

Multiscale interdependence between economic policy uncertainty and industrial production of Central and Eastern European countries

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ABSTRACT

This paper shows how the three economic policy uncertainties (EPUs), namely global economic uncertainty, US economic policy uncertainty and German economic policy uncertainty, impact the industrial production of 8 Central and Eastern European countries. The investigation is done in both time and frequency domains, using the wavelet coherence and wavelet correlation approaches. The US EPU has the strongest effect on all industrial productions, while this effect was recorded during the global financial crisis and the corona virus pandemic. The most intense effect was found in the time-horizon between 4 and 8 months. The Czech Republic and Hungary suffer the strongest impact from EPU, probably because these two economies have relatively high ratio of export (import) *vis-à-vis* GDP. We fail to find very strong and wide areas of coherence in the Slovakian plot, although Slovakia has the highest level of export (import) to GDP. However, the wavelet correlation findings indicate that Slovakia has relatively high negative correlation at third wavelet scale, which is perfectly in compliance with its high export (import) share in GDP.

KEYWORDS

economic policy uncertainty, industrial production, wavelet approaches, Central and Eastern European countries

JEL CLASSIFICATION INDICES

C63, D24, E32

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1. INTRODUCTION

Economic policy uncertainty (EPU) is intrinsically unobservable. Its measurement is not an easy task, although significant steps have been undertaken recently in the estimation, but mainly through textual analysis (Solarin – Gil-Alana 2021). By definition, EPU is an index constructed based on newspaper articles from the leading newspapers in a particular country regarding policy uncertainty. The researchers count the number of newspaper articles containing the terms uncertainty, economy and one or more policy-relevant terms. In other words, each value of monthly national EPU index is in a proportion to the share of own-country newspaper articles which discuss EPU in that month. On the conceptual level, EPU is regarded as a disturbance that economic agents cannot foresee. Increased uncertainty can depress investments, new hiring or general consumption (Jurado et al. 2015). This can happen if companies cannot efficiently deal with the fixed costs, if they are risk-averse, which prevents them from starting new projects, or if accessibility of financial funds becomes a problem in response to higher uncertainty. Tran (2021) contended that EPU can affect corporate businesses from different angles, such as dividend policy, capital structure, equity issuance, corporate cash holdings, and most importantly, delay or abandonment of corporate investments. All these effects can trigger a prolonged downturn of the national economy with serious consequences.

As it is known, the past two decades are not short in events that shook the global economy and increased uncertainty about running business in both developed and emerging countries. Chronologically speaking, some of these important global events are: 9/11 terror attack, Iraqi war, Global financial crisis (GFC), US fiscal cliff, European sovereign debt crisis (ESDC), Syrian civil war, severe oil price drop in 2014, Brexit, US elections in 2016, US-China trade tensions and the COVID-19 pandemic. According to the above, this paper tries to thoroughly analyse the level of interdependence between economic policy uncertainty and industrial production (IP) of eight Central and Eastern European countries (CEECs) that became EU members in 2004 – the Czech Republic, Poland, Hungary, Slovakia, Lithuania, Latvia, Estonia and Slovenia. According to Njegić et al. (2017), all these countries recorder significant rise of import and export in the past two decades, which inevitably implies a high integration of these economies into the global economy, but also their high susceptibility to global turbulences. Referring to Lin et al. (2022), increasing international trade is crucial factor that boost economic integration of emerging markets.

As for the measure of economic uncertainty, we observe three different EPU indices, which *a priori* can be assumed that have an important effect on industrial activity of the selected countries. The first index is Global economic policy uncertainty (GEPU), which accounts a GDP-weighted average of national EPU indices for 21 countries.¹ The second one is the US economic policy uncertainty (US EPU) index, which takes into account terms related to economic and policy uncertainty from 10 large newspapers² in the US. The US is selected because it is the largest and most influential global economy. The third one is the German economic policy

¹These countries are: Australia, Brazil, Canada, Chile, China, Colombia, France, Germany, Greece, India, Ireland, Italy, Japan, Mexico, the Netherlands, Russia, South Korea, Spain, Sweden, the United Kingdom, and the United States.

²These newspapers are: USA Today, the Miami Herald, the Chicago Tribune, the Washington Post, the Los Angeles Times, the Boston Globe, the San Francisco Chronicle, the Dallas Morning News, the Houston Chronicle, and the Wall Street Journal.



uncertainty (GER EPU) index, which is considered because all selected CEECs have the most developed trade connections with Germany. GER EPU is constructed in the same manner as US EPU index, but in this case, information about economic and policy uncertainty is drawn from two newspapers.³ Figure 1 presents dynamics of GEPU index, linking some of the abovementioned events with the specific time period.

Generally speaking, EPU can reflect the changes in government policy and the behaviour of politicians, financial intermediaries, and enterprises, where most papers on this topic refer to developed countries or large emerging market economies. For instance, [Nguyen and Trinh \(2023\)](#) researched the effects of EPU on firm-level innovation activities, using a panel sample of 213 UK largest non-financial firms over the period 1999–2018. They found an evidence that the government EPU has caused a substantial reduction in UK firms' investment in innovation activities. [Nguyen \(2022\)](#) investigated the impact of EPU on the probability and duration of economic recessions in ten major developed European Union countries over the period 1987Q2–2021Q1. They reported that EPU causes not only a higher probability of economic recessions but also longer recessions. [Guo et al. \(2022\)](#) studied the spillover effects of monetary, fiscal, and trade policy uncertainty between China and the US from both static and dynamic perspectives. Their results showed that there exists a strong spillover effects with time-varying characteristics between the policy uncertainties of the two countries. They asserted that the leader of the spillover is monetary policy in China, and fiscal policy in the US. Since CEEC economies are not studied from this aspect, to the best of our knowledge, this paper tries to bridge the gap in the literature by focusing on the emerging European economies. This is where we find a motive to do this research.

