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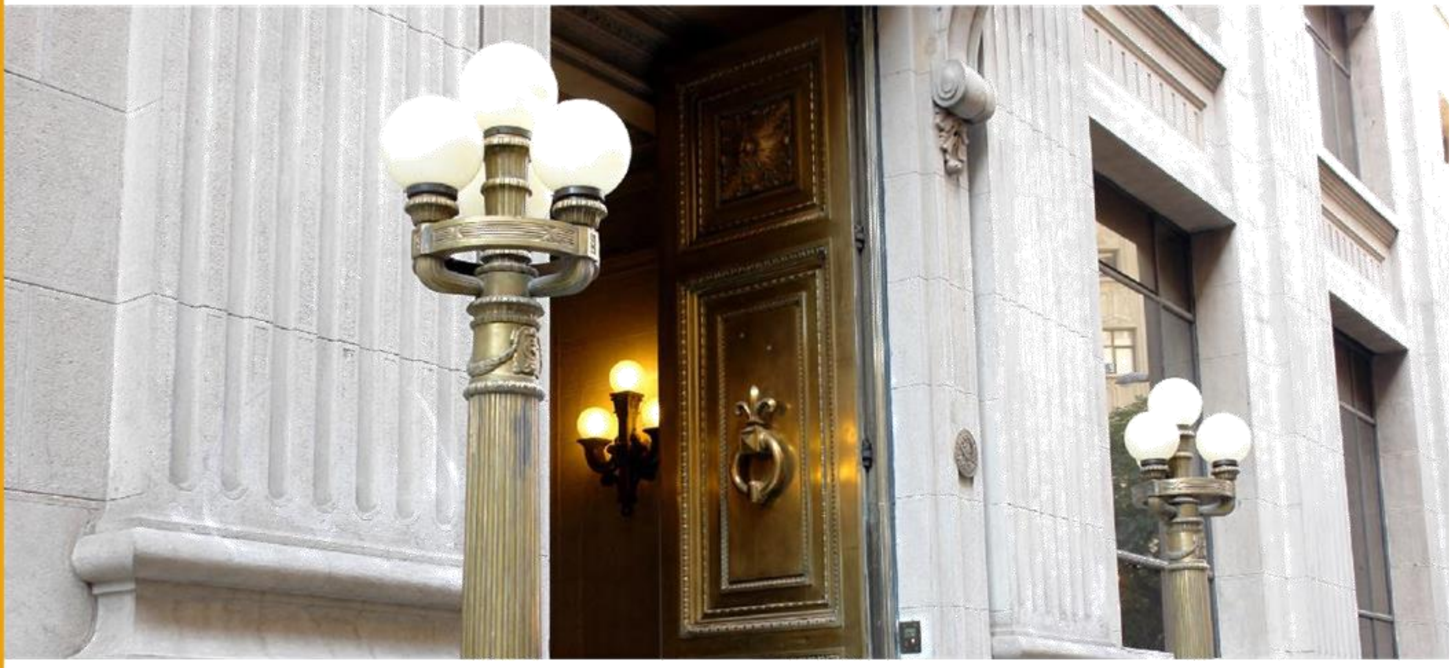

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This Time is Global: Synchronisation in Economic Policy Uncertainty Indices*

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Resumen
Esta nota descompone los índices de Incertidumbre de Política Económica (EPU) para 28 países en componentes nacionales y globales, utilizando estimaciones en estado-espacio para evaluar la influencia reciente del factor global, particularmente originado en EEUU. Los resultados muestran que, en la mayoría de los países, el componente global ha contribuido en mayor medida a los niveles generales de EPU desde fines de 2024 que durante la Crisis Financiera Global de 2007-08 o la pandemia de Covid-19. Además, la sincronización global ha alcanzado niveles récord, como lo indica la coherencia de fase promedio (mean phase coherence), mientras que la coherencia multivariada de ondas (multivariate wavelet coherence) confirma una sincronización tanto en ciclos de alta como de baja frecuencia. Estos resultados sugieren un panorama global debilitado, dado que una reversión de políticas restrictivas al comercio difícilmente restablecerá las condiciones económicas previas.

Abstract
This note decomposes Economic Policy Uncertainty (EPU) indices for 28 countries into domestic and global components, using state-space estimates to evaluate the recent influence of the global factor, particularly that originating from the US. The findings show that, in most countries, the global component has contributed more to overall EPU levels since late 2024 than during the 2007-08 Global Financial Crisis or the Covid-19 pandemic. Additionally, global synchronisation has reached record levels, as indicated by mean phase coherence, while multivariate wavelet coherence confirms alignment across both high- and low-frequency cycles. These results suggest a subdued global outlook, as a reversal of trade-restrictive policies is unlikely to restore prior economic conditions.

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1 Motivation, aim, and main results

The effects of uncertainty on the economy are manifold, including delays in irreversible decisions (*e.g.*, Dixit, 1992; Bernanke, 1983; Bloom, Bond, and Van Reenen, 2007), rising risk premia (*e.g.*, Pástor and Veronesi, 2013; Brogaard and Detzel, 2015), altered consumer behaviour (*e.g.*, Carrière-Swallow and Céspedes, 2013), greater financial market volatility (*e.g.*, Antonakakis, Chatziantoniou, and Filis, 2013), and weakened expectations among economic agents (*e.g.*, Pástor and Veronesi, 2012, and Bijsterbosch and Guérin, 2013)—all terminating in negative real effects (Bloom, 2009; Giraldo *et al.*, 2025).

Given these broad implications, it is vital to rely on accurate and meaningful measures of uncertainty, particularly linked to policy decisions.[1] Several approaches exist to measure macroeconomic uncertainty at both global and domestic levels, based on: (i) macroeconomic indicators and financial market prices (*e.g.*, Jurado, Ludvigson, and Ng, 2015); (ii) automated text-based analysis of newspapers and online portals (*e.g.*, Caldara and Iacoviello, 2022); (iii) survey-based measures (*e.g.*, Sill, 2012); and (iv) structural or econometric models (*e.g.*, Bloom *et al.*, 2018; Chávez, Contreras-Reyes, and Idrovo-Aguirre, 2022). While most of these measures are routinely applied to the global and advanced economies, their use is gradually extending to a growing number of emerging markets.

