother wavelet $\phi(\cdot)$ serves as a prototype for generating other window functions. The term translation, τ , refers to the location of the window (indicating where it is centred). As the window shifts through the signal, the time information in the transform domain is obtained. The term

scaling, s , refers to dilating (if $|s| > 1$) or compressing (if $|s| < 1$) the wavelet (the term scaling controls the length of the wavelet by extracting frequency information from the time-series). The mother wavelet is dilated or compressed to correspond to cycles of different frequencies. In this way, an entire set of wavelets can be generated from a single mother-wavelet function, and this set can then be used to analyse the time-series. If the wavelet function $\phi(t)$ is complex, the wavelet transform W_X will also be complex, meaning that the transform can be divided into the real part ($R\{W_X\}$) and the imaginary part ($I\{W_X\}$); or amplitude, $|W_X|$, and phase, $\tan^{-1}(I\{W_X\}/R\{W_X\})$, where \tan^{-1} stands for the arctangent function.

Coherence is very important when dealing with fluctuating quantities, indicating how closely X and Y are related by a linear transformation. This happens if and only if their degree of coherence is close to its maximum value of unity. In a time series, the degree of coherence of two time-series $x(t)$ and $y(t)$ with zero time-average values, is the magnitude of their temporal correlation coefficient.

Coherence is like a correlation measure that indicates how strongly the two variables are related at business-cycle frequencies. It ranges from 0 (no correlation; completely incoherent) to 1 (perfect correlation; completely coherent). The caveat is that this correlation may not be contemporaneous, but may involve a lead or a lag, being the magnitude measured by the phase lead. Dealing with discrete time-series $\{x_n, n = 0, \dots, N - 1\}$ of N observations with a uniform time step δt , the integral in Eq. (2) has to be discretised, and the CWT of the time-series $\{x_n\}$ becomes

$$W_m^X(s) = \frac{\delta t}{\sqrt{s}} \sum_{n=0}^{N-1} x_n \phi^* \left[(n-m) \frac{\delta t}{s} \right], m = 0, 1, \dots, N-1. \tag{3}$$

It is possible to calculate the wavelet transform using this formula for each value of s and m but we can also identify the computation for all the values of m simultaneously as a simple convolution of two sequences (Aguilar-Conraria et al., 2008; Torrence and Compo, 1998). When applying the CWT to a finite-length time-series, we inevitably suffer from border distortions, due to the fact that the values of the transform at the beginning and at the end of the series are always incorrectly computed (i.e., they are not completely localised in time), involving missing values of the series, which are then artificially prescribed. The region in which the transform suffers from these edge effects (which cannot be ignored), is called the Cone of Influence (COI), and results must be interpreted carefully there. Similar to Torrence and Compo (1998) and Aguilar-Conraria et al. (2008), the COI will be defined here as the e-folding time of the wavelet at scale s , that is, the wavelet power of a Dirac δ at the edges decreases by a factor of e^{-2} . In other words, we take the COI as the area in which the wavelet power caused by a discontinuity at the edge has dropped to e^{-2} of the value at the edge. For the Morlet wavelet under analysis, this is given by $\sqrt{2}s$.

The wavelet power spectrum is just $|W_n^X|^2$. It characterises the distribution of the energy (spectral density) of a time-series across the two-dimensional time-scale plane, leading to a time-scale (or time-frequency) representation. Although Torrence and Compo (1998) have shown how the statistical significance of wavelet power can be assessed against the null hypothesis and that the data-generating process is given by an AR (0) or AR (1) stationary process with a certain background power spectrum (P_k), for more general processes, one has to rely on Monte Carlo simulations. Torrence and Compo (1998) computed the white-noise and red-noise wavelet power spectra, from which they derived, under the null, the corresponding distribution for the local wavelet power spectrum at each time n and scale s as follows:

$$D \left(\frac{|W_n^X(s)|^2}{\sigma_X^2} < p \right) = \frac{1}{2} P_f \chi_v^2, \tag{4}$$

² The description of CWT, XWT and WTC is heavily drawn from Grinsted et al. (2004). We are grateful to Grinsted and co-authors for making codes available at: <http://www.pol.ac.uk/home/research/waveletcoherence/>, which was utilized in the present study.

