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Multiscale Interdependence Between Consumer and Producer Prices in Emerging Eastern European Countries

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Abstract

This paper investigates multiscale causal relations between consumer and producer prices in eight emerging Eastern European countries. We use wavelet coherence to measure the multiscale nexus between inflation types, and wavelet-based Bayesian quantile regression (BQR) to inspect the spillover effect. Wavelet coherence plots indicate low coherence in the short time horizon (up to two months) and higher coherence in the longer time horizons, particularly from four mounts onwards. Areas of very high coherence are found around the Global Financial Crisis and the COVID-19 pandemic. Bidirectional spillover effect exists in all the countries except Poland and Hungary. In the Czech Republic, Slovakia, Estonia and Slovenia, producer prices have the upper hand over consumer prices, and this effect is stronger in the longer time horizons, which is in line with the wavelet coherence results. Only in the case of Lithuania, we find that consumer prices have a stronger effect on producer prices than *vice versa*, and this happens in the short term. In the case of Latvia, the BQR results are inconclusive because both inflation types have a precedence, but in different time horizons.

Keywords: Consumer and producer prices, spillover effect, wavelet coherence, Bayesian quantile regression, emerging East European countries

JEL Classification: C82, E32, C11

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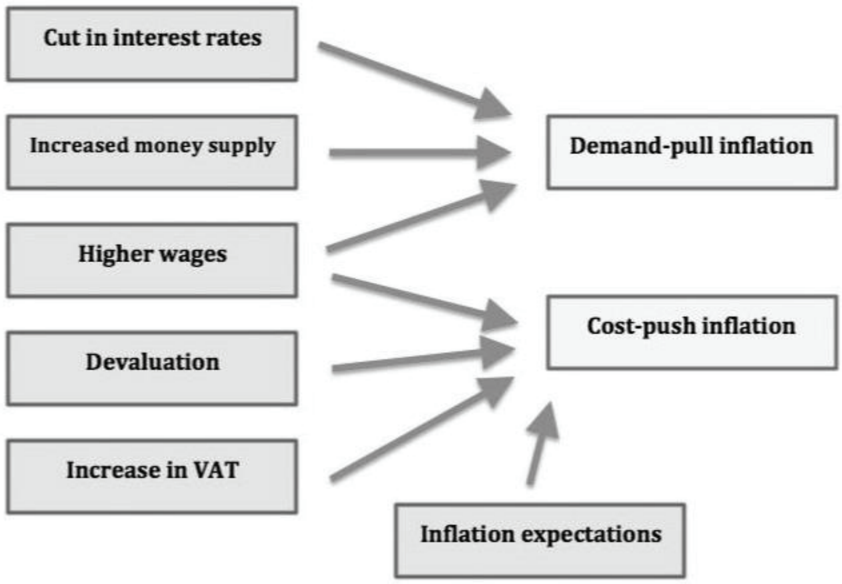
1. Introduction

The connection between producer and consumer prices is one of the hot topics in macroeconomics, while the price transmission mechanism is the key issue of economic analysis (Zhang and Liu, 2018). This is important because high inflation has strong repercussions on high interest rates, reduction in investment and influences on the labour market and living standards (Kandil, 2015; Khan *et al*., 2018). Monetary authorities need to realize what types of factors influence inflation to achieve better inflation forecasts and implicit (explicit) inflation targets (see, *e.g.*, Reigl, 2017; Michl, 2019; Bilgili *et al*., 2022). Thus, understanding the relationship between consumer and producer prices plays a significant role in this process. Tsiaplias (2008) explained that consumer prices measure changes in the prices of goods or services acquired or utilised by households for consumption purposes, while producer prices are used to measure the change in output prices owing to changes in the basic prices received by producers. From the theoretical point of view, causality between consumer and producer prices can be bidirectional. Tiwari *et al*. (2014) asserted that if causality runs from producer to consumer prices, it can be referred to as cost-push inflation, where changes in producer prices in the initial stage of the supply chain are transmitted to the later consumer stage. This process has its foundation in the so-called moderate inflation model (see Pujol and Griffiths, 1996). Different factors can be responsible for this scenario – higher wages, exchange rate devaluation (depreciation), increase in VAT and higher inflation expectations. On the other hand, demand-pull inflation implies that causality runs from consumer price index (CPI) to producer price index (PPI), where changes in consumer prices can galvanize a rise in input prices, which eventually affect producer prices. Factors that might induce inflation from the demand side are cuts in interest rates, increased money supply and higher wages. Figure 1 illustrates which factors affect cost-push and demand-pull inflation. Experience suggests that interdependence between producer and consumer prices is not straightforward; thus, knowing the leading (lagging) role of the particular inflation type can help monetary policymakers adequately formulate measures to tackle inflation. However, the empirical literature in this area is still inconclusive about the nature of the link between PPI and CPI for developed and developing countries, according to Tiwari *et al*. (2014), so further research in this area is necessary. This is the source of our motivation for this research.

According to the above, this paper investigates the relationship between producer and consumer prices from two aspects: multiscale interdependence and multiscale spillover effect. We examine eight Central and Eastern European countries (CEECs) that became members of the European Union in 2004: Poland, the Czech Republic, Hungary, Slovakia, Lithuania, Latvia, Estonia and Slovenia. All these economies registered relatively high growth rates in the past two decades, but, at the same time, the accompanying problem was to successfully curb rising inflation. Understanding the relationship between consumer and producer prices could contribute to this process. Various factors, such as structural reforms in the price, trade liberalisation and currency devaluation (depreciation) caused an increase in the inflation rate (Tiits *et al*., 2008), while all the countries recorded double-digit inflation at some point in the last two decades. Figure 2 jointly presents empirical dynamics of producer and consumer prices from January 1998, where we can see that consumer prices recorded very high values at some instances. On the other hand, producer prices remained relatively low.

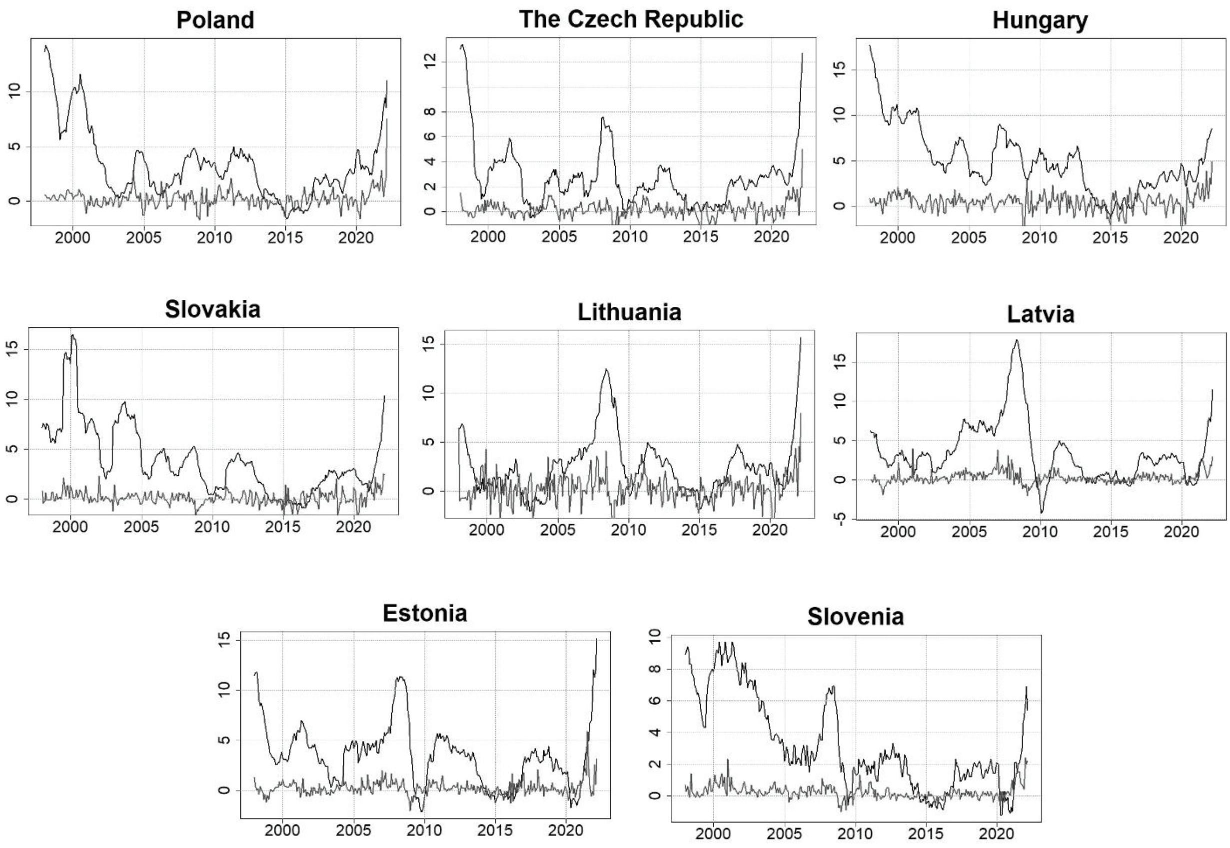
Figure 1: Causes of cost-push and demand-pull inflation



