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Efectos de Traspaso de la Incertidumbre de Política Económica desde Estados Unidos y China hacia las Economías Centroamericanas: Un Enfoque BGVAR

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Abstract

Este documento cuantifica cómo los choques de incertidumbre en la política económica (EPU) originados en Estados Unidos y China se transmiten a siete economías de Centroamérica (Costa Rica, El Salvador, Guatemala, Honduras, Nicaragua, Panamá y República Dominicana). Estimamos un modelo Bayesiano Global Vector Autoregression (BGVAR) con volatilidad estocástica y una selección estocástica de variables (Stochastic Search Variable Selection) utilizando datos mensuales de enero de 2003 a diciembre de 2024, que cubren 19 países y seis series mensuales por país (crecimiento de la actividad, inflación, tipo de cambio real, exportaciones, importaciones y logaritmo del EPU). A partir de las simulaciones posteriores, calculamos respuestas impulso generalizadas y descomposiciones generalizadas de la varianza del error de pronóstico para construir matrices bilaterales de efectos de derrame. La evidencia es triple. Primero, los choques de EPU de EE. UU. son la fuente bilateral dominante de incertidumbre para la mayoría de los receptores centroamericanos, generando participaciones sustancialmente mayores en la varianza pronosticada del EPU a 12 meses que los choques contemporáneos de China en la mayoría de las economías CAPRD. Segundo, al agregarse en todo el panel, China registra una huella significativa en el sistema, aunque sus impactos bilaterales en muchos países centroamericanos son menores que los de EE. UU. Tercero, estos patrones cualitativos son robustos a la exclusión del período COVID-19 y a la estimación de un BGVAR reducido de 12 países que conserva CAPRD y socios principales. Los hallazgos implican que una fracción considerable de la incertidumbre interna en economías pequeñas y abiertas refleja ruido de política extranjera y argumentan a favor de integrar la EPU internacional en la preparación macroprudencial y fiscal.

Palabras clave: Incertidumbre en la política económica; VAR global bayesiano; Efectos de derrame; Vínculos comerciales; Descomposición de la varianza del error de pronóstico.
Clasificación JEL: D8, F4, E6, C30, C32.

Las opiniones y comentarios expresados en este documento son responsabilidad de los autores.

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Economic Policy Uncertainty Spillovers from the United States and China to Central American Economies: A BGVAR Approach

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Abstract

This paper quantifies how economic policy uncertainty (EPU) shocks originating in the United States and China transmit to seven Central American economies (Costa Rica, El Salvador, Guatemala, Honduras, Nicaragua, Panama and the Dominican Republic). We estimate a Bayesian Global Vector Autoregression with stochastic volatility and a Stochastic Search Variable Selection prior on monthly data for January 2003–December 2024, covering 19 countries and six monthly series per country (activity growth, inflation, real exchange rate, exports, imports and log EPU). From posterior draws we compute generalized impulse responses and generalized forecast-error variance decompositions to construct bilateral spillover matrices. The evidence is threefold. First, U.S. EPU shocks are the dominant bilateral source of uncertainty for most Central American recipients, generating materially larger 12-month shares of EPU forecast variance than contemporaneous Chinese shocks in a majority of CAPRD economies. Second, when aggregated across the full panel China registers a substantial system-wide footprint even though its bilateral impacts on many Central American countries are smaller than U.S. impacts. Third, these qualitative patterns are robust to excluding the COVID-19 period and to estimating a reduced 12-country BGVAR that retains CAPRD and principal partners. The findings imply that a sizeable fraction of domestic uncertainty in small open economies reflects foreign policy noise and argue for integrating international EPU into macroprudential and fiscal preparedness.

Palabras clave: Economic policy uncertainty; Bayesian global VAR; Spillovers; Trade linkages; Forecast error variance decomposition.

Clasificación JEL: D8, F4, E6, C30, C32.

1 Introduction

Economic policy uncertainty has emerged as a central determinant of macroeconomic behaviour in open economies, as firms and households postpone investment and consumption under heightened uncertainty and as financial conditions tighten when policy risks rise. Empirical measures of policy-related uncertainty, pioneered by Baker, Bloom, and Davis (2016), have shown pronounced increases in the aftermath of the 2007–2008 global financial crisis and during later geopolitical and policy episodes. These international episodes matter for small open economies because policy-uncertainty shocks in large partners can propagate through trade, financial and commodity channels and thereby amplify local volatility. The empirical literature documents multiple mechanisms by which uncertainty affects real activity and asset prices (Jurado, Ludvigson, and Ng, 2015; Caldara et al., 2019).