where the value of P_f is the mean spectrum at the Fourier frequency f that corresponds to the wavelet scales $s(\approx 1/f)$ and v is equal to 1 or 2, for real or complex wavelet, respectively.³

Cross-wavelet power reveals areas with high common power. The cross-wavelet transform (XWT) of two time-series x_n and y_n is defined as $W^{XY} = W^X W^{Y*}$, where W^X and W^Y are the wavelet transforms of x and y , respectively, and $*$ denotes complex conjugation. We further define the cross-wavelet power as $|W^{XY}|$. The complex argument $\arg(W^{XY})$ can be interpreted as the local relative phase between x_n and y_n in time-frequency space. The theoretical distribution of the cross-wavelet power of two time-series with background power spectra P_k^X and P_k^Y is given in Torrence and Compo (1998) as

$$D\left(\frac{|W_n^X(s)W_n^{Y*}(s)|}{\sigma_X\sigma_Y} < p\right) = \frac{Z_v(p)}{v} \sqrt{P_k^X P_k^Y} \tag{5}$$

where σ_X and σ_Y are the standard deviations of x and y , respectively, and $Z_v(p)$ is the confidence level associated with the probability p for a pdf defined by the square root of the product of two χ^2 distributions. Therefore, the wavelet spectrum can be interpreted as depicting the local variance of a time-series, while the cross-wavelet power of two time-series depicts the local covariance between these series at each scale or frequency.

The phase for wavelets shows any lag or lead relationships between components, and is defined as

$$\phi_{x,y} = \tan^{-1} \frac{I\{W_n^{xy}\}}{R\{W_n^{xy}\}}, \phi_{x,y} \in [-\pi, \pi], \tag{6}$$

where I and R are the imaginary and real parts, respectively, of the smooth power spectrum. Phase differences are useful to characterise phase relationships between two time-series. A phase difference of zero indicates that the time-series move together (analogous to positive covariance) at the specified frequency. If $\phi_{x,y} \in [0, \pi/2]$, then the series move in-phase, with the time-series y leading x . On the other hand, if $\phi_{x,y} \in [-\pi/2, 0]$ then x is leading. We have an anti-phase relation (analogous to negative covariance) if we have a phase difference of π (or $-\pi$) meaning $\phi_{x,y} \in [-\pi/2, \pi] \cup [-\pi, \pi/2]$. If $\phi_{x,y} \in [\pi/2, \pi]$ then x is leading, and the time-series y is leading if $\phi_{x,y} \in [-\pi, -\pi/2]$.

Another useful measure is how coherent the cross wavelet transform is in the time-frequency space. As in the Fourier spectral approaches, Wavelet Coherency (WTC) can be defined as the ratio of the cross-spectrum to the product of the spectrum of each series, and can be thought of as the local correlation, both in time and frequency, between two time-series. Thus, WTC near 1 shows a high similarity between the time-series, while WTC near 0 shows no relationship. While the wavelet power spectrum depicts the variance of a time-series, with times of large variance showing large power, the XWT power of two time-series depicts the covariance between these time-series at each scale or frequency. Aguiar-Conraria et al. (2008, p. 2872) define WTC as “the ratio of the cross-spectrum to the product of the spectrum of each series, and can be thought of as the local (both in time and frequency) correlation between two time-series.” Following Torrence and Compo (1998), we define the WTC of two time-series as

$$R_n^2(s) = \frac{|S(s^{-1}W_n^{XY}(s))|^2}{S(s^{-1}|W_n^X(s)|^2) \cdot S(s^{-1}|W_n^Y(s)|^2)}, \tag{7}$$

where S is a smoothing operator. Notice that this definition closely resembles that of a traditional correlation coefficient, and it is useful to

³ According to Torrence and Compo (1998, p.66), a complex wavelet function returns “information about both amplitude and phase and is better adapted for capturing oscillatory behaviour,” while the real wavelet function “returns only a single component and can be used to isolate peaks or discontinuities.”