Source: Authors' own elaboration

Unlike most papers in this area that have examined only time domain, we apply a somewhat unconventional approach that addresses both time and frequency perspectives of the relationship. This approach can provide a richer insight into the nexus between consumer and producer prices because policymakers can learn about the relationship not only from the empirical frequency level, but also from longer time horizons. This is useful because it provides more possibilities for monetary authorities to devise proper and workable measures to keep inflation within predetermined boundaries. For this task, we use a wavelet technique, which is a powerful signal processing tool capable of calculating the time–frequency relationships between the observed variables. In other words, this model-free approach allows researchers to test the dynamic dependence at different time horizons, circumventing the problem of sample size reduction at the same time. As far as we know, the only studies that have used a wavelet approach for CPI vs PPI investigation are Tiwari *et al*. (2013) and Tiwari *et al*. (2014). The former investigated the case of Romania, while the latter focused on the case of Mexico, and both papers used one specific wavelet technique: wavelet coherence (WTC). WTC indicates the strength of coherence between two variables in colour plots, across time and wavelet scales, where warmer (cooler) colours indicate stronger (weaker) coherence. However, this methodology lacks exact numerical estimates in the contour plot, which makes WTC results rather an indicator than an exact estimator.

Figure 2: Empirical dynamics of producer and consumer prices in eight CEECs



Note: Higher-level inflation (black line) indicates consumer prices, while lower-level inflation (grey line) denotes producer prices.

Source: Authors' own calculation

Unlike the aforementioned papers, we go one step further in the analysis. In other words, we measure the strength of the interdependence via wavelet coherence, which was seen in the aforementioned studies, but we also calculate the spillover effect between the two inflation types in different wavelet scales, which has never been done before to the best of our knowledge. This is done by merging two different methodologies, which in combination allow us to estimate parameters at different frequency levels and in different economic conditions: downturn (lower quantiles), normality (median quantiles) and economic prosperity (upper quantiles). In other words, we couple the maximum overlap discrete wavelet transformation (MODWT) approach with the Bayesian quantile regression (BQR) model. MODWT is used to decompose empirical inflation time series into three wavelet signals, which represent the short-term, medium-term and long-term horizons. Compared to the traditional quantile regression of Koenker and Bassett (1978), the BQR method is an upgrade because it applies Bayesian inference, *i.e.,* Markov Chain Monte Carlo (MCMC) algorithm, to estimate quantile parameters. According to Benoit and van den Poel (2017), BQR has an advantage over traditional QR approach because it produces accurate quantile parameters, which are highly statistically significant and unbiased if confidence intervals are narrow. In other words, the Bayesian QR methodology decreases the length of credible intervals and increases the accurateness of quantile estimates, and this is the reason why BQR is chosen over the traditional QR.

We contribute to the international literature in several dimensions. Firstly, this is a rare paper that considers this topic in Central and Eastern European countries. Secondly, this paper is the first to study the connection between consumer and producer prices by using several elaborate time-frequency methodologies: wavelet coherence and wavelet-based Bayesian quantile regression.

The remainder of the paper is structured as follows. Section 2 provides a brief review of related studies. The wavelet methodology and the Bayesian quantile regression are explained in Section 3. Section 4 introduces the dataset and preliminary findings. Section 5 presents and explains the results of wavelet coherence and wavelet-based BQR. Section 6 contains concluding remarks.

2. Literature Review

The available studies offer diverse and sometimes conflicting findings regarding the interdependence between consumer and producer prices. For instance, Shahbaz *et al*. (2012) investigated the direction of causality between PPI and CPI in Pakistan using monthly frequency data and covering the period 1961–2010. They found that a unidirectional causal relationship runs from CPI to PPI, and they concluded that CPI should be a leading indicator for important fiscal or monetary policy decisions in Pakistan. Tiwari (2012) studied the Granger-causality between producer and consumer prices in Australia. The results showed that consumer prices Granger-cause producer prices at an intermediate frequency level reflecting medium-run cycles, whereas producer prices do not Granger-cause consumer prices at any frequency level. Caporale *et al*. (2002) examined the causal relationship between wholesale and consumer prices in G7 countries and reported that wholesale prices Granger-cause consumer prices. Huang and Liu (2005) investigated how optimal monetary policy should be set when monetary authorities do not know the exact sources of rigidities. They concluded that monetary policy that does not take into account PPI inflation tends to generate larger welfare losses in comparison with the policy rule that targets both CPI and PPI inflation.

Clark (1999) studied the US case and found that monetary tightening could cause producer prices to fall more rapidly and by a larger amount than consumer prices. He argued that PPI is usually more volatile and less persistent than CPI, which implies that PPI could be used as a short-term indicator of CPI inflationary trends. McKnight (2011) suggested that central banks should adopt interest rate rules that focus on CPI. He claimed that targeting CPI is preferable to PPI targeting, because terms-of-trade fluctuations can help stabilize the economy under CPI targeting by preventing self-fulfilling expectations. Contrary to the findings of McKnight (2011), some studies have proposed that central banks should avoid targeting CPI, because it could destabilize the economy by generating self-fulfilling expectations (see, *e.g.*, Linnemann and Schabert, 2006; Leith and Wren-Lewis, 2009; Llosa and Tuesta, 2008). Blomberg and Harris (1995) investigated short- and long-run relationships between PPI and CPI in the USA, and disclosed that PPI inflation has predictive power in explaining CPI inflation.

Very few papers have used the wavelet methodology for CPI vs PPI causality investigation. For instance, Tiwari *et al*. (2013) analysed the Granger-causality between the return series of CPI and PPI in Romania, using monthly data from January 1991 to November 2011. They decomposed the time-frequency relationship between CPI- and PPI-based inflation using a continuous wavelet approach. The wavelet coherence results revealed that both variables were in phase during the studied period, but with changing leading (lagging) relationships. Tiwari *et al*. (2014) studied the causality between CPI and PPI in Mexico for the period from January 1981 to March 2009, by decomposing the time frequency relationship using continuous wavelet methodology. They reported the existence of a bidirectional relationship between CPI and PPI. Particularly, in the short-time period (1 to 7 months) they found that CPI is leading PPI, while for longer periods (8 to 32 months) PPI is the leading variable.