This note examines a decomposition of the widely used *Economic Policy Uncertainty* index (EPU; Baker, Bloom, and Davis, 2016) into domestic and global components using state-space regression techniques. The analysis covers 28 countries from 1997 to 2025 and assesses the extent to which domestic uncertainty is driven by uncertainty originating in the US, the world's dominant economy. Special attention is paid to developments from late 2024, highlighting the growing influence and synchronisation of the global component.[2]

The results indicate that in 22 of the 28 analysed countries, the most recent data show a sharp rise in the global component of uncertainty, with most recording their highest levels to date. In four cases, the latest readings are second only to those during the Covid-19 pandemic. Notably, current values surpass those recorded during the 2007-08 *Global Financial Crisis*. Synchronisation measures—mean phase coherence and multivariate wavelet coherence—reveal an unprecedented degree of alignment, with the latter capturing recent synchronisation across frequencies not previously observed in the sample.

These findings underscore a troubling scenario in which trade policy disruptions and globally synchronised uncertainty may have lasting effects—even if reversed—reflecting how US-driven financial conditions propagate uncertainty worldwide (Miranda-Agrippino and Rey, 2022), and how policy uncertainty depresses investment and global engagement (Handley and Limão, 2022).

The rest of this note is organised as follows. Section 2 outlines the econometric strategy, including the data, the state-space decomposition of EPU indices and the construction of synchronisation measures, along with main results. Section 3 offers concluding remarks on their implications for global uncertainty dynamics.

2 Econometric strategy and results

2.1 Data

The US EPU index (Baker, Bloom, and Davis, 2016) is based on automated text analysis of ten major newspapers, including *The New York Times*, *The Wall Street Journal*, and *The Washington Post*. Articles are identified as referencing economic policy uncertainty if they contain at least one term from each of three categories: (i) economy-related (*e.g.*, "economic", "economy"); (ii) uncertainty-related (*e.g.*, "uncertain", "uncertainty"); and (iii) policy-related (*e.g.*, "Congress", "Federal Reserve", "deficit", "regulation", "White House", and related terms).

[1] The term *uncertainty* is used in its measurable sense, excluding Knightian uncertainty, which cannot be modelled or quantified probabilistically (see Mayberry *et al.*, 2024 for a recent macroeconomic application).

[2] Numerous studies have used the EPU index to examine its effects on financial markets. For example, Ko and Lee (2015) analyse its relationship with stock prices using a wavelet approach. More relevant to this note, Colombo (2013) shows that both global and US-specific EPU have significant spillover effects on the Euro Area. Klößner and Sekkel (2014) further find that, since the 2007-08 *Global Financial Crisis*, the US and UK have been key sources of international policy uncertainty spillovers.

For each newspaper and month, the number of qualifying articles is normalised by the total articles published that month, controlling for variation in article volume. These series are then standardised and averaged across the ten newspapers to produce a composite monthly index. The US EPU index used spans from 1997.1 to 2025.4 (340 monthly observations) and is normalised to an average of 100 over the 2007-2015 period.

The same methodology is applied to 28 additional countries, encompassing both advanced and emerging economies across all income levels and continents. Descriptive statistics for the resulting EPU indices are provided in Table A1 in Annex A.[3] To construct each country-specific index, the main national newspapers are analysed to compute the measure described above. For example, in the case of Spain, Ghirelli, Pérez, and Urtasun (2019) employ a total of seven newspapers (*ABC*, *Cinco Días*, *El Economista*, *El Mundo*, *El País*, *Expansión*, and *La Vanguardia*), whereas for France only *Le Monde* and *Le Figaro* are used (see https://www.PolicyUncertainty.com). This discrepancy is non-trivial, as it shapes the underlying construction of each index and, consequently, affects the decomposition between domestic and global components.

Even within the US, some uncertainty events pertain strictly to domestic affairs, while others reverberate globally. For instance, the terrorist attacks of 11 September 2001 had profound international spillover effects, influencing EPU indices in many countries. In contrast, the 16-day US federal government shutdown in October 2013 was largely confined to the domestic sphere, with no meaningful global transmission.

A similar distinction arises in countries other than the US, where the global component can even exert a negative influence. In Turkey, for example, the EPU index peaked in 2020 not only due to the Covid-19 pandemic, but also owing to rising geopolitical tensions with Cyprus and Greece, which began in February and escalated through September with the involvement of France. As these tensions eased by the end of the year, the Turkish EPU exhibited not only heightened volatility but also a persistent negative contribution from the global component.

2.2 Estimation of domestic and global components

Each EPU index for country i, where $i = 1, ..., 28$, is modelled using a stationary state-space VAR(1) process:

$$\begin{bmatrix} EPU_t^i \\ EPU_t^{US} \end{bmatrix} = \begin{bmatrix} a_t \\ d_t \end{bmatrix} + \begin{bmatrix} b_t & c_t \\ e_t & f_t \end{bmatrix} \begin{bmatrix} EPU_{t-1}^i \\ EPU_{t-1}^{US} \end{bmatrix} + \begin{bmatrix} \varepsilon_t^i \\ \varepsilon_t^{US} \end{bmatrix}, \tag{1}$$

where $\Theta_t = \{a_t, b_t, c_t, d_t, e_t, f_t\}$ are time-varying parameters, and $\{\varepsilon_t^i, \varepsilon_t^{US}\}$ are mutually independent white noise processes, with $\varepsilon_t^i \sim \mathcal{N}(0, \sigma_i^2)$ and $\varepsilon_t^{US} \sim \mathcal{N}(0, \sigma_{US}^2)$. This VAR(1) system serves as the measurement equations, while the state equations for each coefficient are defined as follows:

$$\Theta_t = \Theta_{t-1} + \boldsymbol{\psi}_t, \tag{2}$$

where $\psi_t^i \sim \mathcal{N}(0, \sigma_{\psi_i}^2)$ is a white noise innovation associated with each element of Θ_t. The system, comprising the VAR(1) model and six associated state equations, is estimated via the Kalman filter. Initial values are set by estimating the VAR(1) for each country using Ordinary Least Squares on the full sample. It is worth noting that, contrary to the intended rationale, the equation for EPU_t^{US} includes the lagged value of EPU_t^i, implying that country i share common news with the US. This is not necessarily problematic, as both economies are exposed to common global shocks. In any case, the main interest lies in the first row of the VAR(1), particularly in the estimated effect of EPU_{t-1}^{US} on EPU_t^i, *i.e.*, $\widehat{c}_t$. This specification targets the first moment of the (stationary) EPU_t^i series;[4] the time-varying intercept should not be interpreted as a time trend. Since the raw data are bounded and then standardised around a pivot, a trend would imply a growing share of qualifying terms—contradicting the index's design. This rules out trend-based identification approaches (*e.g.*, Stock and Watson, 2007; Gabaix,

[3] All series are available from the *Economic Policy Uncertainty* website (https://www.policyuncertainty.com/index.html). Some updates follow sources cited on the site, except for Denmark and New Zealand, whose data are obtained from the Federal Reserve Bank of St. Louis (FRED) using an interpolation from quarterly to monthly frequency.

[4] All series are stationary according to the Phillips and Perron (1988) test, based on a regression with intercept and Newey–West lag selection, using data from the first available observation through 2024.12.

2011; Mertens, 2016).[5] The analysis thus focuses on the dynamic behaviour of the first moment, excluding static impulse–response functions and second-moment tools such as variance and historical decompositions.

The estimes for a_t can be interpreted as idiosyncratic uncertainty, while b_t captures the series' persistence. By contrast, the coefficient c_t, capturing the sensitivity of EPU_t^i to EPU_{t-1}^{US} is interpreted as exogenous. Based on the estimated coefficients $\{\widehat{a}_t, \widehat{b}_t, \widehat{c}_t\}$ the "Domestic component" and the "Global component" are constructed as follows:

$$\begin{aligned} \text{Domestic component} \quad &: \quad DC_t^i = \widehat{a}_t^{(i)} + \widehat{b}_t^{(i)} \cdot EPU_{t-1}^i, \\ \text{Global component} \quad &: \quad GC_t^i = \widehat{c}_t^{(i)} \cdot EPU_{t-1}^{US}. \end{aligned} \tag{3}$$

The results for DC_t^i an GC_t^i, alongside EPU_t^i, are presented in Figure 1B of Annex B. In all countries except Greece, the latest value of GC^i contributes positively to domestic EPU; in Greece's case, data are only available up to 2024.12. In 22 countries—Austria, Brazil, Chile, China, Denmark, France, Germany, Hong Kong, India, Ireland, Italy, Japan, South Korea, Mexico, New Zealand, Pakistan, Russia, Singapore, Spain, Sweden, Turkey, and the UK—the latest reading marks the highest recorded contribution of GC^i, spanning economies across Europe, the Americas, Asia, and Oceania.

In contrast, for Belgium, Colombia, Croatia, and Poland, the latest value of GC^i, is not the highest on record but ranks second since the onset of the Covid-19 pandemic, exceeding the peak observed during the *Global Financial Crisis*. In Canada, although GC^i is not at its maximum, this is mainly due to an exceptional surge in its domestic component, which rose to 1,635.40—driven by the same factors affecting other economies. Canada's case is distinctive, as it has been among the most adversely affected by US policy announcements since late 2024, many of which extend beyond purely economic matters.

2.3 Synchronisation measures

Previous evidence points to an unprecedented degree of comovement among indices. This subsection examines two measures of synchronisation: (i) mean phase coherence (Mormann *et al.*, 2000; Mezeiová and Paluš, 2012), and (ii) multivariate wavelet coherence (Rua, 2010; Aguiar-Conraria and Soares, 2011, 2014).

2.3.1 Mean phase coherence

Mean phase coherence is a widely used measure of phase synchronisation between two time series and can be readily extended to larger datasets. It is particularly suited to analysing oscillatory and potentially nonlinear signals, such as those in neurophysiology and macroeconomic indicators with cyclical behaviour.

To illustrate, consider two stationary time series, x_t and y_t. The first step is to compute their *instantaneous phases*, typically via the Hilbert transform or the complex Morlet wavelet transform. Let $\phi_x(t)$ and $\phi_y(t)$ denote the instantaneous phases of x_t and y_t, respectively. The phase difference between the two signals is defined as:

$$\Delta\phi(t) = \phi_x(t) - \phi_y(t). \tag{4}$$

Mean phase coherence is then calculated as the magnitude of the average unit-length phase difference vectors over time:

$$R = \left| \left\langle e^{i\Delta\phi(t)} \right\rangle \right| = \left| \frac{1}{T} \sum_{t=1}^{T} e^{i(\phi_x(t) - \phi_y(t))} \right|, \tag{5}$$