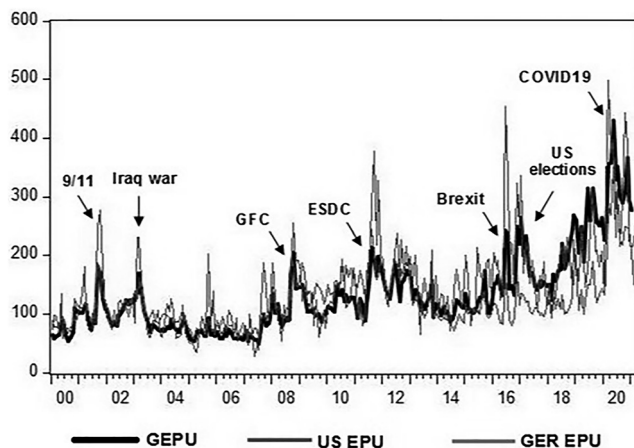


Fig. 1. Empirical dynamics of the GEPU index

Source: Authors' illustration based on https://www.policyuncertainty.com/global_monthly.html.

³These newspapers are: Handelsblatt and Frankfurter Allgemeine Zeitung.

In addition, another important contribution to the literature is the fact that we observe the nexus *via* time-frequency perspective, using a wavelet decomposing methodology. In other words, the nexus between the EPU indices and industrial production of eight CEECs is observed through time, but also across different time horizons. In that sense, we are able to assess the level of connectedness between the variables in relation to specific global events, but also, we can see how the strength of this interdependence differs in various time horizons. In particular, we utilize two wavelet approaches – wavelet coherence (WTC) and wavelet correlation. These methods complement each other, and together they can give a better insight about the researched topic than only one methodology. The key characteristic of the wavelet technique is that it elegantly circumvents the problem of sample size reduction, which is a common issue in traditional econometric tools when different time-horizons are in the focus. In other words, wavelet computation does not lose valuable information.

As for the particular wavelet methods, wavelet coherence decomposes the time-scale relationships between EPU and industrial production, allowing researchers to test the strength of the dynamic dependence at different scales or time-horizons. The strength of the nexus is visible *via* colour spectrum in the wavelet coherence plots. However, these results do not provide a clear numerical value of the coherence strength between variables, and due to that reason, we also utilize wavelet correlation approach, as a complementary analysis. Unlike WTC, wavelet correlation computes exact correlation values at different time-horizons, but it lacks time component. However, when these two methodologies are combined, then we can gain a pretty good indication what is the real nature between EPU and industrial production across different time periods and time-horizons. Wavelet technique is a popular econometric tool, used by many recent papers for various research purposes (see e.g. Kučerová – Poměnková, 2015; Fidrmuc et al., 2020). Regarding this topic, we are only familiar with the papers of Choi (2020) and Dash et al. (2021), which used wavelet methodology in examining the connection between EPU and sectoral industrial activity in the US. Therefore, there is a plenty of room for the contribution to the literature in this area, particularly when CEECs are in the question.

Besides introduction, the rest of the paper is structured as follows. Second section contains literature review. Third section explains used methodologies – wavelet coherence and wavelet correlation. Fourth section introduces dataset. Fifth section presents wavelet coherence and wavelet correlation results in two subsections. The last section gives concluding remarks.

2. LITERATURE REVIEW

EPU indices have been relatively recently developed. The extant papers are mostly focused on the developed countries. For instance, Nilavongse et al. (2020) researched the impact of foreign and domestic EPU shocks on the UK economy. They found that domestic industrial production declines after a shock to the EPU index in the US. On the other hand, disturbances of domestic EPU are proved to be a source of real exchange rate fluctuations. Their results indicated the domestic EPU surge after Brexit referendum as the reason behind a massive depreciation of the British pound. Gulen and Ion (2016) investigated the effect of policy-related uncertainty on the capital investments of U.S. public corporations. They reported a strong negative relationship between policy uncertainty and capital investments. Balli et al. (2017) studied the determinants of cross-country economic policy uncertainty spillovers. They determined that bilateral factors



such as trade and common language play a significant role in explaining the magnitude of the EPU spillovers. Also, they contended that the magnitude of EPU spillovers is higher for those countries that have expressed vulnerability in terms of fiscal, trade or financial liability imbalances. Zhou et al. (2021) investigated the impact of EPU on the choice of entry mode of enterprises' Outward Foreign Direct Investment (OFDI). They asserted that EPU has a significant effect on the entry mode choice of Chinese OFDI. In particular, they determine that when the economic policy uncertainty decreases, enterprises choose cross-border mergers and acquisitions mode with higher propensity than the greenfield investments mode of OFDI.

Attig et al. (2021) researched the link between EPU and dividend policy, considering data from 19 countries. They found that a high level of EPU is positively associated with dividend pay-out, claiming that this evidence is robust to using alternative dividend pay-out measures. They concluded that dividends help mitigate agency problems during the high-EPU periods. The study by Krol (2014) investigated the impact of GEPU and EPU on exchange rate volatility of ten industrial and emerging economies since 1990. Their results suggested that, for more integrated industrial economies, both home-country and US economic policy uncertainty increase currency volatility during bad economic times. On the other hand, for the less integrated emerging economies, only the home-country economic policy uncertainty increases exchange rate volatility during bad economic times. Colombo (2013) studied the effects of the US EPU shock on some Euro area macroeconomic aggregates, using structural VAR model. She reported that one standard deviation shock to the US economic policy uncertainty leads to statistically significant fall in the European industrial production and prices of -0.12% and -0.06% , respectively. The findings indicated that contribution of the US uncertainty shock on the European aggregates is quantitatively larger than the one exerted by the Euro area-specific uncertainty shock. Dash et al. (2021) examined the causality and co-movement between economic policy uncertainties and stock market liquidity using the G7 countries. They determined that a causal relationship exists between economic policy uncertainty and stock market liquidity. The results suggested that stock market illiquidity varies with the uncertainty but in the same direction, whereas liquidity co-moves in the opposite direction.