3. Research Methodologies

3.1. Wavelet coherence

We study the time-frequency interdependence between consumer and producer prices from two aspects: strength of coherence and spillover effect. Wavelet coherence[1] is used to determine strength of coherence across the wavelet scales and the observed sample. Wavelet coherence (WTC) measures the local linear correlation between two stationary time series on each scale, and it is equivalent to the squared correlation coefficient in linear regression (see Tao *et al*., 2018). Torrence and Webster (1999) argued that WTC can be presented as a squared absolute value of the smoothed cross-wavelet spectra normalized by the product of the smoothed individual wavelet power spectra of each selected time series. The cross-wavelet transform of two time series, $x(t)$ and $y(t)$, is defined as $W_{xy}(u, s) = W_x(u, s)W_y^*(u, s)$, where W_x and W_y are the wavelet transforms of x and y, respectively. The symbol u represents the position index, s denotes the scale, while the symbol * indicates a complex conjugate. The squared wavelet coherence coefficient is presented in the following equation:

1 Wavelet coherence is calculated using the "WaveletComp" package in R software.

$$R^2(u,s) = \frac{\left|S\left(s^{-1}W_{xy}(u,s)\right)\right|^2}{S\left(s^{-1}\left|W_x(u,s)\right|^2\right)S\left(s^{-1}\left|W_y(u,s)\right|^2\right)} \tag{1}$$

where $S(.)$ stands for a smoothing operator and s indicates the wavelet scale. The squared wavelet coherence coefficient is within the range $0 \leq R^2(u, s) \leq 1$, where values near zero point to weak correlation, while values near one indicate strong correlation.

The direction of the correlation as well as the lead-lag relationship between consumer and producer prices in different time horizons is determined by phase arrows in WTC plots. Following Torrence and Webster (1999), the wavelet coherence phase difference is defined as follows:

$$\phi_{xy}(u,s) = tan^{-1}\left(\frac{\Im\left\{S\left(s^{-1}W_{xy}(u,s)\right)\right\}}{\Re\left\{S\left(s^{-1}W_{xy}(u,s)\right)\right\}}\right) \tag{2}$$

where $W_{xy}(u, s) = W_x(u, s)\overline{W_y}(u, s)$ is the cross-wavelet transform of two time series, $x(t)$ and $y(t)$, whereas W_x and W_y are the wavelet transforms of x and y, respectively. $\Im$ and $\Re$ are the imaginary and real parts of the smooth power spectrum, respectively. The arrows pointing to the right (left) in WTC plots indicate that the time series are in phase (anti-phase) or are positively (negatively) correlated. If arrows point up, the first variable is leading the second one, whereas if phase arrows point down, the second variable is leading the first one.

3.2 Maximum overlap discrete wavelet transformation

The multiscale spillover effect between consumer and producer prices is calculated using a combination of the wavelet-decomposed series and the Bayesian QR model. Generally speaking, discrete wavelet methodology can decompose empirical time series into their time-frequency components. Wavelet theory distinguishes two basic wavelet functions: the father wavelet (ϕ) and the mother wavelet (ψ). Father wavelets augment the representation of the smooth or low-frequency parts of a signal with an integral equal to 1, and mother wavelets are helpful in describing the details of high-frequency components with an integral equal to 0. The long-term trend over the scale of the time series is portrayed by the father wavelet, while the mother wavelet delineates fluctuations in the trend. The most commonly used wavelets are orthogonal ones, and the approximation to a continuous signal series $y(t)$ in $L^2(R)$ is given as follows:

$$y(t) \approx \sum_k s_{J,k}\phi_{J,k}(t) + \sum_k d_{J,k}\psi_{J,k}(t) + \sum_k d_{J-1,k}\psi_{J-1,k}(t) + \ldots + \sum_k d_{1,k}\psi_{1,k}(t) \tag{3}$$

where the symbol J denotes the number of multi-resolution components or scales, and k ranges from 1 to the number of coefficients in the corresponding component. The coefficients $s_{J,k}$, $d_{J,k}$, …, $d_{1,k}$ stand for the wavelet transform coefficients that can be approximated by the following integrals:

$$s_{J,k} \approx \int y(t)\phi_{J,k}(t)dt, \tag{4}$$

$$d_{\mathrm{j},k} \approx \int y(t)\psi_{\mathrm{J},k}(t)dt, \qquad j = 1, 2, ..., J \tag{5}$$

These coefficients calibrate the contribution of the corresponding wavelet function to the total signal. The functions $\phi_{J,k}$ and $\psi_{J,k}$ are the approximating wavelet functions, that is, the scaled and translated versions of ϕ and ψ. Generally, these functions are generated from ϕ and ψ in the following way:

$$\phi_{J,k}(t) = 2^{-J/2}\phi\left(\frac{t-2^J k}{2^J}\right), \qquad \psi_{J,k}(t) = 2^{-J/2}\psi\left(\frac{t-2^J k}{2^J}\right) \tag{6}$$

According to Equation (4), the scale or dilation factor is 2^J, whereas the translation or location parameter is $2^J k$. As much as J grows, so does the scale factor 2^J, which is a measure of the width of the functions $\phi_{J,k}(t)$ and $\psi_{J,k}(t)$, and it affects the underlying functions to become shorter and more dilated. Besides, when J increases, the translation steps automatically get larger in order to accommodate the level of the scale parameter 2^J.

Most frequently used types of wavelet transformations are the discrete wavelet transformation (DWT) and the maximum overlap discrete wavelet transformation[2] (MODWT). The former utilizes orthonormal transformation of the original series, while the latter is based on a highly redundant non-orthogonal transformation. For our research, we use MODWT, which is a linear filtering operation that transforms series into coefficients related to variations over a set of scales. A number of researchers have used wavelet methodology for analysis of various economic phenomena (see, *e.g.*, Dajčman, 2013; Živkov *et al*., 2019; Bhuiyan *et al*., 2019; Compains *et al*., 2021).

3.3 Bayesian quantile regressions

The created wavelet-decomposed signals of consumer and producer prices are embedded in the Bayesian quantile regression[3] framework. Generally speaking, quantile regression extends the mean regression model to conditional quantiles of the response variable. More specifically, QR provides a more complex and informative view of the relations between regressand and regressors. In other words, QR estimates how a set of covariates affects the different parts of dependent variable distribution.

The interdependence between y and x is shown in Equation (7), where y and x are both continuous variables:

2 Maximum overlap discrete wavelet transformation is done via R software, using the “waveslim” package.

3 Bayesian quantile parameters are calculated using the “bayesQR” package in R software.

$$y_i = \mu\left(x_i\right) + \varepsilon_i \tag{7}$$

In Equation (7), y_i can be both consumer or producer wavelet-based inflation, while x_i is an opposite counterpart of y_i. According to Benoit and van den Poel (2017), the regression coefficient in the case of all quantiles can be estimated by solving Equation (8):

$$\hat{\beta}\left(\tau\right) = \text{argmin}\sum_{i=1}^{n} \rho_\tau (y_i - x_i'\beta); \quad \beta \in \Re \tag{8}$$

where $\tau \in (0, 1)$ is any quantile of interest, while $\rho_\tau(z) = z\ (\tau - I\ (z < 0))$ and $I(\cdot)$denotes the indicator function. The loss function ρ_τ assigns a weight of τ to positive residuals and a weight of $(1 - \tau)$ to negative residuals. The quantile $\hat{\beta}(\tau)$ is called the τ^{th} regression quantile, while $\tau = 0.5$ corresponds to median regression. In the Bayesian procedure, QR parameters are estimated with the MCMC algorithm. An important characteristic of this process is that all estimated quantile parameters are regarded as statistically significant, while their reliability depends on their confidence intervals. In other words, if confidence intervals are narrower (wider), the reliability of the estimated BQR parameters is higher (lower). Kruschke and Liddell (2018) explained that the Bayesian estimation process produces an explicit distribution of credibilities, which is called the posterior distribution across the parameter values. This type of distribution is subsequently used to determine which parameter values are most credible, that is, what range of parameter values covers the most credible values. This means that the posterior distribution can be directly interpreted, where the most credible parameter values can be read off, so there is no need for *p*-values and *p*-value-based confidence intervals, because measures of uncertainty are based directly on posterior credible intervals.