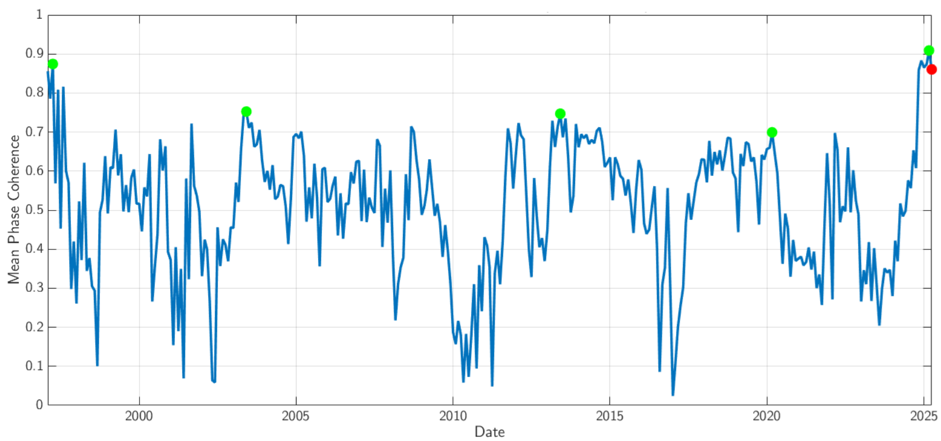
where $\langle \cdot \rangle$ denotes the temporal average, T is the number of observations, and $i = \sqrt{-1}$ is the imaginary unit. When extending to more than two series, the phase difference is simply the average of all possible pairwise phase differences at each time t. The resulting value $R \in [0,1]$ reflects the strength of phase locking: $R = 1$ indicates perfect synchronisation (a constant phase difference), while $R = 0$ express complete independence (a uniform distribution of phase differences around the unit circle).

[5]The analysis does not focus on the second moment, ruling out methods such as Rigobon and Sack (2004). Likewise, as the objective is to assess synchronisation in the global component of EPU_t^i, causal identification strategies are not pursued.

To statistically validate mean phase coherence, particularly in noisy datasets, a surrogate data approach is often employed. The null hypothesis assumes no phase synchrony between signals. By comparing the observed R to the distribution of R values from surrogate data, a z-score can be computed as $z = (R \quad \mu_{R^S})/\sigma_{R^S}$, where μ_{R^S} and σ_{R^S} are the mean and standard deviation of surrogate-derived coherence values. This normalisation helps identify statistically significant phase locking beyond what is expected by chance.

Figure 1 presents the estimated mean phase coherence over time for the 28 GC_t^i series. The average value is 0.507. Notably, the series begins showing a peak of 0.874 in 1997.3, potentially linked to the onset of the *Asian Financial Crisis* in 1997.6, when Thailand abandoned its fixed exchange rate after exhausting foreign reserves. Four distinct periods show synchronisation rising from below to above the average: (i) mid-2002 to a peak of 0.752 in 2003.5; (ii) 2011 to 0.747 in 2013.3; (iii) 2017 to 0.699 in 2020.2; and (iv) 2023 to 0.909 in 2025.2. The most recent value, from 2025.3, is 0.860.

Figure 1. Global synchronisation index for EPU, 28 series (*)



(*) Average: 0.507. Red dot: latest estimation (=0.86). Green dots: peaks registered. in 1997.3, 2003.5, 2013.3, 2020.2, and 2025.3. Source: Author's calculations using data obtained from the "Economic Policy Uncertainty" database.

2.3.2 Multivariate wavelet coherence

Multivariate wavelet coherence generalises the bivariate framework to detect time-frequency localisation of common cyclical behaviour across multiple stationary time series (Torrence and Compo, 1998). This multivariate version allows for a more comprehensive analysis of synchronisation among groups of variables. This is especially valuable in contexts involving spillovers or coordinated cycles—such as global economic uncertainty.

Let $\mathbf{x}(t) = [x_1(t), ..., x_N(t)]'$ be a $N \times 1$ vector of stationary time series. The *continuous wavelet transform* of a time series $x_k(t)$, with respect to a mother wavelet $\psi(t)$, is defined as:

$$W_{x_k}(\tau, s) = \int_{-\infty}^{+\infty} x_k(t)\psi^*\left(\frac{t-\tau}{s}\right) dt, \tag{6}$$

where τ is the time translation parameter, s is the scale (inversely related to frequency), and $\psi^*(\cdot)$ is the complex conjugate of the wavelet function. The *wavelet cross-spectrum* between two time series $x_k(t)$ and $x_j(t)$ is defined as:

$$W_{x_k x_j}(\tau, s) = W_{x_k}(\tau, s) \cdot W^*_{x_j}(\tau, s), \tag{7}$$

and the *wavelet power spectrum* of $x_k(t)$ is:

$$P_{x_k}(\tau, s) = \left|W_{x_k}(\tau, s)\right|^2. \tag{8}$$

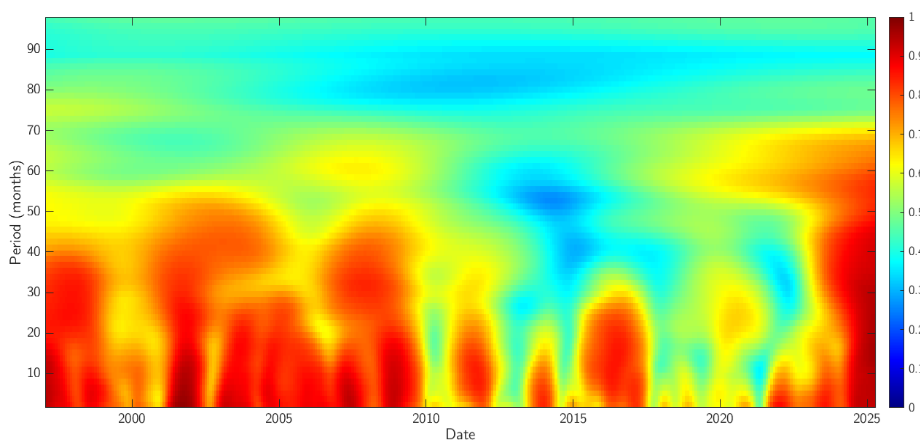
The *multivariate wavelet coherence* at time τ and scale s, denoted $R^2(\tau, s)$, is then defined as:

$$R^2(\tau, s) = \frac{\lambda^{\max}(\mathbf{S_{XX}}(\tau, s))}{\mathsf{trace}(\mathbf{S_{XX}}(\tau, s))}, \tag{9}$$

where $\mathbf{S_{XX}}(\tau, s)$ is the smoothed cross-wavelet spectral density matrix, $\lambda^{\max}$ denotes its largest eigenvalue, and $\mathsf{trace}(\cdot)$ is the trace operator. This definition, following Rua and Silva Lopes (2015) and is analogous to *principal component coherence*: the multivariate wavelet cohesion measures the proportion of total wavelet power explained by the first principal mode of co-movement across all series. It provides a time- and frequency-specific indicator of the degree of joint synchronisation. Values of $R^2(\tau, s)$ close to 1 indicate strong multivariate coherence, while values near 0 imply an absence of joint cyclical behaviour at that point in time and frequency.