3. RESEARCH METHODOLOGIES

3.1. Wavelet theory and wavelet coherence

The goal of this paper is to measure the dependence structure between the three EPU indices and industrial production of eight CEECs in time-frequency domain. For that task, we use complex, but elegant methodological tool, known as wavelet technique. Wavelet approach can be described as a nonlinear and energy preserving transformation method that projects original time-series onto a sequence of basic functions, which are called wavelets. On the theoretical basis, wavelet operates with the two elementary wavelet functions: father wavelet (ϕ) and mother wavelet (ψ). Father wavelets depict the smooth or low frequency parts of a signal with an integral equal to 1, and mother wavelets describe the details of high frequency components with an integral equal to 0. Father ($\phi_{j,k}(t)$) and mother ($\psi_{j,k}(t)$) wavelet functions can be generated in the following way:



$$\phi_{J,k}(t) = 2^{-J/2} \phi\left(\frac{t - 2^J k}{2^J}\right), \psi_{J,k}(t) = 2^{-J/2} \psi\left(\frac{t - 2^J k}{2^J}\right). \quad (1)$$

In the above equations, the scale or dilation factor is 2^J , whereas the translation or location parameter is $2^J k$. For wavelet correlation computation, we use the non-orthogonal wavelets, known as the maximum overlap discrete wavelet transformation (MODWT), which calculates highly redundant non-orthogonal transformation. Decomposed signals in MODWT framework are given in the following way:

$$S_{J,k} \approx \int (t) \phi_{J,k}(t) dt, \quad (2)$$

$$D_{j,k} \approx \int (t) \psi_{j,k}(t) dt, j = 1, 2, \dots, J. \quad (3)$$

where symbols $s_{j,k}$ and $d_{j,k}$ denote the fluctuation and scaling coefficients, respectively, at the j -th level wavelet that decomposes empirical signal or time-series in terms of a specific frequency (trending and fluctuation components). According to equations (2) and (3), an empirical time-series $y(t)$ can be expressed in terms of those signals as:

$$(t) = \sum_k S_{J,k} \phi_{J,k}(t) + \sum_k D_{j,k} \psi_{j,k}(t) + \sum_k D_{j-1,k} \psi_{j-1,k}(t) + \dots + \sum_k D_{1,k} \psi_{1,k}(t), \quad (4)$$

Earlier in the paper, we have said that we use two wavelet approaches – wavelet coherence⁴ and wavelet correlation.⁵ In order to avoid misunderstanding, wavelet correlation uses discrete wavelet transformation, i.e. MODWT approach as in equation (4), while wavelet coherence is based on the continuous wavelet transformation. Our intention is to first calculate wavelet coherence, and later wavelet correlation, which will complement the WTC results. According to Athari et al. (2021), the function of the continuous wavelet transform, $W_x(u, s)$, can be obtained by projecting a specific wavelet $\psi(\cdot)$ onto the examined time series $x(t) \in L^2(\mathbb{R})$. This can be seen in expression (5):

$$W_x(u, s) = \int_{-\infty}^{\infty} x(t) \frac{1}{\sqrt{s}} \psi\left(\frac{t - u}{s}\right) dt, \quad (5)$$

where u denotes the position of the wavelet in the time domain, while s defines the position in the frequency domain. According to equation (5), information on both time and frequency can be simultaneously obtained by mapping the original time-series into a function of u and s in the wavelet transform.

Wavelet coherence gives an information about the strength of the correlation throughout the wavelet scales and the observed sample. According to Tao et al. (2018), WTC measures the local linear correlation between two stationary time-series at each scale, and it is equal to the squared

⁴Wavelet coherence is calculated via ‘WaveletComp’ package in ‘R’ software.

⁵Wavelet correlations are calculated via ‘waveslim’ package in ‘R’ software.



correlation coefficient in linear regression. Kirikkaleli and Gokmenoglu (2020) explained that wavelet coherence can be presented as a squared absolute value of the smoothed cross wavelet spectra, where it is normalized by the product of the smoothed individual wavelet power spectra of each selected time-series. The cross wavelet transform of the 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 represent the wavelet transforms of x and y , respectively. Symbols u and s denote position and scale index, while the symbol $*$ indicates to a complex conjugate. The squared wavelet coherence coefficient is presented in equation (6):

$$R^2(u, s) = \frac{|\mathbb{S}(s^{-1}W_{xy}(u, s))|^2}{\mathbb{S}(s^{-1}|W_x(u, s)|^2)\mathbb{S}(s^{-1}|W_y(u, s)|^2)} \quad (6)$$

where $\mathbb{S}(\cdot)$ stands for the smoothing operator. The squared wavelet coherence coefficient ranges between $0 \leq R^2(u, s) \leq 1$, where values near zero indicate weak correlation, while values near one point to strong correlation.

Wavelet coherence can indicate positive (negative) coherence, but only in areas of very high coherence, and also the lead-lag relationship between variables. This information provides phase difference *via* phase arrows in WTC plots. Referring to Torrence and Webster (1999), the wavelet coherence phase difference is defined as in equation (7):

$$\phi_{xy}(u, s) = \tan^{-1} \left(\frac{\Im \{S(s^{-1}W_{xy}(u, s))\}}{\Re \{S(s^{-1}W_{xy}(u, s))\}} \right) \quad (7)$$

where $\Im$ and $\Re$ are the imaginary and real parts, respectively, of the smooth power spectrum. If arrows point to right (left), this indicates that time series are in-phase (anti-phase) or they are positively (negatively) correlated. If arrows are directed to right and upward, the second variable is lagging, whereas if they are directed to right and downward, the second variable is leading. Contrary, if arrows point to the left and upward, the second variable is leading and if arrows point to the left and downward, the second variable is lagging.