think of the wavelet coherence as a localised correlation coefficient in time-frequency space. Without smoothing, coherency is identically 1 at all scales and times. We may further write the smoothing operator S as a convolution in time and scale:

$$S(W) = S_{scale}(S_{time}(W_n(s))), \tag{8}$$

where S_{scale} denotes smoothing along the wavelet scale axis and S_{time} denotes smoothing in time. The time convolution is done with a Gaussian and the scale convolution is performed with a rectangular window (see Torrence and Compo, 1998, for more details). For the Morlet wavelet, a suitable smoothing operator is given by

$$S_{time}(W)|_s = \left(W_n(s) * c_1^{-t^2/2s^2}\right)|_s \tag{9}$$

$$S_{scale}(W)|_n = (W_n(s) * c_2 \Pi(0, 6s))|_n, \tag{10}$$

where c_1 and c_2 are normalisation constants and Π is the rectangle function. The factor of 0.6 is the empirically determined scale de-correlation length for the Morlet wavelet (Torrence and Compo, 1998). In practice, both convolutions are done discretely and therefore the normalisation coefficients are determined numerically.

The cross-wavelet coherence gives an indication of the correlation between rotary components that are rotating in the same direction as a function of time and periodicity. It can be defined as the ratio of the cross-spectrum to the product of the spectrum of each series, and can be thought of as the local correlation between two CWTs.

Because theoretical distributions for wavelet coherency have not been derived yet, one has to rely on Monte Carlo simulation methods to assess the statistical significance of the estimated wavelet coherency. We generate a large ensemble of surrogate dataset pairs with the same AR1 coefficients as the input datasets. For each pair we calculate the Wavelet Coherency. We then estimate the significance level for each scale using only values outside the COI. However, following Aguiar-Conraria and Soares (2011), we will focus on the WTC, instead of the wavelet cross-spectrum. Aguiar-Conraria and Soares (2011, p. 649) give two arguments for this: “(1) the wavelet coherency has the advantage of being normalised by the power spectrum of the two time-series, and (2) that the wavelets cross spectrum can show strong peaks even for the realisation of independent processes suggesting the possibility of spurious significance tests.”

2.2. Cross-wavelet phase angle

As we are interested in the phase difference between the components of the two time-series, we need to estimate the mean and confidence interval of the phase difference. We use the circular mean of the phase over regions with higher than 5% statistical significance, that is, we use the regions outside the COI to quantify the phase relationship. This is a useful and general method for calculating the mean phase. The circular mean of a set of angles $(a_i, i = 1, \dots, n)$ (for more details regarding the fixing of a_i 's see Grinsted et al., 2004; Zar, 1999) is defined as

$$a_m = \arg(X, Y) \text{ with } X = \sum_{i=1}^n \cos(a_i) \text{ and } Y = \sum_{i=1}^n \sin(a_i) \tag{11}$$

It is difficult to calculate the confidence interval of the mean angle reliably because the phase angles are not independent. The number of angles used in the calculation can be set arbitrarily high simply by increasing the scale resolution. However, it is interesting to know the scatter of angles around the mean. For this we define the circular standard deviation as

$$s = \sqrt{-2 \ln(R/n)}, \tag{12}$$

Table 1
Estimation of unit root tests.

Variables	ADF test: Constant model		ADF test: Constant and trend model		PP test: Constant model		PP test: Constant and trend model	
	T-calculated	Prob-value	T-calculated	Prob-value	T-calculated	Prob-value	T-calculated	Prob-value
$\ln PPI_t$	-6.143798	0.0000	-3.060767	0.1182	-7.482196	0.0000	-2.855238	0.1792
$\Delta \ln PPI_t$	-6.915159	0.0000	-10.49444	0.0000	-8.992995	0.0000	-10.53286	0.0000
$\ln CPI_t$	-6.295044	0.0000	-3.796439	0.0183	-9.236919	0.0000	-3.713035	0.0232
$\Delta \ln CPI_t$	-4.903127	0.0000	-7.076299	0.0000	-6.993801	0.0000	-10.00476	0.0000