This methodology is well suited to identifying periods of heightened global synchronisation, such as financial crises, pandemics, or geopolitical shocks. Figure 2 presents the multivariate wavelet coherence results over time for the 28 GC_t^i series. Episodes of strong synchronisation (in red and orange) are concentrated mainly in shorter cycles (10-30 months), with pronounced peaks during the early 2000s, the *Global Financial Crisis* (2007-09), and the Covid-19 pandemic (2020). From 2023 onwards, coherence rises sharply, culminating in 2025 with a unique episode of broad-based synchronisation across a wide frequency range—extending from short- to long-term cycles (up to $\sim$70 months). This unprecedented frequency-spanning coherence suggests a shift towards more systemic and globally coordinated policy uncertainty, likely fuelled by shared external shocks and increasingly interconnected economic narratives.

Figure 2. Multivariate wavelet coherence, average over pairs (*)



(*) Source: Author's calculations using data obtained from the "Economic Policy Uncertainty" database.

3 Concluding remarks

This note presents new evidence of historically high synchronisation in EPU across 28 countries, largely driven by spillovers from US uncertainty. The decomposition into domestic and global components shows that, since late 2024, the global factor has contributed more to national EPU indices than during previous global shocks, including the 2007-08 *Global Financial Crisis* and the Covid-19 pandemic. Complementary time-frequency analyses—mean phase coherence and multivariate wavelet coherence—indicate that this synchronisation is both unprecedented and widespread across short- and long-term cycles.

These findings highlight a concerning shift in the global economic landscape, where policy-driven uncertainty appears increasingly systemic and potentially persistent. Even under more favourable policy conditions, the effects of recent shocks may prove difficult to reverse, particularly given the depth of international synchronisation. This pattern is closely linked to the *Global Financial Cycle*, which is largely driven by US monetary and financial conditions. As emphasised by Miranda-Agrippino and Rey (2022), fluctuations in US policy produce strong co-movement in asset prices, capital flows, and credit across both advanced and emerging markets, transmitting financial volatility on a global scale.

In this context, policy uncertainty—especially that originating in the US—acts as a reinforcing mechanism within the global cycle. For instance, Bajraj, Carlomagno, and Wlasiuk (2023) show that inflation dynamics across countries have become increasingly synchronised, revealing common exposure to global shocks that affect both real and nominal variables. Handley and Limão (2022) further demonstrate that rising trade and policy uncertainty reduces firm-level investment and export participation, thereby generating persistent economic costs. Together, these findings suggest that elevated and synchronised uncertainty undermines financial stability and real economic performance, with pronounced effects for globally integrated economies.

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A Dataset description

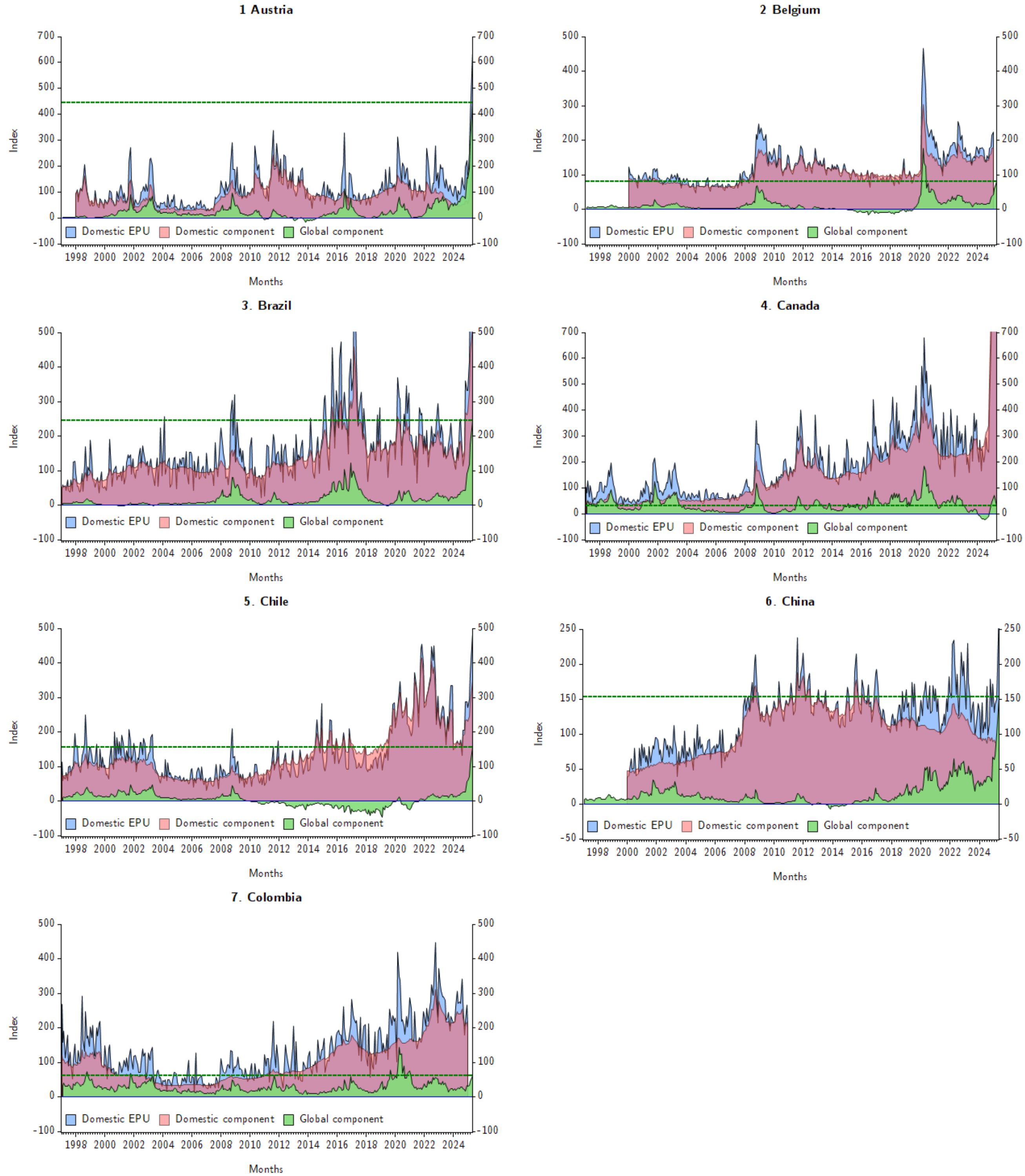
Table A1. Summary statistics and data sources (†)