Benoit and van den Poel (2017) asserted that BQR estimation begins with formatting of a likelihood comprised of independent asymmetric Laplace densities with $\mu = \beta$. The quantile of interest (τ) has to be specified and priors should be put on the model parameters β and σ. Accordingly, the resulting posterior distribution has the following form:

$$\psi\left(\beta, \sigma | y, x, \tau\right) \propto \pi\left(\beta, \sigma\right)\prod_{i=1}^{n} ALD\left(y_i | x_i^T\beta, \sigma, \tau\right) \tag{9}$$

where $\pi\ (\beta, \sigma)$ is the joint prior on the regression parameters.

4. Dataset and Preliminary Findings

We use monthly data of the consumer and producer prices of eight CEECs. The data are retrieved from the OECD statistics website, and all samples range from January 1998 to March 2022. All inflation time series are seasonally adjusted, using the filter-based methods of seasonal adjustment, also known as the X11 style method. Table 1 shows descriptive statistics of the empirical consumer and producer prices.

The average consumer price inflation is significantly higher than its producer price counterpart. Also, the variability of the consumer prices is much higher than the variability of the producer prices. All the prices have positive skewness, except the producer prices of Hungary. This means that most empirical observations are to the right of the mean; only in the case of producer prices of Hungary, they are to the left of the mean. On the other hand, the presence of outliers is more visible in the producer prices, as the kurtosis suggests. This applies particularly for the cases of Hungary and Poland. The reason for these findings probably lies in the recent developments, where energy commodities, *i.e.,* natural gas and oil, have recorded a significant rise due to the war in Ukraine. These happenings spill over to producer prices almost immediately in energy-importing countries. This can be seen in Figure 2. According to Table 1, none of the time series has normal distribution, which justifies the use of wavelet methodology, since wavelets are capable of dealing with outliers, but they can also remove noises in original data (see Tabak and Feitosa, 2009; Jammazi, 2012).

Table 1: Descriptive statistics of consumer and producer prices of selected CEECs

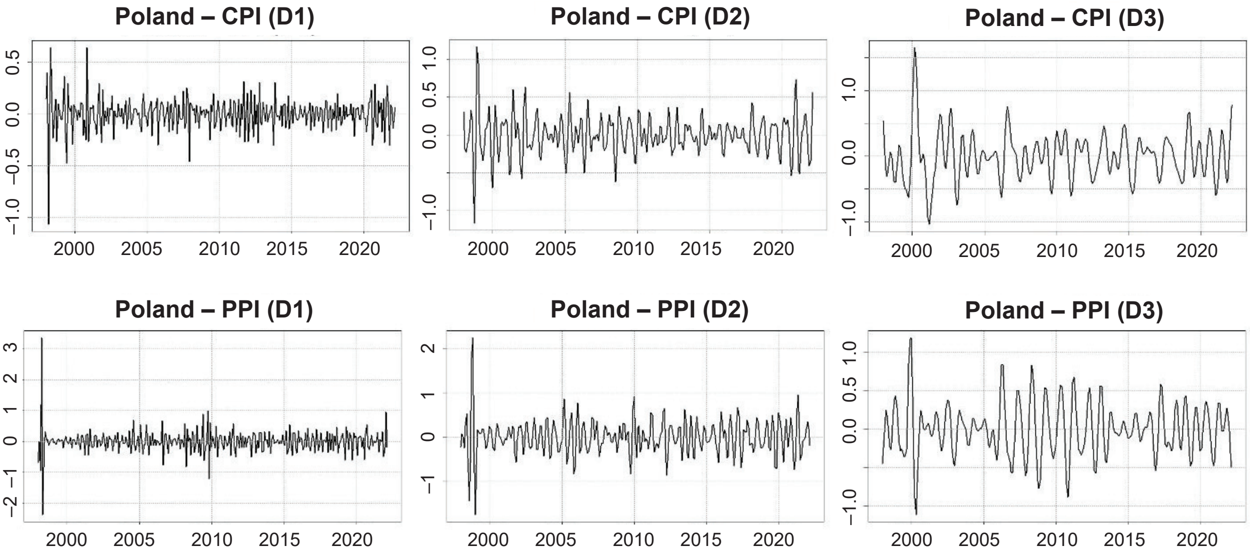
	Consumer prices					Producer prices				
	Mean	**St. dev.**	**Skew.**	**Kurt.**	**JB**	**Mean**	**St. dev.**	**Skew.**	**Kurt.**	**JB**
POL	3.343	3.180	1.243	4.442	100.2	0.257	0.808	2.595	24.570	5967.8
CZE	2.784	2.504	2.104	8.562	589.7	0.165	0.661	1.234	12.856	1251.6
HUN	4.992	3.493	0.827	3.954	44.3	0.427	1.142	–2.659	28.548	8256.7
SLK	3.918	3.535	1.288	4.870	122.9	0.133	0.677	0.223	4.919	47.1
LIT	2.639	3.052	1.498	5.773	202.1	0.266	1.517	0.321	7.488	249.2
LAT	3.558	3.841	1.490	5.837	205.3	0.297	0.776	1.248	6.979	267.5
EST	3.551	3.104	0.796	3.991	42.7	0.247	0.741	2.057	15.243	2022.6
SLO	3.251	2.909	0.646	2.300	26.1	0.261	0.451	1.484	7.523	354.8

Note: JB stands for Jarque-Bera test of normality.

Source: Authors' own calculation

Most empirical time series have a unit root, but these results are not presented in Table 1 because we do not work with empirical time series, but with wavelet signals, which are stationary by default. In order to be as concise as possible, we present in Figure 3 three levels of the Polish wavelet-decomposed time series of both inflation types. Wavelet-decomposed inflation of the other countries can be obtained on request. Utilizing wavelet methodology, we can observe causal interdependence between consumer and producer prices at the three different scale levels, which corresponds to the following time horizons: scale 1 (2–4 months), scale 2 (4–8 months) and scale 3 (8–16 months). We treat the first scale as the short time horizon, the second scale is the medium term, while the third scale is considered the long time horizon.