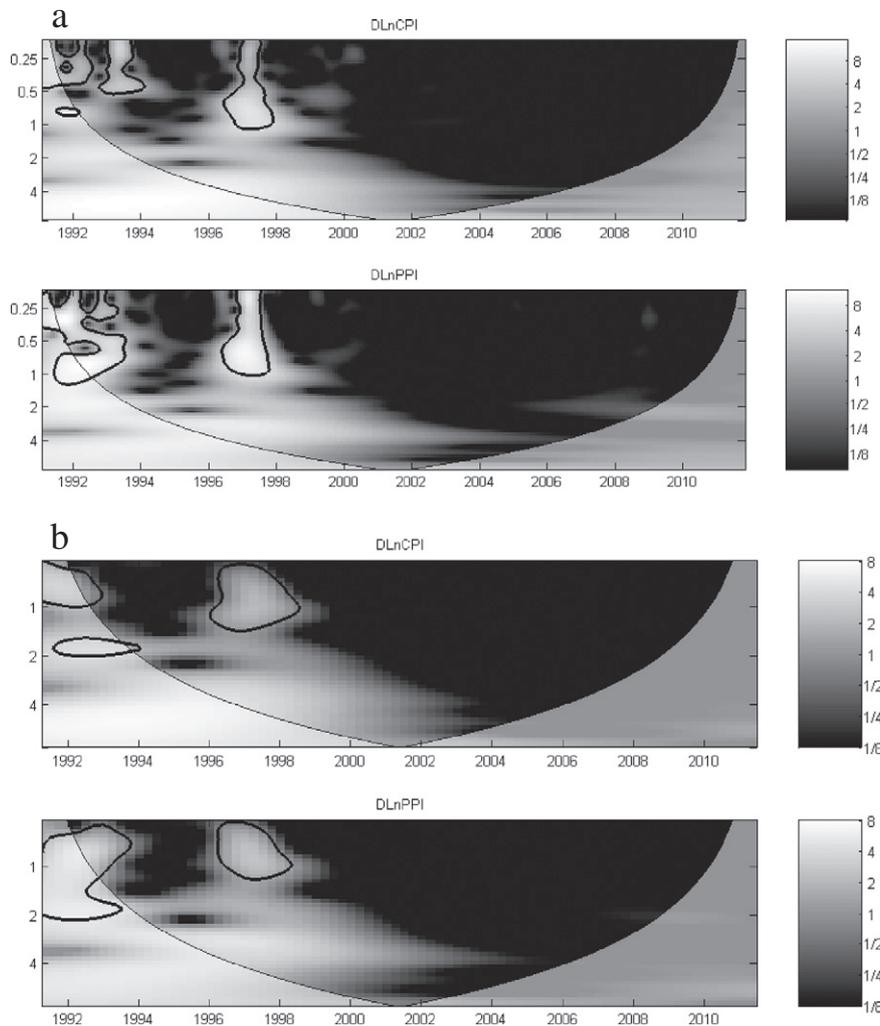
Note: The asterisk * denotes the significance at %1 level. The figure in the parentheses is the bandwidth for the PP unit root test and is determined by the Schwert (1989) formula and lag length for ADF test determined by Schwarz Info Criterion SIC.

Source: Authors' calculation.

where $R = \sqrt{(X^2 + Y^2)}$. The circular standard deviation is analogous to the linear standard deviation in that it varies from zero to infinity. It gives similar results to the linear standard deviation when the angles are distributed closely around the mean angle. In some cases there might be reasons for calculating the mean phase angle for each scale, and then the phase angle can be quantified as a number of years.