The present paper asks whether and to what extent policy-uncertainty shocks originating in the United States and China transmit to the domestic policy-uncertainty indexes of Central American economies, specifically the CAPRD block (Costa Rica, Dominican Republic, Panama, El Salvador, Guatemala, Honduras and Nicaragua). These economies are highly open, feature concentrated export baskets in several cases, and maintain sizable remittance and financial ties with the United States. These structural features, formalized under regional agreements such as CAFTA-DR, the prevalence of U.S.-dollar invoicing in trade and finance, and sizeable remittance inflows, amplify the transmission of external demand and policy shocks. (International Monetary Fund, 2019); at the same time, increasing trade and investment linkages with China (Rojas-Suárez and Albe, 2025) have altered exposure patterns in recent decades (Abdel-Latif and Popescu, 2025). Such structural features make the CAPRD group an informative setting for studying asymmetric cross-border uncertainty transmission. The regional focus supplements and refines the broader cross-country EPU literature by delivering bilateral, country-to-country measures of connectedness that are directly relevant for policy design in small open economies.

Methodologically, the paper exploits the Bayesian Global Vector Autoregression (BGVAR) framework to characterise heterogeneous exposure and to quantify bilateral transmission. The GVAR family models each country as a local VAR augmented with trade-weighted foreign aggregates; this structure yields transparent, economically interpretable channels for cross-border spillovers while keeping the system tractable (Pesaran, Schuermann, and Weiner, 2004; Dées et al., 2007). Combining the GVAR with Bayesian shrinkage and a Stochastic Search Variable Selection (SSVS) prior improves finite-sample inference in high-dimensional settings and helps avoid overfitting when dozens of country-specific equations are stacked into a single global system (Koop, 2003; George and McCulloch, 1995; Böck, Feldkircher, and Huber, 2022). Our empirical strategy therefore blends the economic intuition of trade-weighted foreign variables with modern Bayesian regularisation to produce stable impulse responses and generalized forecast-error variance decompositions (GFEVDs) that form the basis of bilateral spillover tables.

The empirical analysis covers monthly data from January 2003 through December 2024 for nineteen economies (the CAPRD block plus key advanced and large emerging partners) and uses six variables per country: annualized monthly real activity growth, the first difference of log CPI, log real exchange rate, annualized growth of seasonally adjusted exports and imports, and the log national EPU index. For the United States we construct a monthly proxy for GDP using the Brave-Butters-Kelley monthly GDP approximation so that all series are available at monthly frequency and comparable across units. The BGVAR is estimated with four lags, stochastic volatility and an SSVS prior; inference is drawn from MCMC posteriors (5,000 burn-in and 2,500 retained draws after thinning). From the estimated model we compute generalized impulse response functions (GIRFs) and the GFEVDs that underpin Diebold and Yilmaz (2012) style spillover matrices and total connectedness measures.

The principal empirical findings are threefold and robust to several checks. First, United States EPU shocks are the dominant bilateral transmitter to the CAPRD economies. The bilateral 12-month GFEVD cells indicate that US EPU innovations explain materially larger shares of the forecast-error variance of many Central American EPUs than do contemporaneous Chinese innovations. For instance, in the full-sample 2003–2024 estimates the direct US contributions to CAPRD recipients (12-month horizon) are largest for Costa Rica (0.1608) and Guatemala (0.1219), while El Salvador and Honduras register negligible direct shares. Second, China emerges as a substantial system-wide transmitter once contributions are aggregated across the full 19-country panel: aggregate row sums place China among the largest external sources of EPU connectedness even though its bilateral effects on many Central American recipients are smaller than those of the United States. Thus China exerts broad global influence while bilateral magnitudes vary according to recipient exposure. Third, the key qualitative pattern is robust to two important robustness exercises. Excluding the COVID-19 period and reestimating the BGVAR over January 2003–December 2019 preserves the ranking of principal transmitters and the asymmetric exposure of CAPRD members, with only moderate changes in magnitudes. A second robustness check that restricts the BGVAR to a 12-country panel (CAPRD plus major trading partners) yields similar conclusions: both China and the United States remain the lead transmitters in the reduced system, with the United States particularly important for several Central American economies. These results are consistent with previous findings that the geography of trade and financial linkages conditions the transmission of global uncertainty (Baker, Bloom, and Davis, 2016; Jurado, Ludvigson, and Ng, 2015; Caldara et al., 2019; Pesaran, Schuermann, and Weiner, 2004; Diebold and Yilmaz, 2012; Abdel-Latif and Popescu, 2025; Giraldo et al., 2025; Onipede, Bashir, and Abubakar, 2023).