3.2. Wavelet correlation

In addition to wavelet coherence, we also compute wavelet correlation, since wavelet correlation gives accurate values of correlation, while combination of both methods provides more detailed results. Wavelet correlation relies on the discrete wavelet transformation as in equation (4), where bivariate stochastic process of the two time-series, $x(t)$ and $y(t)$, is $\mathbb{Z}_t = (x_t, y_t)$. Each wavelet coefficient is obtained by applying the MODWT process in $\mathbb{Z}_t$. The time-dependent wavelet variance for scale j of each time-series is then presented as $\sigma_{x,j,t}^2 = \text{Var}(\hat{D}_{x,j,t})$ and $\sigma_{y,j,t}^2 = \text{Var}(\hat{D}_{y,j,t})$, where $\hat{D}_{j,t} = (\hat{D}_{x,j,t}, \hat{D}_{y,j,t})$ is a scale j wavelet coefficient computed from $\mathbb{Z}_t$. Accordingly, the time-dependent wavelet covariance for scale j is $\gamma_{x,y,j,t} = \text{COV}(\hat{D}_{x,j,t}, \hat{D}_{y,j,t})$. Combining wavelet variances and wavelet covariance, we can obtain wavelet correlation coefficients as in equation (8):

$$\rho_{x,y,j,t} = \frac{\text{COV}(\hat{D}_{x,j,t}, \hat{D}_{y,j,t})}{(\text{Var}(\hat{D}_{x,j,t})\text{Var}(\hat{D}_{y,j,t}))^{1/2}}. \quad (8)$$



4. DATASET

In order to estimate multiscale interdependence between IP and EPU, we use monthly data of industrial production of the analysed 8 CEEC countries. All IP time-series are collected from the *stats.oecd.org* website, and they are seasonally adjusted, using the filter-based methods of seasonal adjustment, known as X11 style method. Also, we use the three economic policy uncertainty indices – GEPU, US EPU and GER EPU. These indices are retrieved from the *policyuncertainty.com* website, and they are all transformed to log-returns according to the expression $r_{i,t} = 100 \times \log(P_t/P_{t-1})$, where P is the value of a particular EPU index. Time-span of all time-series ranges from 2000:M1 to 2021:M1.

Table 1 contains basic statistics of the deseasonalized IP time-series and three EPU log-return indices. As can be seen, all IPs are positive on average, which means that all industrial productions of the CEECs grew on average in the observed sample. Slovakia and Lithuania report the highest volatility, but also positive skewness, while all other countries have higher number of negative IP observations, i.e., negative skewness. For all CEECs, except the Baltic States, we find very high kurtosis values, which indicates presence of extreme observations, and they are probably caused by a particular global event. Figure 3 presents seasonally adjusted IP time-series of the 8 CEECs, where it can be seen that very high IP oscillations are recorded

Table 1. Descriptive statistics of the selected time-series

	Mean	St. dev.	Skewness	Kurtosis	JB	DF-GLS
Panel A. Industrial production						
Czech Republic	0.292	2.770	−1.499	34.989	10,796.2	−12.955
Poland	0.447	2.536	−1.688	26.350	5,821.2	−16.018
Hungary	0.370	3.621	−1.854	29.650	7,571.4	−4.339
Slovakia	0.506	4.313	0.339	20.644	3,260.5	−12.011
Lithuania	0.493	4.870	0.036	5.210	51.1	−2.876
Latvia	0.306	1.995	−0.368	4.227	21.4	−18.604
Estonia	0.392	2.822	−0.323	4.757	36.6	−2.842
Slovenia	0.234	2.644	−1.598	12.669	1,084.7	−15.969
Panel B. Economic policy uncertainty						
GEPU	0.617	18.474	0.643	4.586	43.590	−18.202
US EPU	0.393	19.289	0.486	5.282	64.352	−11.504
GER EPU	0.307	38.265	0.303	3.155	4.098	−11.406

Notes: JB stands for Jarque-Bera test of normality. DF-GLS stands for Dickey-Fuller generalized least squares unit root test. Critical values of 1% and 5% for DF-GLS test with 5 lags, assuming only constant, are −2.574 and −1.942, respectively.

Source: Authors' calculation.



around 2020, which is associated with the COVID-19 pandemic. Figure 3 clearly shows that the COVID-19 pandemic affected IPs much worse than the global financial crisis in 2008 in most of the CEECs, except Lithuania and Latvia. Undoubtedly, this is the reason for the high kurtosis values in Table 1. Jarque – Bera normality test suggests that none of the IP time-series follows Gaussian distribution. Dickey-Fuller generalized least squares (DF-GLS) test results indicate that all selected time series are stationary.

As have been said, in the estimation process of multiscale nexus between EPU and IP, we use wavelet coherence and wavelet correlation methods. In this process, we consider four wavelet time-scales, which allow us to assess the strength of interlink in different time-horizons. These time-horizons corresponds to: scale 1 (2 months), scale 2 (4 months), scale 3 (8 months) and scale 4 (16 months). We regard the first two scales as short-term, midterm is represented by the third scale, while the fourth scale correspond to the long-term dynamics.

5. EMPIRICAL RESULTS

5.1. Wavelet coherence findings

This section presents the wavelet coherence results between the three EPU indices and IPs of the eight CEECs. Figure 2 contains the WTC plots of the Visegrad group countries, while Figure 3 presents the plots of the Baltic States and Slovenia. As have been said, this methodology can simultaneously observe two dimensions – time and frequency, where time component is placed on the horizontal axis, while levels of wavelet scales are depicted on the left vertical axis, which go up to fourth scale (16 months). The strength of the coherence between the variables is shown *via* colour surface, where light-grey indicates low coherence, while dark-grey points to higher coherence. Delineated dark-grey islands indicate very strong co-movement, and these areas also contain phase arrows, which tell about the direction of coherence. The colour pallet is presented on the right vertical axis, ranging from 0 to 1. The cone of influence defines statistically significant area at 5% significance level.