No	Country	Sample	Mean	Median	Std. dev.	Minimum	Maximum	No. obs.	Source
1	Austria	1998.1 - 2025.4	109.55	97.26	61.14	25.66	381.93	327	Baker, Bloom, and Davis (2016)
2	Belgium	2000.1 - 2025.2	120.82	103.65	54.82	46.59	465.35	302	Algaba *et al.* (2020)
3	Brazil	1997.1 - 2025.4	155.51	134.21	93.82	22.30	676.96	339	Baker, Bloom, and Davis (2016)
4	Canada	1997.1 - 2025.4	189.82	155.51	157.99	30.10	1635.40	339	Baker, Bloom, and Davis (2016)
5	Chile	1997.1 - 2025.4	140.00	116.39	82.85	31.60	454.58	339	Cerda, Silva, and Valente (2017)
6	China	2000.1 - 2025.4	122.54	127.75	40.58	38.20	238.32	303	"EPU in China" website
7	Colombia	1997.1 - 2025.1	132.55	111.42	80.79	10.08	446.04	337	Fedesarrollo.org.co
8	Croatia	2003.1 - 2025.3	126.06	128.89	77.78	1.74	495.98	267	Sorić and Lolić (2017)
9	Denmark	1997.1 - 2025.3	68.93	62.29	49.34	-3.60	243.86	339	Federal Reserve Bank of St. Louis (FRED)
10	France	1997.1 - 2025.4	191.87	185.96	117.83	11.29	574.63	339	Baker, Bloom, and Davis (2016)
11	Germany	1997.1 - 2025.4	207.54	134.37	197.98	28.43	1095.93	339	Baker, Bloom, and Davis (2016)
12	Greece	1998.1 - 2024.12	95.43	90.85	28.99	32.98	189.99	324	Hardouvelis *et al.* (2023)
13	Hong Kong	1998.4 - 2024.11	138.20	126.28	75.39	23.01	425.36	320	Luk *et al.* (2020)
14	India	2003.1 - 2025.4	92.99	80.29	48.37	23.35	283.69	267	Baker, Bloom, and Davis (2016)
15	Ireland	1997.1 - 2025.4	98.31	85.94	54.73	20.46	345.06	339	Rice (2023)
16	Italy	1997.1 - 2025.4	112.31	106.48	39.89	31.70	279.39	339	Baker, Bloom, and Davis (2016)
17	Japan	1997.1 - 2025.4	110.03	104.52	34.30	48.41	239.06	339	Arbatli Saxegaard *et al.* (2022)
18	South Korea	1997.1 - 2025.1	147.90	129.99	93.23	22.43	872.88	337	Cho and Kim (2023)
19	Mexico	1997.1 - 2025.4	94.39	75.81	68.08	8.51	428.73	339	Baker, Bloom, and Davis (2016)
20	New Zealand	1997.1 - 2025.3	155.81	124.95	148.78	-52.12	761.28	339	Federal Reserve Bank of St. Louis (FRED)
21	Pakistan	2010.8 - 2025.4	102.40	87.83	55.29	26.97	359.76	176	Choudhary, Pasha, and Waheed (2020)
22	Poland	2003.4 - 2025.4	129.48	107.45	66.02	31.12	369.56	264	Białkowski, Klepka, and Sławik (2025)
23	Russia	1997.1 - 2025.4	182.93	123.90	160.29	12.40	964.14	339	Baker, Bloom, and Davis (2016)
24	Singapore	2003.1 - 2025.3	166.52	142.32	90.98	50.03	576.85	267	Davis (2016)
25	Spain	1997.1 - 2025.4	112.45	108.44	40.04	31.02	261.61	339	Ghirelli, Pérez, and Urtasun (2019)
26	Sweden	1997.1 - 2025.1	95.79	94.55	20.79	53.73	185.69	337	Armelius, Hull, and Stenbacka Köhler (2017)
27	Turkey	2006.1 - 2024.12	155.21	141.65	77.88	49.90	521.29	228	Kilic and Balli (2024)
28	United Kingdom	1997.1 - 2025.4	204.71	172.01	150.79	25.34	1141.80	339	Baker, Bloom, and Davis (2016)
29	United States	1997.1 - 2025.4	136.03	120.30	66.10	44.78	504.10	339	Baker, Bloom, and Davis (2016)

(†) Source: Author's calculations using data obtained from the "Economic Policy Uncertainty" database.