This paper contributes to three strands of literature. First it complements the growing empirical work that documents international spillovers of policy-related uncertainty by offering a bilateral, high-frequency account focused on Central America; this regional emphasis helps to reconcile cross-country heterogeneity documented in broader panels (Abdel-Latif and Popescu, 2025). Second it demonstrates the value of combining GVAR architecture with Bayesian SSVS shrinkage when the object of interest is bilateral connectedness among many heterogeneous economies; the methodological approach produces well behaved impulse responses and variance decompositions even in a large multi-country setting. Third it provides direct policy-relevant measurements of exposure for the CAPRD countries, quantifying which economies are net transmitters or net receivers of EPU within the regional block and in the global system. These contributions speak to both academic audiences interested in international transmission mechanisms and to policymakers who need concrete measures of external EPU risks to integrate into macroeconomic planning and contingency frameworks (Caldara et al., 2019; Pesaran, Schuermann, and Weiner, 2004; Böck, Feldkircher, and Huber, 2022).

The remainder of the paper proceeds as follows. Section 2 situates the analysis in the relevant literatures on uncertainty measurement and international spillovers. Section 3 describes the data construction and the CAPRD indices. Section 4 presents the BGVAR specification, the SSVS prior and the computation of GIRFs and GFEVD-based spillovers. Section 5 reports the baseline findings and robustness checks including the no-COVID subsample and the reduced 12-country system. Section 6 interprets the macroeconomic significance of the spillovers and Section 7 concludes with implications for policy and avenues for future research.

2 Literature Review

Ghirelli et al. (2021) identify three principal approaches quantify economic uncertainty: financial-market indicators that reflect asset-price and interest-rate volatility and thus capture rapid, globally transmitted shocks; disagreement measures that proxy uncertainty through dispersion in professional forecasts and survey responses and thereby reveal heterogeneity in expectations; and economic-policy indicators that combine political-risk series, fiscal-forecast dispersion and text-based EPU indices.

The foundational work on quantifying economic policy uncertainty was pioneered by Baker, Bloom, and Davis (2016), who developed a news-based, text-mining approach. Their method counts the frequency of articles in major newspapers that contain a trio of terms related to the "economy," "uncertainty," and "policy" to produce a time series index of EPU. This methodology has since been adapted and applied globally, demonstrating that uncertainty spikes often coincide with major political and economic events such as the Global Financial Crisis, and Brexit.

The challenge of constructing EPU indices for developing and smaller economies, particularly due to limited press coverage, has been addressed in recent years. For the specific Central American countries under examination (Costa Rica, El Salvador, Guatemala, Honduras, Nicaragua, and Panama), EPU indices have been constructed through a collaboration between the Bank of Spain and the Executive Secretariat of the Central American Monetary Council (SECMCA) by Diakonova, Ghirelli, and Quiñónez (2025). A key aspect of these indices is their empirical validation, which demonstrates that an increase in EPU translates into a decrease in economic activity, a conclusion derived from a BVAR model analysis.

A growing body of research documents that uncertainty shocks can propagate internationally, and that large economies often exert strong influence over smaller ones. The canonical policy uncertainty index was introduced by Baker, Bloom, and Davis (2016), and many subsequent studies use it to examine macro impacts. For instance, Trung (2019) employ a GVAR to show that U.S. policy uncertainty shocks significantly drive global business cycle fluctuations, though the spillover effects vary with country characteristics (trade openness, institutional quality, etc.). Salisu, Gupta, and Demirer (2022) build a large-scale GVAR of 33 countries and confirm the dominant role of U.S. uncertainty in affecting global output; they also show that this impact is amplified when the global financial cycle is weak (stressed) and is particularly strong for other advanced economies (Europe and G7) relative to emerging ones.