The WTC plots give us an opportunity to see in which time period stronger coherence exists, and this can help us to link higher coherence with the particular global event. Also, WTC can suggest in which time-horizon the strongest coherence is recorded, which signals the delay effect. As can be seen, all the WTC plots show that strength of the coherence is heterogeneously distributed across time and wavelet scales, which speaks about complexity of the nexus between the EPU indices and IPs. It is obvious in all the WTC plots that light-grey surface dominates at the lower wavelet scales, i.e. up to fourth scale. This finding indicates that correlation between the EPU indices and IP is not particularly strong at the short-term horizon, which means that IPs do not react immediately, but some time need to pass before the effect occurs. Our results coincide with the paper of Choi (2020), who investigated coherence between economic uncertainty and several sectors of industrial economy in the US. He also reported relatively low coherence in short-term.

However, from 4 months upwards, dark-grey surface dominates in all the WTC plots, which means that stronger coherence comes to the fore in the midterm and long-term horizons. Besides, in these lower frequency scales, it is evident the presence of delineated islands, which denote very strong EPU-IP relationship. It is interesting to see that the surface under very strong coherence is different across the periods and countries. For instance, Figure 2 indicates that the



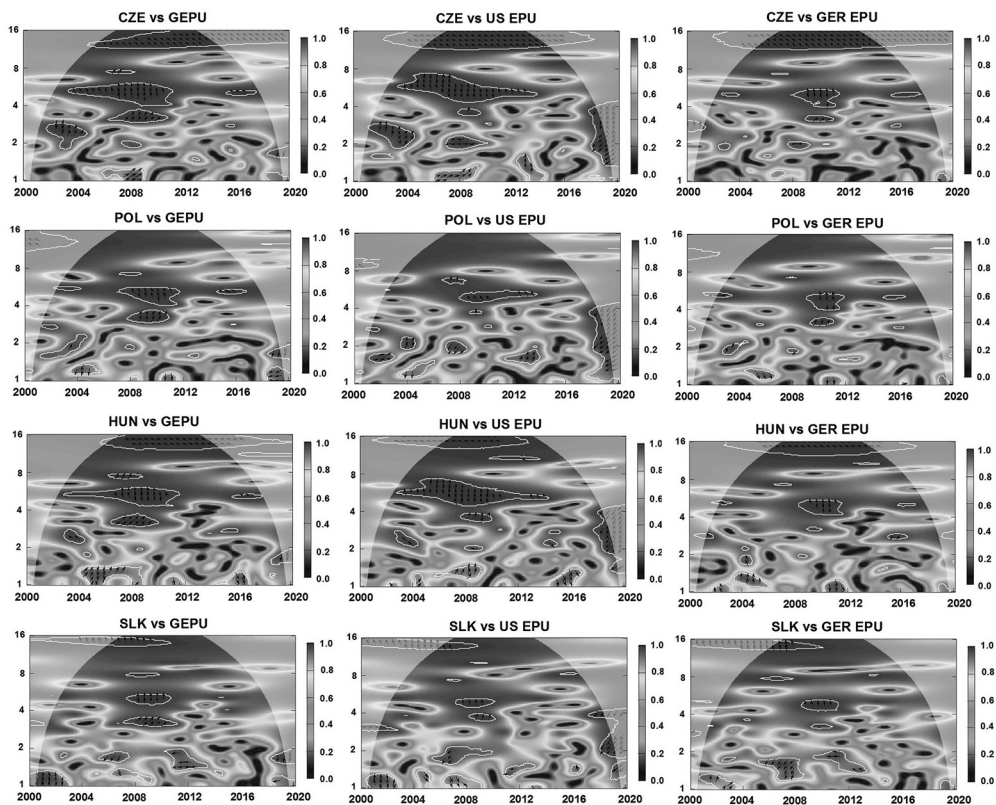


Fig. 2. Wavelet coherence plots of the Visegrad group countries

Notes: Left (right) vertical axis denote wavelet scales (colour) pallet. X axis indicates a length of the sample.

Source: Authors' calculation.

Czech Republic and Hungary have the widest high coherence areas between four and eight months. These high coherence areas are placed around the period 2008–2012, which can be linked with the GFC and subsequent ESDC crisis. Our results are very much in line with the paper of Njegić et al. (2017) who investigated business cycles synchronisation between eight CEECs and the EU-15, using wavelet coherence approach. They reported very high coherence in the Czech and Hungarian cases, while in the Polish case they found an absence of high coherence, which is also the case in this research (see Figure 2). The high coherence in Figure 2 is particularly conspicuous when IP is observed *vis-à-vis* GEPU and US EPU. As a matter of fact, the high coherence islands are the broadest in the US EPU plots. This means that information that arrived from the US market impacts the strongest IPs in the Czech Republic and Hungary. This is expected because GFC started in the US. On the other hand, high coherence areas in the GEPU plots are somewhat smaller than the US EPU counterparts. The reason probably lies in the fact that GEPU incorporates global information from 21 countries around the world, i.e., the