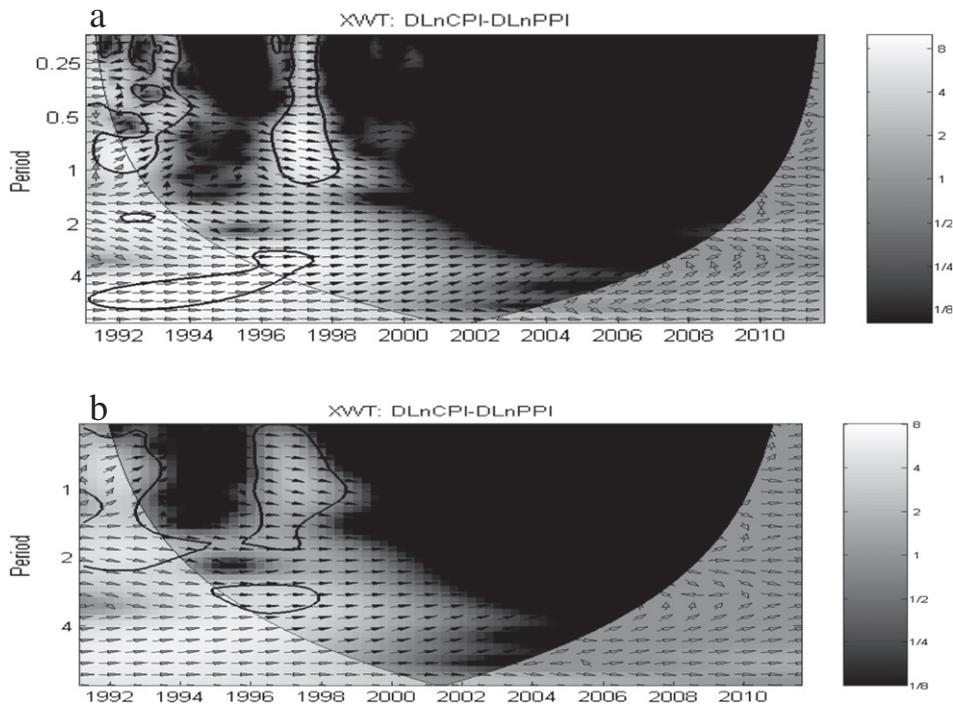
3. Data analysis and empirical findings

For the analysis we obtain data of Producer Price and Consumer Price Indices (PPI and CPI) from IMF CD ROM (2012) with monthly observations covering the period from 1991m1 to 2011m11.



Note: The continuous wavelet power spectrum of both CPI (in the top) and PPI (in the bottom) series are shown here. The thick black contour designates the 5% significance level against red noise, and the cone of influence (COI) where edge effects might distort the picture, is shown as a lighter shade. The colour code for power ranges from black (low power) to white (high power). The Y-axis measures frequencies or scale (measured in years) and the X-axis represents the time period studied.

Fig. 1. a: Continuous wavelet power spectra of CPI and PPI monthly series. b: Continuous wavelet power spectra of CPI and PPI quarterly series.



Note: Cross-wavelet power - The thick black contour designates the 5% significance level against red noise which is estimated from Monte Carlo simulations using phase-randomised surrogate series. The cone of influence, which indicates the region affected by edge effects, is shown with a lighter shade black line. The colour code for power ranges from black (low power) to white (high power). The phase difference between the two series is indicated by arrows. Arrows pointing to the right mean that the variables are in phase. To the right and up, PPI-based inflation is leading. To the right and down, PPI-based inflation is lagging. Arrows pointing to the left mean that the variables are out of phase. To the left and up, PPI-based inflation is lagging. To the left and down, PPI-based inflation is leading. The Y-axis measures frequencies or scale (measured in years) and the X-axis represents the time period studied.

Fig. 2. a: Cross-wavelet transform of the CPI and PPI monthly time-series. b: Cross-wavelet transform of the CPI and PPI quarterly time-series.

First of all, descriptive statistics of variables⁴ have been analysed to see the sample property. As the stationarity is a required status for investigations of time-series, in the next step, this property of the data-series has been tested through the Augment Dickey-Fuller (ADF test) and Phillips–Perron (PP test) tests and results are reported in Table 1. Concretely, using ADF and PP tests, we analyse for the unit root, the natural logarithm of PPI and CPI series, in level and first difference, with constant, and also with constant and trend, respectively.

Table 1 reports that both variables are non-stationary at their level form, but stationary at their first-differenced form at 1% level of significance. Therefore, for further analysis we transformed both our variables in the first-difference form. The CWT power spectra of the CPI- and PPI-based inflation-series for monthly data are shown in Fig. 1a. For robustness, in Fig. 1b, we illustrate the results for the quarterly approach of the considered series.