In contrast, studies focusing on Latin America often find more muted responses. Using two-country SVARs for the U.S. and each of Mexico, Colombia, Brazil, and Chile (1997–2019), Coronado, Martínez, and Venegas-Martínez (2020) report that positive shocks to U.S. EPU lead to significant currency depreciations in all four Latin American countries (largest for Mexico), with only small effects on output or inflation (a brief rise in Colombian output, higher Mexican interest rates). They also find that Latin economies became slightly more sensitive to U.S. EPU after the 2008 crisis. Similarly, Caggiano, Castelnuovo, and Figueres (2019) estimate a nonlinear VAR for the U.S. and Canada and find that U.S. EPU shocks raise Canadian unemployment during recessions (busts) but not in booms. They identify an "EPU spillovers channel", U.S. uncertainty shocks first raise Canadian uncertainty, which in turn temporarily raises unemployment in Canada. (Similar evidence for U.S. EPU affecting the U.K. in downturns is found by the same authors.) These studies illustrate that policy uncertainty spillovers can be state-dependent and that a change in one country's EPU may induce increases in another country's EPU.

More broadly, there is extensive literature on global shock transmission using GVAR or related multi-country models. Pesaran, Schuermann, and Weiner (2004) developed the GVAR framework for interdependent economies, estimating individual-country VARs with foreign variables constructed as trade-weighted averages. GVAR models have been applied to study international spillovers of output, commodity prices, and monetary shocks. In a Bayesian context, Cuaresma, Feldkircher, and Huber (2016) and Feldkircher and Huber (2016) demonstrate that Bayesian shrinkage priors can substantially improve GVAR forecasting performance, and provide software tools for estimation. In particular, Cuaresma, Feldkircher, and Huber (2016) show that applying a Bayesian global VAR with appropriate priors yields more accurate predictions of macro-financial variables, justifying the use of Bayesian methods in this setting. Onipede, Bashir, and Abubakar (2023) apply a BGVAR with time-varying parameters and stochastic volatility to small open economies and conclude that the USA, Europe, and China are all major drivers of those economies' cycles. In short, the empirical consensus is that large trading partners are important sources of shocks for smaller economies (see also Tran, Tran, and Vu (2021) on U.S. monetary policy spillovers to Asia and Georgiadis (2016)). Our approach builds on this literature by using a BGVAR to focus specifically on policy uncertainty channels.

EPU shocks originating in a major economy can propagate across borders through a variety of channels. Studies identify common shocks, country-specific shocks, and the transmission of the latter through channels such as trade and financial flows (Andrews and Kohler, 2005). A significant finding in the literature is that the impact of foreign EPU is often more pronounced in recipient countries during recessions, with effects on major macroeconomic indicators being quantitatively and qualitatively different compared to periods of expansion (Popp and Zhang, 2024).

The trade channel is a fundamental vehicle for spillovers, as shocks to trade policy or demand in a major economy directly affect the exports and imports of its trading partners (Andrews and Kohler, 2005). For many Central American countries, which have a high share of exports destined for the United States, the trade channel serves as a direct and potent transmission mechanism for US shocks (Rojas-Suárez and Albe, 2025). Similarly, China's influence on commodity-exporting economies in Latin America is heavily reliant on this channel, as a slowdown in Chinese demand can significantly depress regional growth and commodity prices (International Monetary Fund, 2019).

Beyond trade, financial and capital flow channels are also critical. EPU shocks can trigger significant financial spillovers by increasing asset price volatility, raising financing costs for firms, and inducing capital outflows from emerging markets, which are often regarded as less "safe" during periods of global uncertainty (Baker, Bloom, and Davis, 2016). This can lead to currency depreciation, a direct effect documented in countries like Mexico, Colombia, Brazil, and Chile following US EPU shocks (Coronado, Martínez, and Venegas-Martínez, 2020). The IMF has noted that the negative spillovers from slowdowns in the US and China could be significantly amplified if they lead to tighter financial conditions in emerging market economies (International Monetary Fund, 2019). A more nuanced view suggests that while country-specific EPU can hinder capital flows, global EPU can, in some cases, induce a "flight-to-safety" or a search-for-yield dynamic that may have a more complex effect on capital flows (Odionye, Ikpe, and Odo, 2025).The greater susceptibility of developing economies to these shocks is often attributed to weak institutional arrangements and shallow financial markets (Balli et al., 2017).