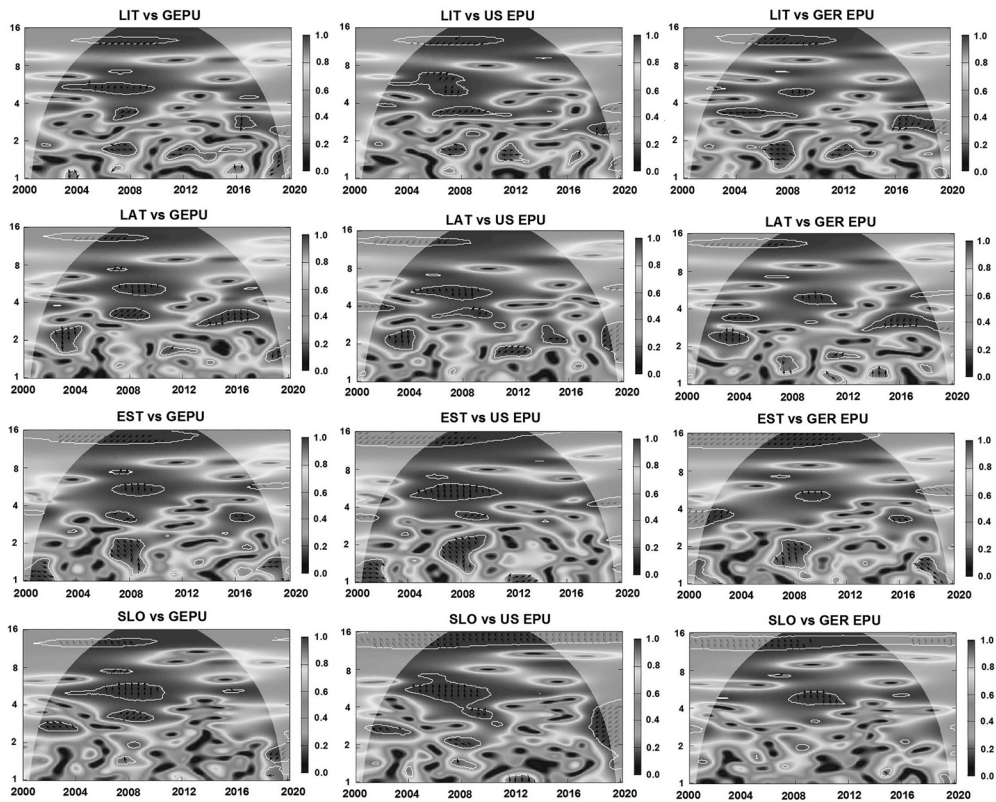


Fig. 3. Wavelet coherence plots of the Baltic states and Slovenia

Notes: Left (right) vertical axis denotes wavelet scales (colour pallet). X axis indicates a length of the sample.

Source: Authors' calculation.

relative frequency of the own-country newspaper articles, while not all countries in the world were affected by the same intensity of GFC.

Besides, we find very high coherence around 2020 in the US EPU plots for all the Visegrad countries at the higher frequencies up to four months. These findings undoubtedly indicate to the COVID-19 pandemic, which is, by these results, more serious global crisis than GFC, because this crisis comes to the fore more quickly in the Visegrad economies. Choi (2020) inclines to the same thinking, claiming that the corona virus crisis has influenced the sector volatility in the US more than GFC, taking into account all US sectors. The US economy is affected particularly hard by corona virus, and because of that, we find very high coherence areas around 2020 only in the US EPU plots. However, due to the fact that this crisis is in the progress, an in-depth analysis and a thorough comparison between these two global crises can only be made once the pandemic has ended globally. Regarding the GER EPU plots, we find relatively limited areas of high coherence, which indicates that German economic policy uncertainty has



relatively limited effect on the Visegrad countries, in spite of the fact that Germany is the most important trading partner of all the Visegrad countries.

In order to offer an explanation why the Czech Republic and Hungary are affected harder than Poland and Slovakia, we present Table 2 with average annual amounts of export and import weights in GDP. This table has shown that the Czech Republic and Hungary have among the highest ratio of export (import) to GDP throughout the years. The levels of export and import might indicate how strong the countries are integrated in the global economy, particularly with developed western countries. According to Table 2, Hungary and the Czech Republic have relatively high ratios of export and import to GDP, which is in line with the relatively wide areas of high coherence during GFC. Poland has the lowest ratio, which also coincides with very restricted high coherence areas in the Polish plots. However, in the case of Slovakia, we find very limited high coherence surface in all the three WTC plots, although Slovakia has the highest ratios of export and import to GDP. Dark-grey surface dominates at low frequencies in the Slovakian case, as in the cases of other three Visegrad countries, but very high coherence that last for several years is not detected during GFC and ESDC. The reason probably lies in the limitation of the WTC methodology. Namely, WTC plots cannot provide clear results and it cannot show actual numbers regarding the level of coherence. This is the reason why we additionally use the wavelet correlation approach, which complements the WTC findings.

As for Baltic States and Slovenia, the results are pretty much similar with the findings of the Visegrad countries, in a sense that stronger effect of EPU is detected at higher wavelet scales, i.e. in the longer time-horizons. The strongest coherence around GFC is present in the Estonian and Slovenian plots, while Lithuania and particularly Latvia have relatively narrow high coherence areas. These results concur very well with the level of export (import) in Table 2, where can be seen that Estonia and Slovenia have the highest percentage of export (import) of these four countries, while Lithuania and particularly Latvia lag behind. This suggests that former countries are more integrated in the global economy, and thus, more exposed to global crises, which WTC plots confirm. Njegić et al. (2017) also asserted that Latvia has the lowest level of business cycle synchronization with EU-15.

At the end, we comment phase arrows which indicate a direction of the coherence. Every caption in WTC plots tells which variable is the first and which one is the second in the process of WTC computation. This is important because phase arrows then can suggest a direction of the coherence, but also the leading (leading) relationship. As can be seen, most phase arrows in high coherence areas point to the left and upwards, which suggests negative coherence, where EPU leads IP. This means that every rise in EPU results in decline of IP, which is expected. Also, it is highly logical that EPU leads IP, as phase arrows suggest.

Table 2. Average annual weight of export and import in GDP of the selected CEECs

	CZE	POL	HUN	SLK	LIT	LAT	EST	SLO
Export in GDP, %	66	41	76	80	61	49	70	67
Import in GDP, %	63	42	74	79	65	57	71	64

Note: Export and import are for the period of 2000–2020.

Source: World bank, <https://data.worldbank.org/indicator/NE.EXP.GNFS.ZS>.



5.2. Wavelet correlation findings

Wavelet correlation results can complement the WTC findings, but also can be useful for the robustness check. As has been said, wavelet correlations compute exact correlation in every wavelet scale, which WTC cannot do, but wavelet correlation does not have time component, which is an intrinsic feature of WTC. When both methodologies are combined, a holistic picture emerges. Table 3 contains calculated wavelet correlations between every EPU and IP of every country. Besides, it also gives a size of correlation at the empirical level – one month. Figures 4 and 5 graphically illustrate wavelet correlations presented in Table 3.