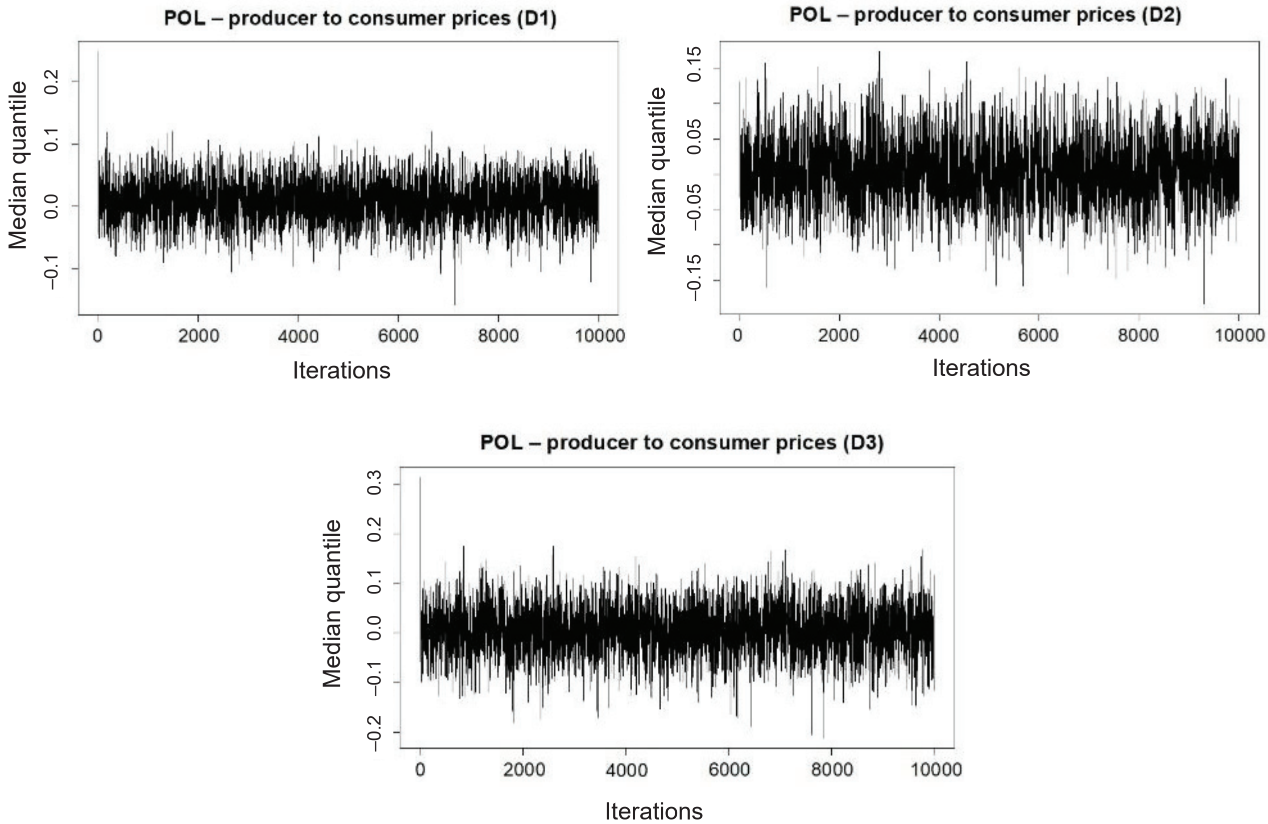
Figure 3: Wavelet-decomposed series of Polish consumer and producer prices



Source: Authors' own calculation

After construction of the wavelet-decomposed time series, we embed them in the Bayesian QR framework. We can check the validity of the estimated Bayesian QR parameter by inspecting a visual presentation of the MCMC chain convergence. In order to save space, we present three trace plots of the Polish case, where consumer prices affect producer prices, in Figure 3. The three median quantile plots represent different wavelet scales. Figure 4 shows the evolution of the MCMC draws over the iterations, and we use 10,000 iterations for our computations, which is significantly longer than the length of the empirical time series (291 monthly observation). In addition, we use 200 burn-in observations. We use a relatively long MCMC chain because more reliable quantile parameters are estimated when the MCMC chain is longer. As can be seen in Figure 4, all MCMC chains converge very quickly, which implies the absence of large bias of the estimated parameters (see Živkov *et al*., 2020). This means that the estimated BQR parameters can be regarded as trustworthy.

Figure 4: Trace plots of median quantile for Poland



Source: Authors' own calculation

5. Empirical Results

5.1 Wavelet coherence results

This subsection presents the wavelet coherence results for the selected CEECs, and Figure 5 contain these plots. Wavelet coherence lacks exact numerical estimates so we consider it an auxiliary method to the wavelet-based BQR approach, which can produce accurate numerical parameters. Wavelet coherence shows how strongly consumer and producer prices are connected in different time periods and wavelet scales. We use the two different methodologies for this study because the presence of high coherence could imply that the spillover effect is also high. Although this connection is not straightforward, some authors have found their existence (see, *e.g.*, Dajčman, 2012; Gulzar *et al.*, 2019). In this sense, wavelet coherence can serve as a complementary analysis and also as a robustness check.

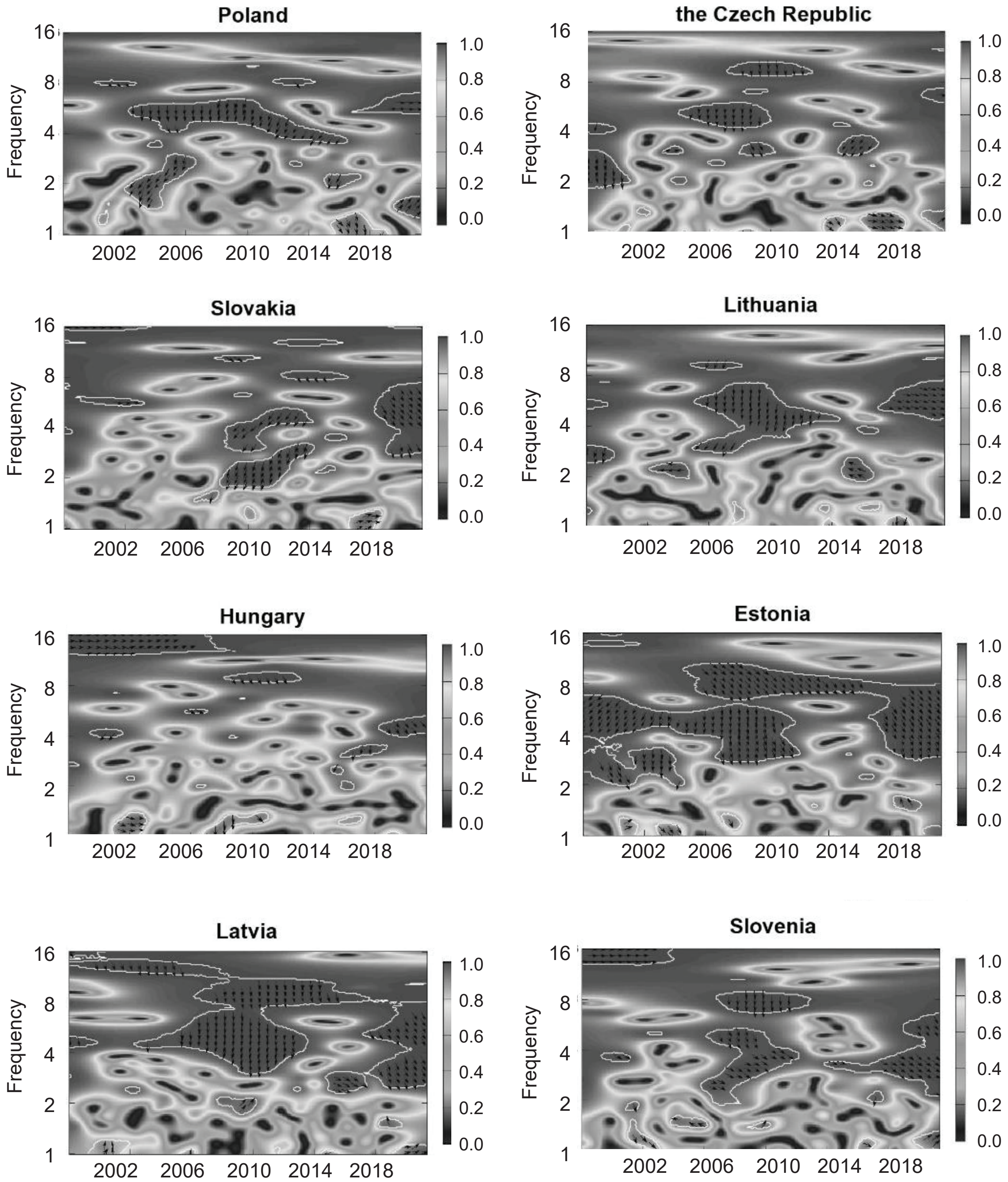
Wavelet coherence plots show two dimensions simultaneously: time and frequency, *i.e.,* the time component is placed on the horizontal axis, while frequency is represented by the levels of wavelet scales on the left vertical axis (see Njegić *et al.*, 2017). Wavelet scales indicate different time horizons, which are expressed in months, *i.e.,* from 1 month to 16 months. The strength of the coherence between the two inflation types is depicted via a colour surface, where a light-grey shade indicates a low level of coherence, while a dark-grey shade points to a high coherence. The delineated dark-grey areas indicate very strong coherence between variables, while phase arrows in these areas show the direction of the coherence. The right vertical axis contains the colour palette that ranges from 0 to 1, connecting strength of coherence with a particular colour.