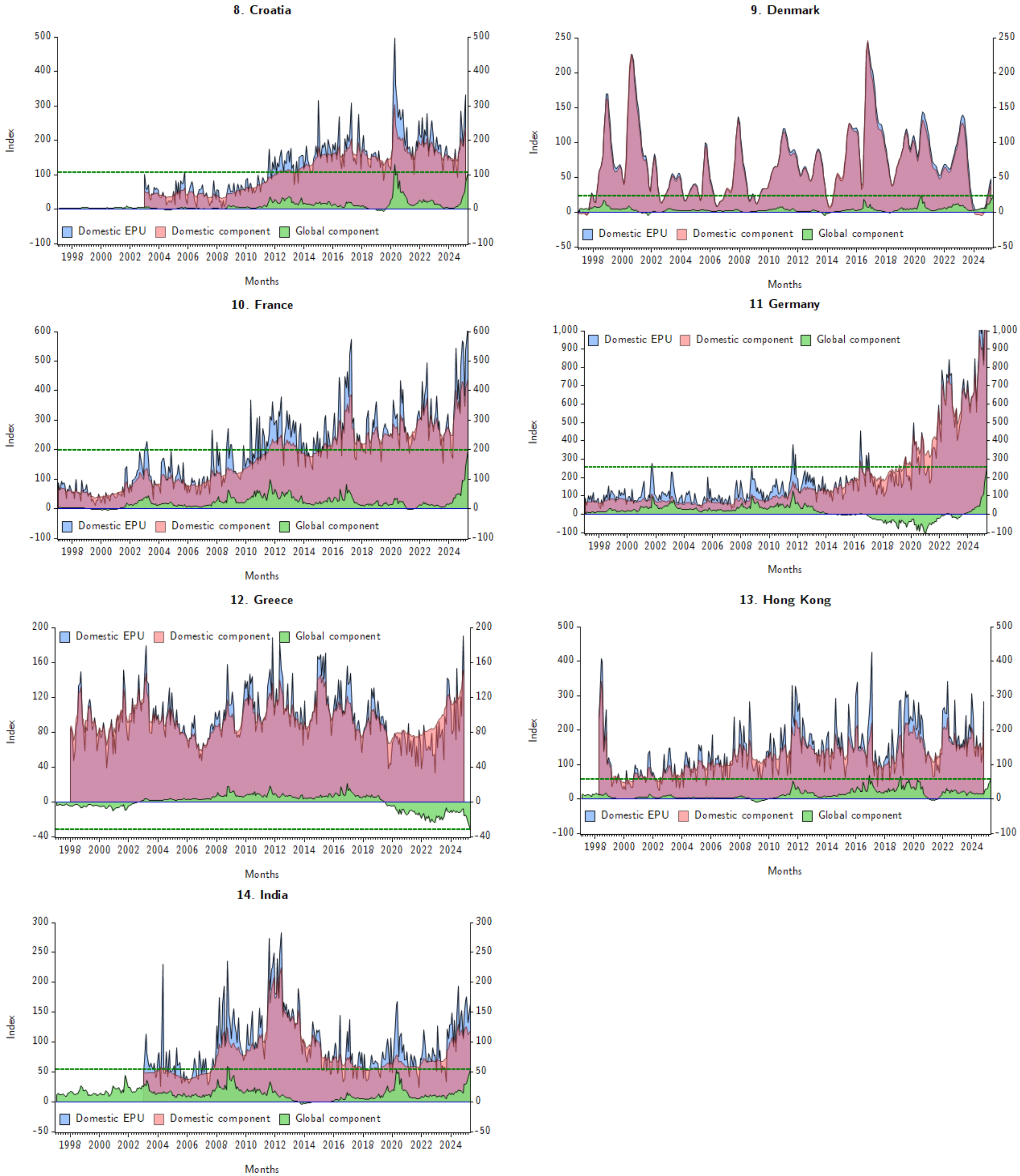
B Domestic and global components of EPU

Figure B1a. EPU_t^i and its domestic and global components (*)



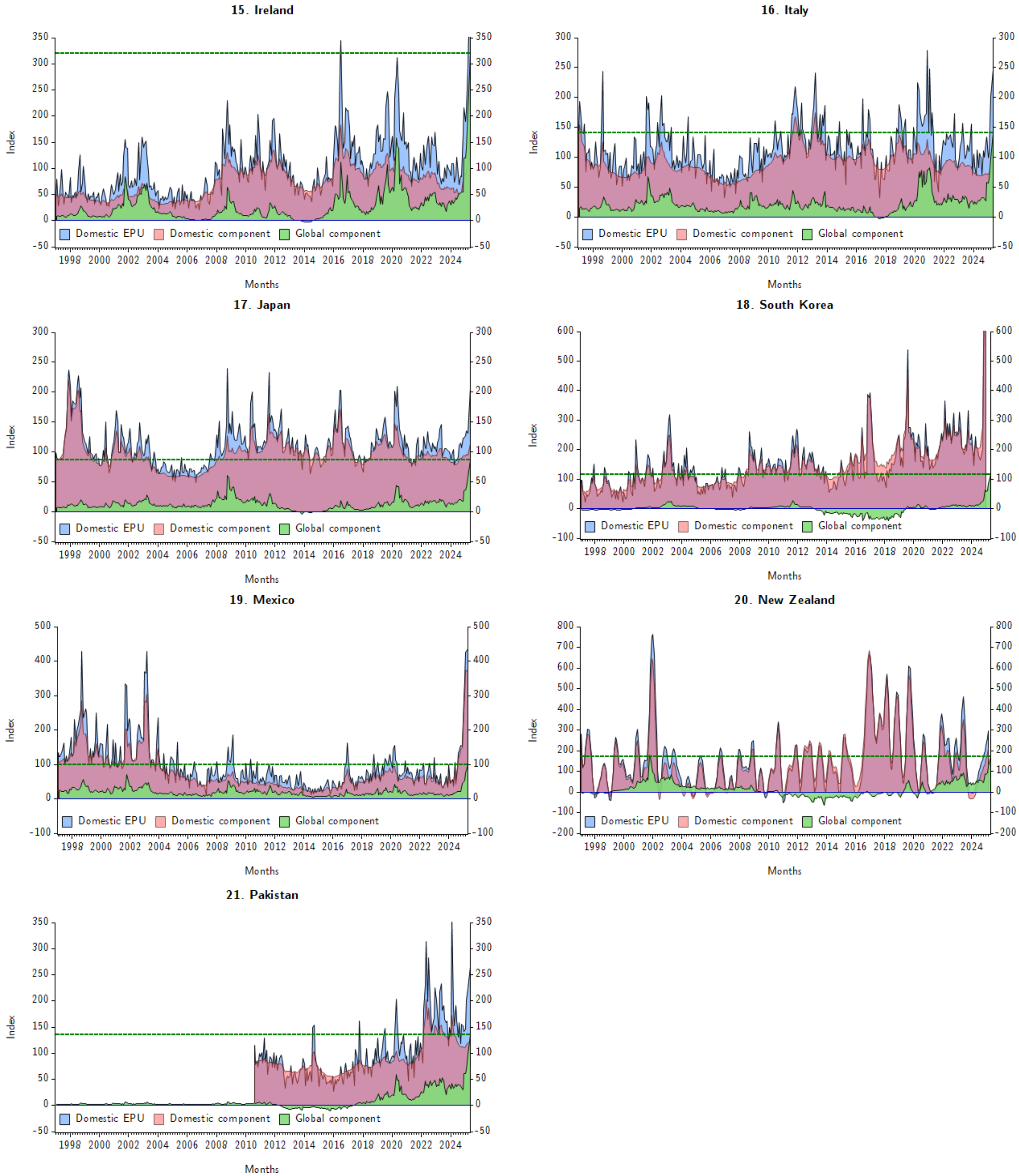
(*) Horizontal line = latest value of GC_t^i. Source: Author's calculations using data obtained from the "Economic Policy Uncertainty" database.