Wavelet correlations can indicate explicitly the level of average correlation at particular wavelet scale, as well as its direction. As can be noticed, wavelet correlations do not report very

Table 3. Computed wavelet correlations between EPUs and IPs of the selected CEECs

	Czech Republic			Poland			Hungary		
	GEPU	US EPU	GER EPU	GEPU	US EPU	GER EPU	GEPU	US EPU	GER EPU
1 month	0.017	0.087	0.147	−0.001	0.028	−0.011	−0.061	−0.059	−0.054
D1	−0.033	−0.025	−0.032	0.088	0.070	0.053	0.012	0.012	−0.040
D2	0.106	0.045	0.014	0.113	0.114	0.109	0.110	0.160	0.062
D3	−0.164	−0.188	−0.177	0.115	0.027	0.156	−0.034	−0.111	−0.076
D4	−0.072	−0.027	0.128	−0.235	−0.199	−0.034	−0.095	−0.049	0.097
	Slovakia			Lithuania			Latvia		
	GEPU	US EPU	GER EPU	GEPU	US EPU	GER EPU	GEPU	US EPU	GER EPU
1 month	−0.012	0.025	0.013	0.015	0.008	0.109	0.146	0.142	0.154
D1	−0.054	−0.074	−0.026	−0.226	−0.129	−0.090	0.062	0.159	0.035
D2	−0.055	−0.026	−0.130	−0.169	0.001	−0.155	0.205	0.210	−0.052
D3	−0.129	−0.211	−0.218	−0.067	0.105	−0.099	0.191	0.063	0.151
D4	0.110	0.138	0.266	0.273	0.307	0.419	0.078	0.104	0.264
	Estonia			Slovenia					
	GEPU	US EPU	GER EPU	GEPU	US EPU	GER EPU			
1 month	0.050	0.041	0.094	0.057	0.057	0.155			
D1	0.044	0.089	0.001	0.147	0.164	0.095			
D2	−0.173	−0.061	−0.132	0.003	0.030	−0.009			
D3	0.105	−0.034	0.010	−0.052	−0.236	−0.126			
D4	0.045	0.098	0.234	0.034	0.073	0.215			

Source: Authors' calculation.



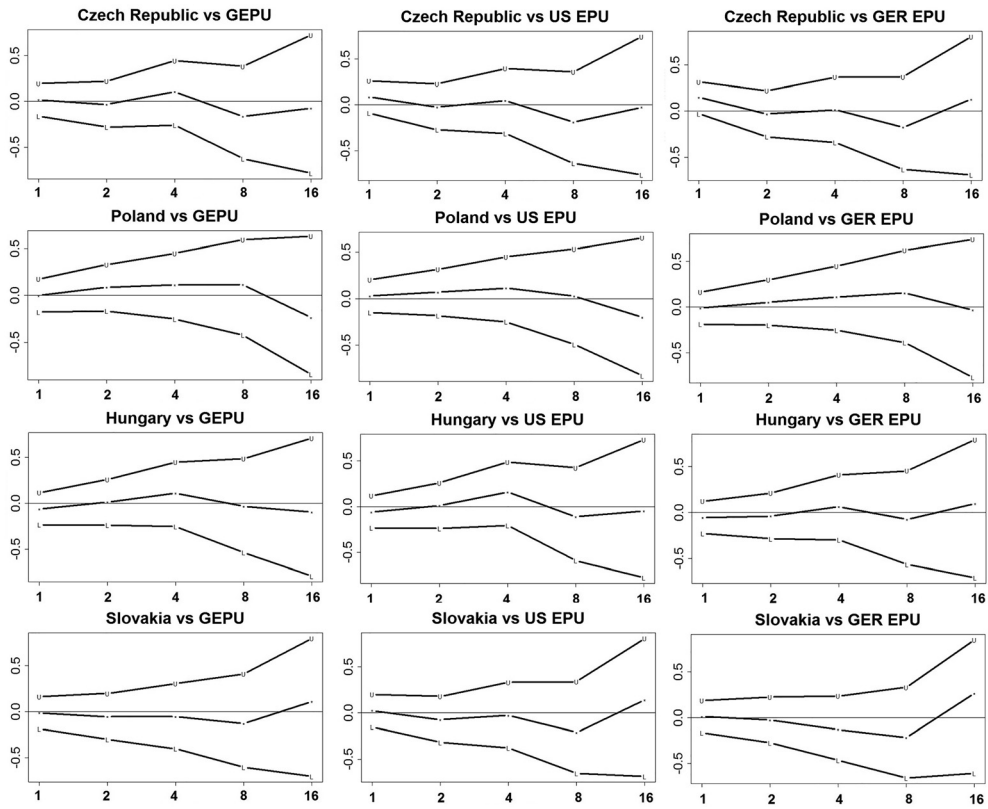


Fig. 4. Calculate wavelet correlations of the Visegrad countries
Note: Y axis presents the level of wavelet correlation, while X axis denotes wavelet scales.
Source: Authors' calculation.

high correlations at higher wavelet scale, which is somewhat different vis-à-vis the WTC plots, but this does not mean that WTC results are wrong. It should be said that wavelet coherence rather stands as indicator than a numerical result, and from that point of perception, wavelet coherence and correlation findings are pretty much harmonized.

For instance, wavelet correlation in the Czech case is negative and relatively high at D3 scale, which is consistent with the WTC plots. In the CZE-US EPU case, wavelet correlation is -0.188 , which means that 100% rise of economic policy uncertainty in the US results in decline of industrial production in the Czech Republic by about 19% in eight months' time-horizon. For Hungary it is 11% and for Slovenia it is 24%. It is interesting to note that, for Slovakia, we also find relatively high correlation at D3 scale (-0.211), which is in line with the high level of Slovakian export and import as Table 2 suggests. For Lithuania and Estonia, the highest negative correlation is detected at D2 scale in relation to GEP, amounting -0.226 and -0.173 , respectively. All these clear-cut results are not obviously visible on the WTC plots, and that is why wavelet correlations are very useful complementary tool.