It is obvious that strength of coherence differs across time and wavelet scales, which justifies the use of this methodology. The same pattern repeats on the all WTC plots. In other words, in the very short time horizon, up to two months, light-grey shades dominate, which means that the connection between consumer and producer prices is weak in the short term. These results are expected because idiosyncratic factors that affect the two inflation types come to the fore in the short term, and these factors are not usually synchronized. Therefore, weak coherence exists in all WTC plots up to two months. On the other hand, in the longer time horizons, particularly from four mounts onwards, dark-grey shades prevail. In longer time horizons, fundamental factors play a more important role than idiosyncratic ones, and these factors affect both inflation types concurrently. This assertion can be verified by looking at the delineated areas of very high coherence. Most of the high-coherence areas are placed around the Global Financial Crisis (GFC) and the coronavirus pandemic, and these crises affected both inflation types to move in the same direction synchronically. In other words, before the GFC, both consumer and producer prices recorded an upsurge because the global economy was in expansion, and demand was rising. After the onset and spreading of the GFC, the global economy went into recession, demand fell, and this caused a significant drop in both inflation types (see Figure 2).

On the other hand, when the pandemic erupted in 2020, which was followed by the Ukrainian war in 2022, the upsurge in prices in all the CEECs was caused not by the demand side, but by the supply side. Factors such as broken supply chains, counter-pandemic measures, government assistance to the people in the form of helicopter money and a significant rise in energy prices due to sanctions against Russia, induced a notable rise in producer prices, which was followed by a rise in consumer prices as well, in all the CEECs (see Figure 2). These developments galvanized the prices to move in the same direction, and this is why we find very high coherence around the period 2020–2022, particularly in Slovakia, the Baltic States and Slovenia.

Our distribution of coherence coincides very well with Tiwari *et al*. (2013) and Tiwari *et al*. (2014), who also found higher coherence in the longer time horizons and lower coherence in the shorter time horizons. In addition, one more thing in WTC plots should be mentioned, and that is the direction of the phase arrows. The majority of the phase arrows point down, which means that producer prices play a leading role in the periods of high coherence, because producer prices are the second variable in the WTC computation process. Cushing and McGarvey (1990) explained that primary goods are used as input with a lag period in the production process of consumption goods; hence, producer prices lead consumer prices, which is in line with our higher--coherence results in the longer time horizons.

Figure 5: Wavelet coherence results for selected CEECs



Source: Authors' own calculation

5.2 Wavelet-based Bayesian quantile estimates

Wavelet coherence can indicate the strength of the multiscale nexus between consumer and producer prices, but this is not enough for a thorough analysis because WTC plots do not contain numerical estimates and say nothing about the spillover effect. In an effort to be more comprehensive in our research, we estimate the wavelet-based Bayesian quantile regression. Table 2 contains the estimated wavelet-based BQR parameters calculated from both directions. The estimated BQR parameters do not have asterisks because they are all regarded as statistically significant as long as their confidence intervals are relatively narrow. Figures 6 and 7 present quantile plots for the Visegrad countries and the Baltic States and Slovenia, respectively, regarding the spillover effect from CPI to PPI. All the confidence intervals are set at 90% probability.

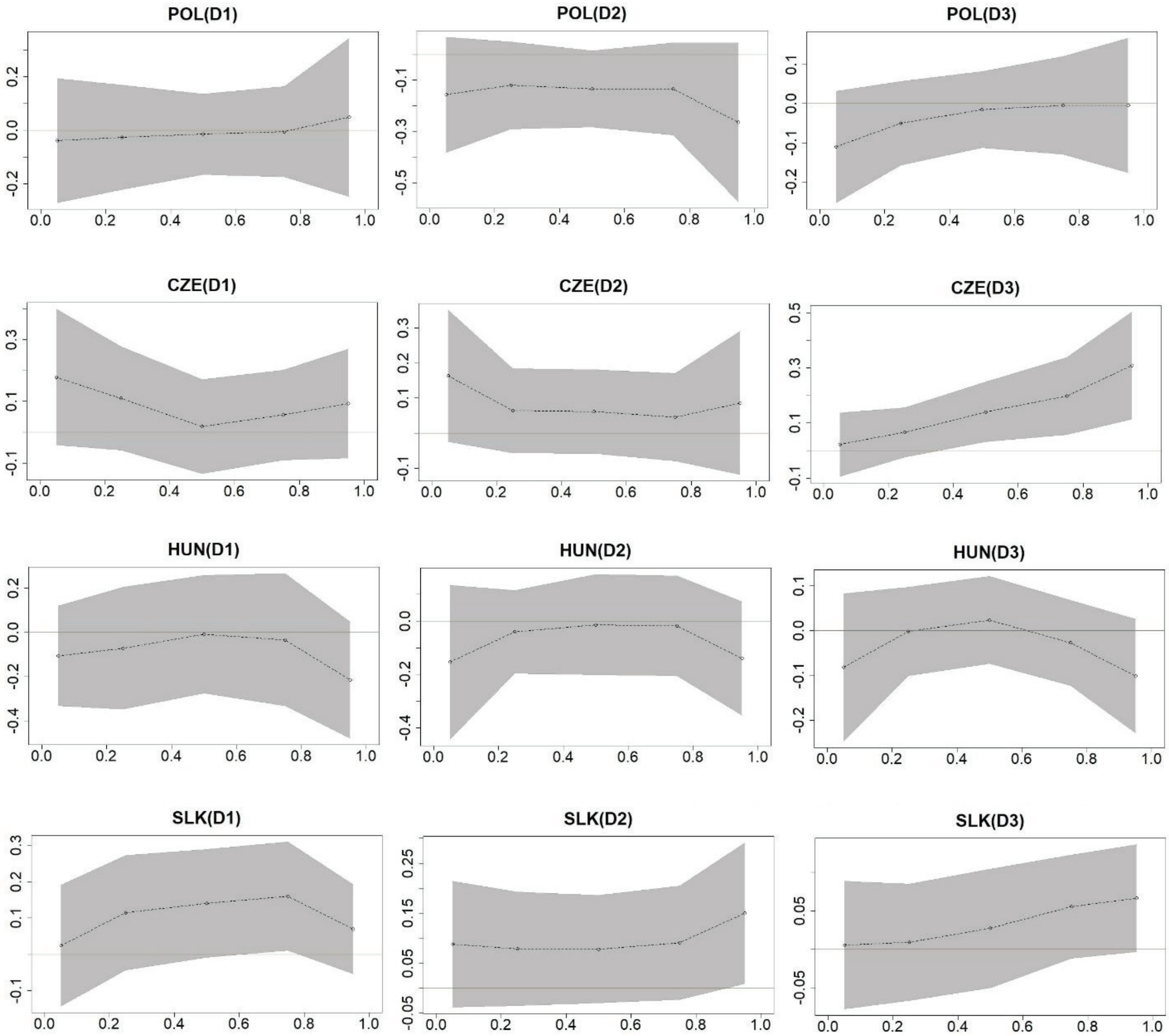
Figures 6 and 7 show the spillover effect from consumer to producer prices; figures for the opposite effect are not presented due to space constraints, and they can be obtained by request. We estimate the spillover effect under five different quantiles: 0.05, 0.25, 0.5, 0.75 and 0.95, where the first two quantiles indicate low inflation, the median quantile represents moderately high inflation, while the last two quantiles correspond to high inflation. According to Table 2, Bayesian QR estimates both positive and negative parameters. Positive parameters imply that a rise in one inflation type increases the other inflation type, while negative parameters indicate that the receiving inflation type decreases when the transmission inflation type increases. Negative parameters essentially mean that the spillover effect between inflation types does not exist, so these parameters will not be commented on, only the positive ones.