Figure B1b. EPU_t^i and its domestic and global components (*) (cont.)



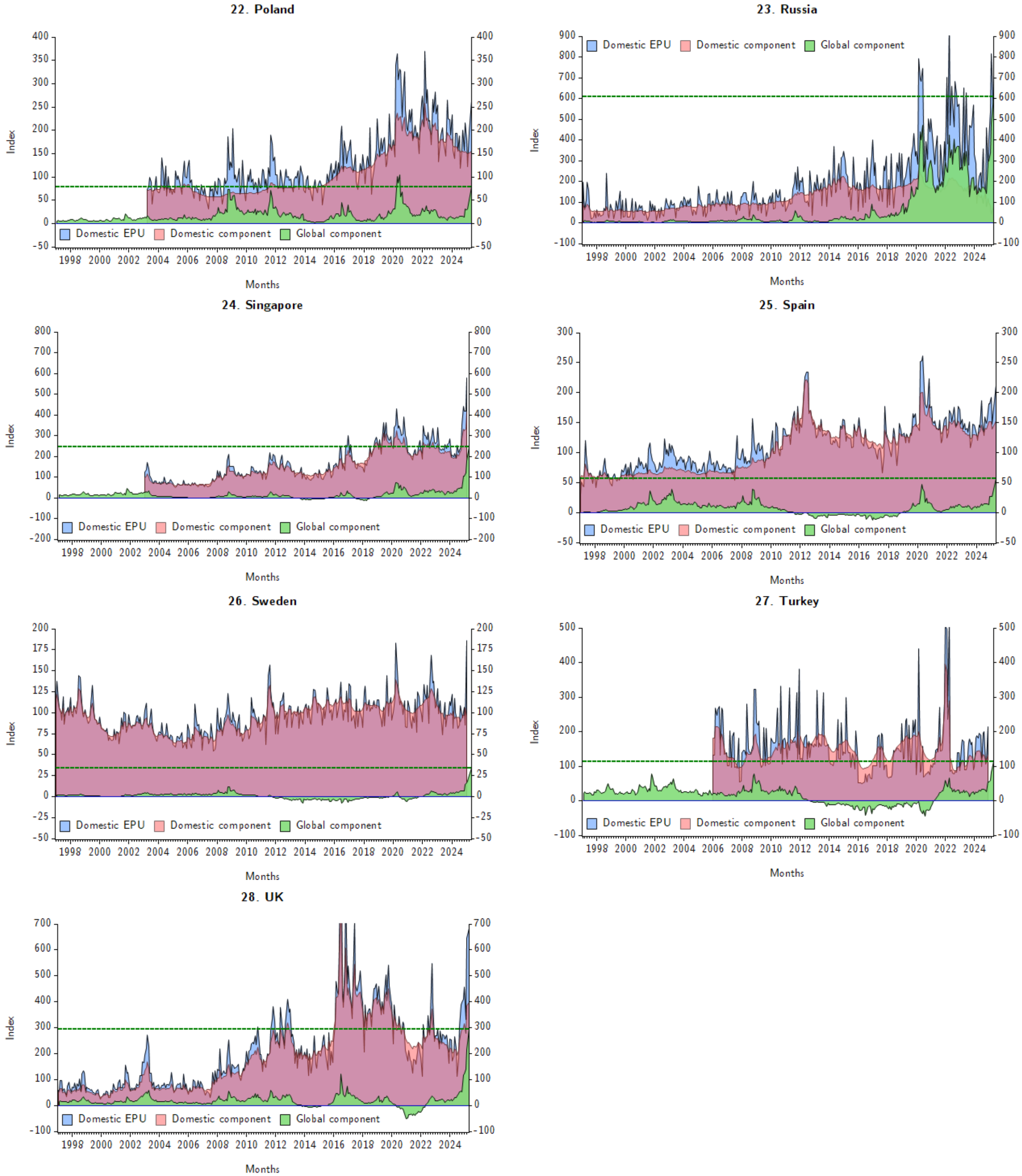
(*) Horizontal line = latest value of GC_t^i. Source: Author's calculations using data obtained from the "Economic Policy Uncertainty" database.

Figure B1c. EPU_t^i and its domestic and global components (*) (cont.)



(*) Horizontal line = latest value of GC_t^i. Source: Author's calculations using data obtained from the "Economic Policy Uncertainty" database.

Figure B1d. EPU_t^i and its domestic and global components (*) (cont.)



(*) Horizontal line = latest value of GC_t^i. Source: Author's calculations using data obtained from the "Economic Policy Uncertainty" database.

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