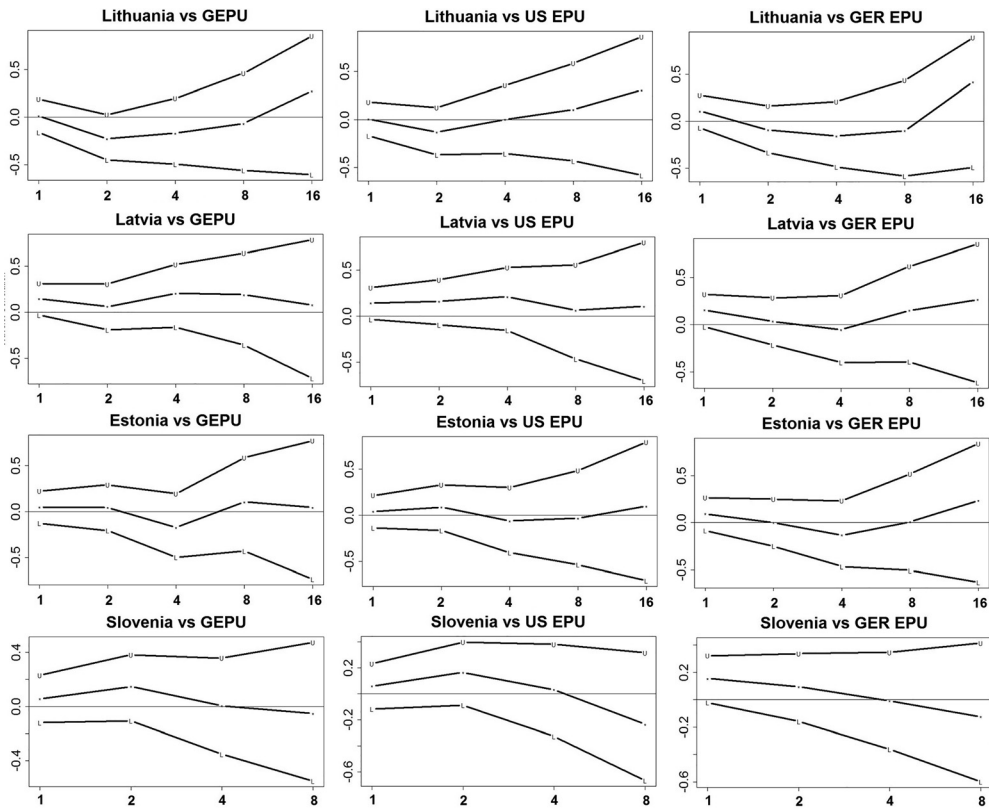


Fig. 5. Calculate wavelet correlations of the Baltic States and Slovenia

Note: Y axis presents the level of wavelet correlation, while X axis denotes wavelet scales.

Source: Authors' calculation.

As for Poland and Latvia, the countries with the lowest level of trade integration, wavelet correlations are actually positive, which means that the three types of EPUs do not affect IPs of these two economies. Analysing the WTC plots in the previous subsection, we also find the absence of high coherence in the period of GFC crisis in these two countries, which means that both results from two different methodologies coincide very well. Relatively low negative wavelet correlation results of the six countries concur with the findings of [Colombo \(2013\)](#), who investigated the effects of US EPU shock on some Euro area macroeconomic aggregates. He found that 100% rise in standard deviation shock of the US EPU leads to statistically significant fall in the European industrial production by -0.12% , which is very much in line with our findings.

6. CONCLUSION

We investigated how three forms of the economic policy uncertainty – GEP, US EPU and GER EPU – affect industrial production in 8 CEECs. The analysis was done from time-frequency



perspective, using two elaborate methodologies – wavelet coherence and wavelet correlation. Both methodologies complement each other.

Wavelet coherence indicates the strength of coherence in time-frequency domain *via* colour surface. This method is good for showing in which time periods and in which time-horizon a stronger coherence is present. According to the WTC plots, the Czech Republic and Hungary have the widest areas of very high coherence that are recorded around GFC, in the time-frame between 4 and 8 months. Generally, the US EPU has the strongest effect on CEECs, which means that all CEECs react the most intense on information from the US, in spite the fact that Germany is the most important trading partner to all CEECs. Slovenia also reports very high coherence around GFC, but with somewhat smaller surface than the Czech Republic and Hungary counterparts. Both the Czech Republic and Hungary have relatively high ratio of export (import) to GDP, which implies high integration of these economies in the global economy. It is possible that both countries suffered a strong impact in the period of GFC due to the high level of their international integration that is reflected in the significant ratio of their export (import) in GDP. On the other hand, Poland and Latvia have the lowest levels of export (import) in GDP, and they are affected modestly by GFC, according to the WTC results. We also find a significant impact of the current COVID-19 crisis on the Visegrad economies and Slovenia.

We fail to find very strong and wide areas of coherence in the Slovakian plot, although Slovakia has the highest level of export (import) to GDP. A rationale could be the fact that WTC plots do not provide exact numbers and sometimes can be inconclusive in showing the results. Due to that reason, we also compute wavelet correlation, which serves as a supplement to WTC. The wavelet correlation findings support the WTC results in great deal and also indicate that Slovakia has relatively high negative correlation at third wavelet scale, which is in compliance with its high export (import) share in GDP.

The result from this paper could be interesting for policy makers of the selected CEECs, because they can obtain a guideline about which information affects the industrial production of their country most. Based on the fact that the US EPU has the most influential effect on the most IPs, policy makers can gain an insight in which time-horizon recession could be expected, and accordingly, can devise some counter-recession measures.

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