3 Data

The analysis uses monthly data from January 2003 through December 2024 for each country. The variable definitions are as follows, $y_{i,t}$ is the annualized growth rate of a broad economic activity index (for

Latin American economies, the Monthly Economic Activity Index or national industrial production index; for advanced economies, an appropriate production index). For the U.S. specifically, we construct a monthly GDP proxy using the Indiana University BBKMGDP (Brave-Butters-Kelley) index. $p_{i,t}$ is inflation defined as the first difference of the log CPI. $e_{i,t}$ is the log real exchange rate index (domestic currency per USD times relative price level). $x_{i,t}$ and $m_{i,t}$ are the annualized growth rates of seasonally-adjusted exports and imports (FOB/CIF values) respectively. Finally, $epu_{i,t}$ is the log of the country's policy uncertainty index. We use the natural logarithm of the EPU series for two reasons. First, the EPU indices, constructed from newspaper-article counts, are right-skewed and occasionally subject to large spikes; the log transformation reduces skewness and stabilizes variance, improving the finite-sample properties of the VAR estimation. Second, log differences of EPU map to approximate proportional changes in the intensity of policy-uncertainty coverage, thereby making impulse-response magnitudes more comparable across countries with differently scaled indices. EPU indices for the U.S., UK, Canada, etc. come from the Baker, Bloom, and Davis (2016) data repository. The Chinese EPU index is taken from Davis, Liu, and Sheng (2019), who construct a Chinese EPU series using domestic newspapers. All series are seasonally adjusted and transformed to ensure stationarity (e.g. using first differences of logs for I(1) series). In Table 1 is presented the ID of every country analyzed in this research. Also the countries mark with a * are those included in the 12 country BGVAR model used for robustness, the choice of only this 12 countries is related to included the CAPRD region and the major trading partners by total bilateral trade.

To ensure full transparency and replicability, Table 2 below provides a detailed summary of data sources and notes on construction for each variable and country. The dataset spans January 2003 to December 2024 and combines national statistical agencies, international databases, and widely-used research proxies (for example, BBKMGDP for monthly US GDP approximation). The careful assembly of these series allows the BGVAR to capture multi-directional spillovers across advanced and developing economies.

Table A1 documents important regularities and heterogeneity across the 19-country panel. Real exchange rates (e) are comparatively stable across units (means clustered around the mid-4s and small standard deviations), whereas the EPU index (`epu`) exhibits substantial cross-country dispersion, typical means lie in the 4–5 range but some economies (e.g. `DR`, `HN`, `NI`) display markedly lower average EPU

Table 1: Country names and ID

ID	Country
BR	Brazil
CA	Canada
CH	Chile
*CN	China, People's Republic of
CO	Colombia
*CR	Costa Rica
*DR	Dominican Republic
*SL	El Salvador
*EA	Euro Area
*GT	Guatemala
*HN	Honduras
IN	India
JP	Japan
KO	Korea, Republic of
MX	Mexico
*NI	Nicaragua
*PA	Panama
*UK	United Kingdom
*US	United States

and larger relative volatility. Monthly trade-growth indicators (`x`, `m`) and the activity variable (`y`) show the greatest volatility. Several countries report very large standard deviations and extreme minima/maxima (for instance, `IN` and `PA` have exceptionally wide ranges in `y` and `x`, respectively), reflecting episodic swings in output and trade flows over the 2003–2024 sample, explain mainly in the pandemic shock. Inflation (`p`) is small in level terms for most countries but with occasional large positive spikes in a few cases (as shown by the maxima reported). The panel also presents that smaller or more open economies (several CAPRD members) combine modest average EPU with sizeable tail risk in activity and trade, an empirical pattern that helps explain why external EPU shocks can translate into large domestic volatility even when average uncertainty levels are moderate. The summary statistics underscore substantial cross-sectional heterogeneity in volatility and extremes, motivating the BGVAR's use of SSVS shrinkage and stochastic volatility to capture both common and idiosyncratic dynamics.

In the Appendix 7.2 we present the Figure A1 that plots each CAPRD country EPU as a separate panel. The comparative analysis reveals that peaks in the US and China Economic Policy Uncertainty indices coincide with heightened uncertainty in Central American, Panama and Dominican Republic (CAPRD) countries, particularly during episodes such as the 2008 global financial crisis, the 2016 US