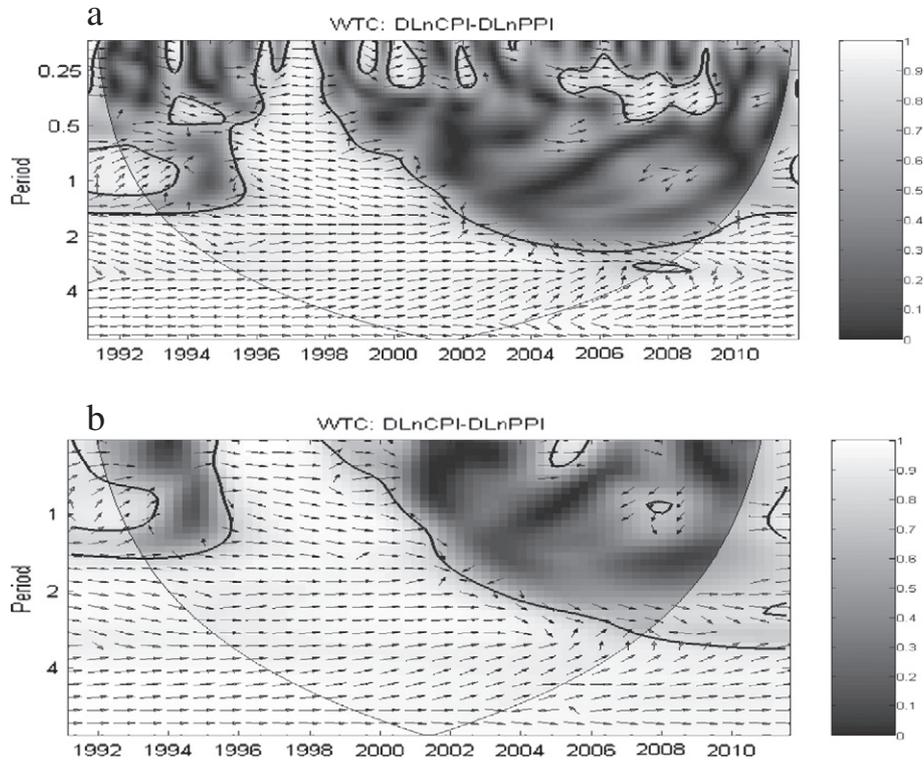
From Fig. 1a and b we find that there are clearly common features in the wavelet power of the two time-series such as the 0.25–1 year of scale (band) that corresponds to the 1993s. Both series also have high power in the 0.5–1.25 year of scale (band) that corresponds to 1996–1997, and for both series the power is above the 5% significance level. However, the similarity between the portrayed patterns in this period is low and it is therefore hard to tell if it is merely a coincidence. The cross-wavelet transform helps in this regard.

⁴ Time-series plot and descriptive statistics of the variables are presented in Fig. A1 and Table A1 respectively, in the Appendix. In Table 1, we only present results of the unit root analysis for monthly data; however, for quarterly data, results can be accessed from the authors upon request.

For there to be a simple cause-and-effect relationship between the phenomena recorded in the time-series, we would expect that the oscillations are phase-locked. Therefore, it is comforting that the XWT shows that CPI- and PPI-based inflations are in the phase in all the sectors (i.e., in the significant region) with significant common power. The monthly and quarterly estimations for XWT are presented in Fig. 2a and b, respectively.

For both figures, because CPI- and PPI-based inflations are in the phase across all scales in the significant region and arrows in the frequency 0.25–1 year of scale that corresponds to 1991–1992 are right and up, this indicates that PPI-based inflation is leading. Interestingly, within the frequency range 0.25–1 year of scale that corresponds to the years 1996–1997, arrows are right and down, indicating that PPI-based inflation is lagging. This phenomenon coincides with a period that was marked by the pre-eminence of exchange rate stabilisation over monetary targeting considerations, and with unstable macroeconomic conditions caused by the drastic macroeconomic adjustment in the context of an IMF-backed stabilisation programme and an adverse international environment (Gabor, 2008). However, outside the areas with significant power, the phase relationship is also predominantly in the phase. We therefore speculate that there is a stronger link between CPI- and PPI-based inflation than that implied by the cross-wavelet power.

The squared WTC of CPI- and PPI-based inflation, for monthly and quarterly data, are shown in Fig. 3a and b, respectively. Compared with the XWT, a larger section stands out as being significant, and all these areas show a phase relationship between CPI- and PPI-based inflation.