Table 2: Estimated bidirectional Bayesian quantile parameters

	Panel A: From consumer to producer prices					Panel B: From producer to consumer prices				
	$\tau^{0.05}$	$\tau^{0.25}$	$\tau^{0.5}$	$\tau^{0.75}$	$\tau^{0.95}$	$\tau^{0.05}$	$\tau^{0.25}$	$\tau^{0.5}$	$\tau^{0.75}$	$\tau^{0.95}$
	Poland					**Poland**				
D1	−0.039	−0.027	−0.015	−0.006	0.050	−0.008	−0.006	−0.013	−0.013	−0.025
D2	−0.157	−0.119	−0.134	−0.134	−0.256	−0.102	−0.059	−0.064	−0.086	−0.122
D3	−0.110	−0.051	−0.015	−0.004	−0.005	0.006	−0.028	−0.033	−0.018	−0.113
	Czech Republic					**Czech Republic**				
D1	0.179	0.111	0.018	0.057	0.092	0.075	0.046	0.034	0.020	0.060
D2	0.165	0.063	0.062	0.046	0.085	0.110	0.063	0.060	0.086	0.080
D3	0.022	0.066	0.141	0.197	0.308	0.320	0.251	0.224	0.146	0.169
	Hungary					**Hungary**				
D1	−0.107	−0.073	−0.010	−0.034	−0.217	−0.003	0.008	0.017	0.011	−0.024
D2	−0.154	−0.040	−0.014	−0.017	−0.142	−0.051	0.025	0.023	0.006	−0.093
D3	−0.081	−0.002	0.024	−0.027	−0.102	−0.102	−0.039	0.020	0.018	−0.062
	Slovakia					**Slovakia**				
D1	0.024	0.115	0.140	0.161	0.070	0.041	0.046	0.047	0.051	0.050
D2	0.088	0.079	0.078	0.091	0.150	0.154	0.076	0.072	0.075	0.189
D3	0.006	0.009	0.028	0.056	0.066	0.096	0.033	0.087	0.206	0.333
	Lithuania					**Lithuania**				
D1	0.325	0.419	0.500	0.262	0.107	0.018	0.044	0.045	0.049	0.058
D2	0.361	0.410	0.231	0.258	0.095	0.027	0.051	0.070	0.084	0.098
D3	0.188	0.057	0.093	0.157	0.340	0.124	0.049	−0.003	0.022	0.157
	Latvia					**Latvia**				
D1	0.204	−0.003	−0.055	0.019	0.282	0.021	−0.005	−0.007	0.016	0.077
D2	0.096	0.038	0.050	0.119	0.146	0.121	0.023	0.001	0.025	0.120
D3	0.016	0.056	0.048	0.046	0.048	0.047	0.013	−0.002	0.139	0.163
	Estonia					**Estonia**				
D1	0.059	0.022	0.041	0.032	0.141	0.054	0.032	0.014	0.008	0.029
D2	0.096	0.062	0.067	0.063	0.094	0.059	0.104	0.097	0.087	0.112
D3	0.044	0.073	0.084	0.090	0.126	0.105	0.094	0.071	0.129	0.206
	Slovenia					**Slovenia**				
D1	−0.046	−0.059	−0.105	−0.111	−0.145	−0.114	−0.033	−0.043	−0.094	−0.155
D2	−0.059	−0.030	−0.032	−0.018	−0.055	−0.137	−0.121	−0.083	−0.112	−0.112
D3	0.036	0.039	0.029	0.024	0.054	0.265	0.219	0.127	0.069	0.010

Source: Authors' own calculation

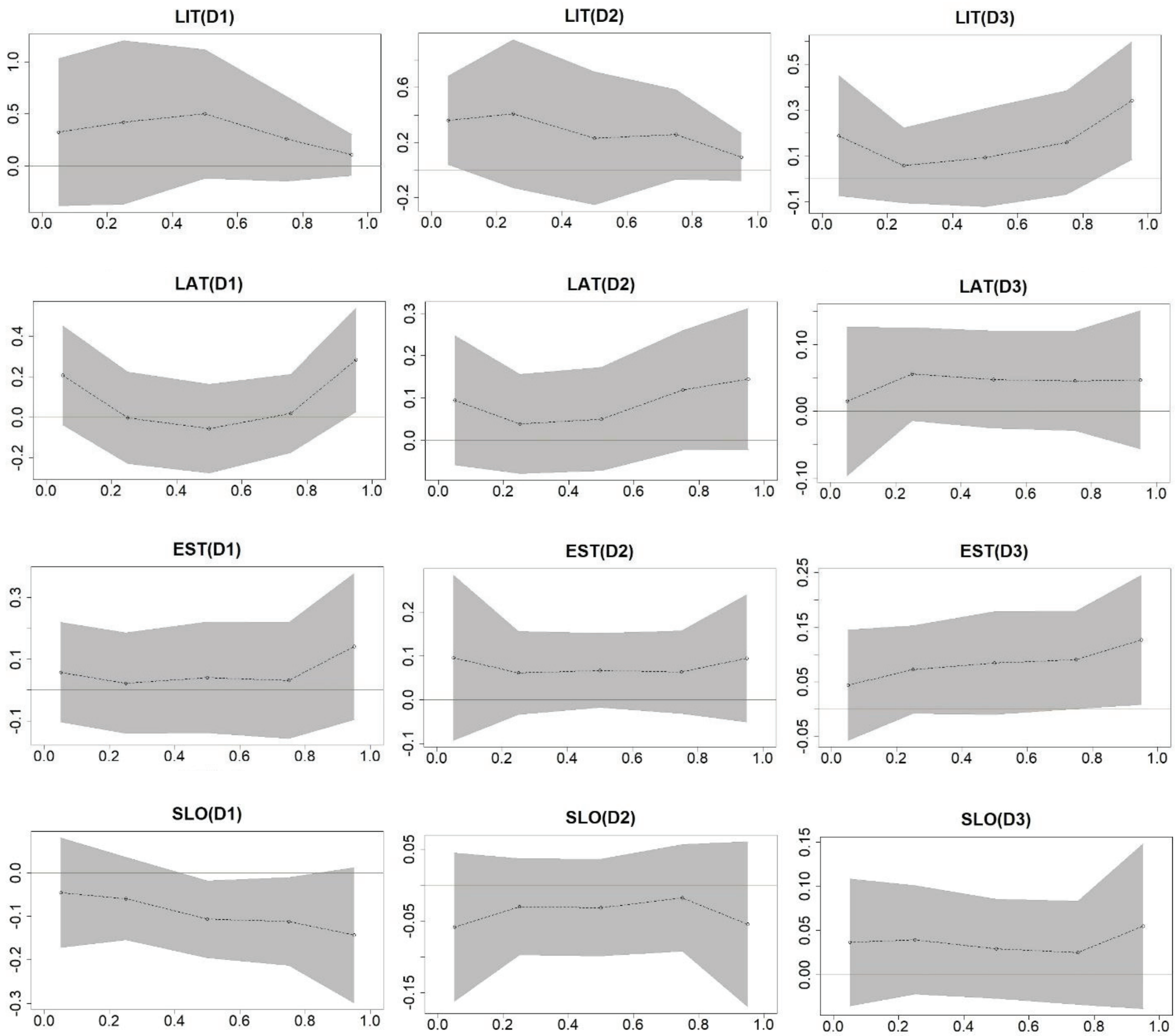
Figure 6: Estimated BQR parameters for Visegrad countries



Note: Shaded areas represent Bayesian confidence intervals at the 90% probability level.
Source: Authors' own calculation

Observing the Visegrad countries, it can be seen that only negative parameters are present in the case of Poland, while in the case of Hungary they are either negative or very low. This means that the transmission effect between consumer and producer prices does not exist in these countries in the all wavelet scales and all the market conditions. In the case of the Czech Republic, we find relatively high BQR parameters only in the long time horizon, while in the first two wavelet scales, these parameters are below 10%. Khan *et al*. (2018) asserted that CEE countries have adopted various approaches to manage inflation, and inflation targeting policy is one of them. However, the responses of the Czech Republic, Hungary and Poland were quicker compared to the remaining economies. This might be the reason why the spillover effect does not exist or is very low in these countries.

Figure 7: Estimated BQR parameters for Baltic States and Slovenia



Note: Shaded areas represent Bayesian confidence intervals at the 90% probability level.
Source: Authors' own calculation

The wavelet coherence findings are in line with the BQR results in a sense that high-coherence areas in these countries are very limited, and this is particularly true for the plot of Hungary. In other words, neighbouring inflation is not significantly responsible for the rise of consumer or producer prices in these countries, but arguably some other factors are causers. Stoica and Damian (2013) contended that the EU accession and the exchange rate of the Czech Republic, Poland and Hungary have contributed to CPI variations, since international trade of the countries relies significantly on commercial relationships with other EU countries. In addition, these three Visegrad countries do not conduct a fixed exchange rate regime, so exchange rate fluctuations are reflected in the prices of imported commodities, which plays a further major role in the formation of CPI, according to these authors. Beside these three Visegrad countries, Slovenia also reports only negative BQR parameters in the first two wavelet scales, which means that the spillover effect does not exist in the short and medium term. In the long-term horizon, the spillover effect is stronger from producer to consumer prices, than *vice versa*, and this effect is stronger when inflation is lower, which is represented by the lower BQR parameters.

As for Slovakia and the Baltic States, almost all BQR parameters are positive, while only in a few cases in Latvia, these parameters are negative. This means that consumer and producer prices interact in different time horizons and economic conditions. This effect is the strongest in the case of Lithuania, where the parameters go even beyond 40% when inflation spills over from consumer to producer prices. As a matter of fact, Lithuania is the only case where consumer prices have a stronger effect on producer prices than *vice versa*. It is also interesting that this effect is particularly strong in the short and medium term.

In the cases of Slovakia and Estonia, we find the highest spillover effect from producer to consumer prices in the long time horizon, at the highest quantile parameters, which means that the effect comes to the fore in cases when consumer prices reach the peak. In the case of Slovakia, this increase was mainly caused by an adjustment in energy prices and changes in value added tax and regulated prices for households (see Khan *et al*., 2018). All these changes increased input costs, and this is why we find positive and relatively high BQR parameters in the case of Slovakia (see Panel B). In the case of Latvia, we find that producer prices have a higher effect on consumer prices in the longer term, whereas in the short and medium term, the situation reverses. Therefore, in the case of Latvia, the situation is inconclusive as to which inflation type has the upper hand.

Looking at the overall results, a bidirectional spillover effect exists between the two inflation types in all the countries except Poland and Hungary, which coincides with conventional wisdom (see Shahbaz *et al*., 2010). In the cases of the Czech Republic, Slovakia, Estonia and Slovenia, producer prices have the upper hand over consumer prices, which is in line with the moderate inflation model. This theory indicates that producer prices play a pivotal role in the formation and fluctuation of consumer prices, *i.e.,* the cost-push inflation has the upper hand over the demand-pull inflation. Also, this effect is stronger in the longer time horizons, when fundamental factors play a crucial role in shaping domestic inflation. Only in the case of Lithuania, we find that consumer prices strongly affect producer prices, and this happens in the short term. In the case of Latvia, the BQR results are inconclusive because both inflation types have a precedence, but in different time horizons.

6. Summary and Conclusion

This paper investigated the multiscale interdependence and spillover effect between the consumer and producer prices of eight emerging CEECs. For the research purposes, we used several elaborate methodologies. In particular, we used wavelet coherence to inspect the multi-frequency nexus between the inflation types, while we combined the wavelet-decomposed time series and the Bayesian quantile regression to calculate the spillover effect.

We have several noteworthy findings to report. Firstly, wavelet coherence results indicate that the multiscale nexus between the inflation types is time-varying and scale-varying, where we find low coherence in the short term and higher coherence in the longer time horizons, particularly from four mounts onwards. Areas of very high coherence are visible around the crisis periods, *i.e.,* the GFC and the COVID-19 pandemic. The reason for such findings lies in the fact that fundamental factors come to the fore in the longer time horizons, and these factors affect both inflation types at the same time.

As for the spillover effect, the results are heterogeneous. In other words, a bidirectional spillover effect is found between the two inflation types in all the countries except Poland and Hungary. In the Czech Republic, Slovakia, Estonia and Slovenia, producer prices have the upper hand over consumer prices, which is in line with the moderate inflation model. This effect is stronger in the longer time horizons, when fundamental factors play a crucial role in shaping domestic inflation, which is in line with the wavelet coherence results. Only in the case of Lithuania, we find that consumer prices have a stronger effect on producer prices than *vice versa*, and this happens in the short term. In the case of Latvia, the BQR results are inconclusive because both inflation types have a precedence, but in different time horizons.

The results of this study can be useful for policymakers to learn whether and how producer prices affect consumer prices. In the cases of the Czech Republic, Slovakia, Estonia and Slovenia, the results can be helpful because producer prices affect consumer prices significantly. These results would imply that central banks need to take care about producer prices in order to control consumer prices. However, there are some thoughts that this process is not easy to implement. For instance, McKnight (2011) contended that central banks in open economies would be ill-advised to shift from consumer to producer price targeting, because CPI helps to prevent self-fulfilling expectations. In addition, Gautier (2008) asserted that unlike consumer prices, producer prices are by definition unobserved because there are no retail outlets where they can be measured, which makes consumer prices a more preferable and more practical measure to pursue. Therefore, the results of this paper should be used rather as a means of raising awareness about the connection between the two inflation types than as a solution to inflation controlling.

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