Note: Cross-wavelet coherency -The thick black contour designates the 5% significance level against red noise which is estimated from Monte Carlo simulations using phase-randomised surrogate series. The cone of influence, which indicates the region affected by edge effects, is also shown with a light black line. The colourcode for coherency ranges from black (low coherency - close to zero) to white (high coherency - close to one). The phase difference between the two series is indicated by arrows. Arrows pointing to the right mean that the variables are in phase. To the right and up, PPI-based inflation is leading. To the right and down, PPI-based inflation is lagging. Arrows pointing to the left mean that the variables are out of phase. To the left and up, PPI-based inflation is lagging. To the left and down, PPI-based inflation is leading. In phase indicates that variables will be having cyclical effect on each other, and out of phase or anti-phase shows that variables will be having anti-cyclical effect on each other. The Y-axis measures frequencies or scale (measured in years) and the X-axis represents the time period studied.

Fig. 3. a: Cross-wavelet coherency for the monthly data. b: Cross-wavelet coherency for the quarterly data.

The area of a time-frequency plot above the 5% significance level is not a reliable indication of causality. These results give us a quite interesting picture of the causality between CPI- and PPI-based inflation. During 1991–1993, in the frequency band of 0.5–1.25 years of scale, arrows are pointing to the right and up, indicating that the variables are in phase and that PPI-based inflation is leading. The dramatically high inflation rates at the beginning of the 1990s were the result of the policy choices that may appear unsystematic, myopic and even inconsistent. And, in the absence of a functioning tax system, seigniorage was simply the only way to finance government expenditures aside from borrowing (Dăianu and Kallai, 2008). During 1993–1994, in 0.25–0.5 year of scale, the arrows are pointing to the right and down indicating that the variables are in phase and that PPI-based inflation is lagging. This could be caused by the increasing of NBR's indirect control over the money supply and its strategy to control base money.

Further, during 1995–1999 in all frequency ranges (particularly at higher scales), arrows are pointing to the right and down indicating that the variables are in phase and that PPI-based inflation is lagging. However, during the observation range of 2004 to 2010, arrows are pointing to the right and up, indicating that the variables are in phase and that PPI-based inflation is leading. Considering that the inflation-targeting strategy adopted by the NBR in 2005 is a CPI-based inflation target, this result shows that the Romanian monetary authority should reconsider its strategy and to include in its strategy the Producer Price Index.

As the estimations reveal, we also note that, in all the considered cases, the quarterly results confirm the monthly obtained outputs.

4. Conclusions and policy implications

By adopting inflation targeting, the National Bank of Romania assumed more clearly the task of consistently pursuing the fulfilment of its fundamental objective, to ensure and maintain price stability. Because there is a lag between monetary-policy actions and their impact on the central bank's target variables, monetary policy is more effective if it is guided by inflation and other target variables (Svensson, 2010). Central banks frequently state that past domestic inflation and economic growth matter in considering how to set the target. Several central banks mention more specific factors, such as price convergence and foreign inflation, zero interest rate bounds or statistical overvaluation in inflation measurement (Horváth and Matějů, 2011).

In both policy practice and academic research, the inflation target is usually measured using the CPI, even though the PPI is also readily observable and the cyclical behaviours of the two measures of inflation are quite different. Huang and Liu (2005) show that the central bank should also care about variations in PPI inflation and the gap of the real marginal cost in the production of intermediate goods, not only the variations in CPI inflation and the output gap.

Especially, as Clark's (1999) result shows, an exogenous monetary tightening causes producers' prices to fall more rapidly and by a

larger amount than consumers' prices. PPI inflation rate is typically more volatile and less persistent than the CPI inflation rate. In this case, the PPI could be used as a short-term indicator of CPI inflationary trends. De Mendonça and de Guimarães e Souza (2012) show that the adoption of inflation targeting is an ideal monetary regime for developing economies and, in addition to reducing inflation volatility, can drive inflation down to internationally acceptable levels. However, in order to achieve these results, central banks should state a clear and credible long-run inflation target (Faust and Henderson, 2004).

This study analysed Granger-causality between the return series of CPI and PPI (i.e., inflation measured by CPI and PPI) for Romania by using monthly data covering the period of 1991m1 to 2011m11. To analyse the issue in depth, this study decomposes the time-frequency relationship between CPI- and PPI-based inflation through a continuous wavelet approach. To the best of our knowledge, this is the first ever study in this direction with the present approach to any economy. We found through ADF and PP unit root tests, that both variables are non-stationary in log-level form, and stationary in log first-difference form. From the continuous power spectrum figure, we found that the common features in the wavelet power of the two time-series are evident in 0.25–1 year of scale that corresponds to 1993. Both series also have high power in the 0.5–1.25 years of scale (band) that corresponds to 1996–1997. Results of XWT, which indicate the covariance between CPI- and PPI-based inflation series, are unable to give clear-cut results, or these results may be merely by chance. However, our results of Cross-Wavelet Coherency or Squared Wavelet Coherency (WTC), which can be interpreted as a correlation, reveal that both variables are in phase during the studied period (if we consider the significant region only). During 1991–1993, in the frequency band of 0.5–1.25 years of scale, arrows are pointing to the right and up indicating that the variables are in phase and that PPI-based inflation is leading. During 1993–1994, in the 0.25–0.5 year of scale, the arrows are pointing to the right and down indicating that the variables are in phase and that PPI-based inflation is lagging. Further, during 1995–1999 in all frequency ranges (particularly at higher scales), arrows are pointing to the right and down indicating that the variables are in phase and that PPI-based inflation is lagging. However, during the observation range of 2004 to 2010, arrows are pointing to the right and up indicating that the variables are in phase and that CPI-based inflation is leading. Therefore, our results provide strong evidence that there are cyclical effects from variables (as variables are observed in phase) and anti-cyclical effects are not observed.

These findings are an improvement with respect to the studies of Tiwari (2012a,b) and Shahbaz et al. (2012). While the frequency-domain approach used by Tiwari (2012a,b) and Shahbaz et al. (2012) is able to show the cyclical nature of the relationship, it fails to provide evidence for (a) whether there is any anti-cyclical relationship, and (b) in which year these cyclical and anti-cyclical relationships (if any) are observed. Hence, our study is an advancement over the studies of Tiwari (2012a,b) and Shahbaz et al. (2012) with respect to these directions.

The present study can be extended by analysing the trivariate wavelet-based approach which might include different interest rates and/or stock market returns as a third variable, as theoretically all the three variables are expected to be highly correlated with each other.

Regarding the policy implications, our study suggests that CPI and PPI are two indicators that are very important in policy discussion for macroeconomic targets of domestic policies, such as monetary or fiscal areas. Our results show that the relation between CPI and PPI depends on the internal and external macroeconomics conditions and, in order to set an accurate and more credible inflation target, the NBR should examine the response of aggregate and disaggregate prices at different stages of production to monetary policy shocks.

Appendix A

Table A1
Summary statistics of the variables.

Indicator	Variable	
	PPI	CPI
Mean	62.21219	59.93908
Median	51.09000	57.32000
Maximum	168.1300	143.8200
Minimum	0.080000	0.060000
Std. dev.	56.59967	50.60689
Skewness	0.391557	0.171096
Kurtosis	1.664596	1.476960
Jarque-Bera	25.06414	25.48430
Probability	0.000004	0.000003
Sum	15615.26	15044.71
Sum sq. dev.	800880.7	640264.4
Observations	251	251

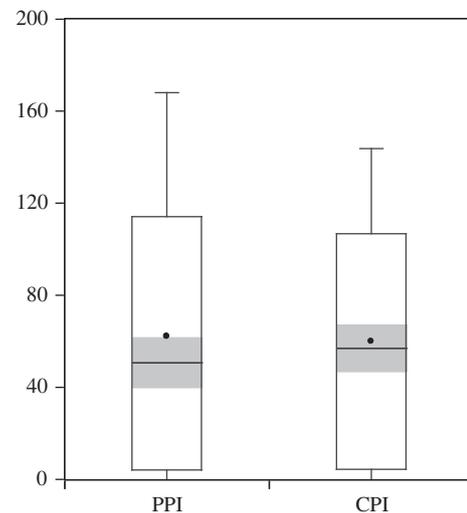


Fig. A1. Time-series plot of the variables.

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