Table 2: Data sources and construction notes for each variable used in the BGVAR

Variable	**Data Source(s)**	**Notes on Construction**
Economic Activity (y)	National central banks and statistical offices (e.g., Banco de Chile, Banco de México), IMF, FRED	Natural logarithm of the monthly activity/production index; transformed to annualized MoM growth. For the US the Brave–Butters–Kelley monthly GDP proxy (BBKMGDP) is used as a monthly approximation and transformed identically.
Inflation (p)	World Bank global inflation database, IMF IFS, national statistical offices (e.g., BLS for US)	CPI index transformed as the first difference of the natural logarithm (i.e., approximate inflation rate). Sources combined to ensure cross-country comparability.
Real Exchange Rate (e)	IMF IFS, FRED, national sources	Real exchange rate index taken in natural logarithm.
Exports (x)	National trade statistics, IMF Direction of Trade / national databases,	Seasonally adjusted FOB exports series. Converted to an annualized month-on-month growth rate (natural log differences annualized).
Imports (m)	National trade statistics, IMF Direction of Trade / national databases, customs agencies	Seasonally adjusted CIF imports series. Converted to an annualized month-on-month growth rate (natural log differences annualized).
Economic Policy Uncertainty (epu)	Baker, Bloom & Davis EPU dataset and collaborating researchers' country-level EPU pages	Natural logarithm of the country-level EPU index (constructed from textual analysis of major newspapers).

presidential election, the escalation of US–China trade tensions in 2018, the COVID-19 pandemic in 2020, and the onset of the Russia–Ukraine conflict in 2022. While the magnitude of the responses differs across countries, the alignment of local spikes with external shocks indicates that regional EPU dynamics are strongly influenced by international policy and geopolitical events, underscoring the transmission of uncertainty from the world's two largest economies into smaller open economies. The identification of synchronized peaks in the CAPRD indices with major US and China EPU events provides strong empirical motivation for modeling regional economies within a global framework. In a BGVAR setup, such contemporaneous co-movements are consistent with the presence of common shocks that transmit across borders through trade, financial, and remittance channels. Recognizing that uncertainty originating in the US and China propagates into CAPRD countries strengthens the rationale for using spillover analysis, since the BGVAR explicitly captures how global shocks are absorbed and redistributed

The bilateral trade-weight matrix in Table A2 reports, for each row country, the average share of annual bilateral trade (FOB exports + CIF imports) with each column country over 2003–2024. For each year we compute the row-normalized bilateral share (row country's bilateral trade with partner divided by that row country's total trade), and the matrix entries are the simple averages of these annual row-shares across the sample period; diagonal elements are set to zero. These trade weights are used to form the trade-weighted foreign aggregates and the spatial weighting scheme that enter each country block in the BGVAR, following the standard GVAR construction in Pesaran, Schuermann, and Weiner (2004) and the practical implementation in the BGVAR package and companion documentation (Böck, Feldkircher, and Huber, 2022). Using annually averaged, row-normalized weights reduces high-frequency measurement noise while preserving the relative intensity of bilateral linkages that drive cross-country transmission in the BGVAR framework. The trade-weight matrix emphasize the dominance of the United States as the primary external partner for a large subset of the panel (notably Canada, Mexico, the Dominican Republic, Honduras and several Central American economies), while China and regional partners (e.g. Japan for Panama, and China for Brazil and the East Asian suppliers) assume leading roles for other specific rows. This pronounced heterogeneity in bilateral exposure both motivates the use of row-normalized trade weights in constructing foreign aggregates and helps explain the asymmetric EPU spillovers documented in the GIRFs and GFEVDs, countries with larger trade shares vis-à-vis a shock-origin country tend to receive proportionally larger uncertainty transmission.

4 Methodology

4.1 BGVAR Model Specification

We construct a Bayesian Global VAR (BGVAR) model following the two-step procedure of Pesaran, Schuermann, and Weiner (2004). A Global VAR (GVAR) models each country with its own small VAR while summarizing the rest of the world by trade-weighted foreign aggregates. Conceptually, each country responds to its own past and to a weighted average of other countries' variables, where the weights encode economic exposure (trade). Estimating the resulting large system in a Bayesian way with shrinkage (SSVS) reduces overfitting. It keeps the model flexible enough to capture important cross-border links while suppressing spurious coefficients, and accounts for changing volatility over time through stochastic volatility. The BGVAR thereby provides transparent impulse-response functions and variance decompositions that measure how much of a country's uncertainty can be traced to external sources such as U.S. or Chinese EPU.

In the first step, for each country i we estimate a country-specific VAR augmented with foreign variables. Let $x_{i,t} = (y_{i,t}, p_{i,t}, e_{i,t}, x_{i,t}, m_{i,t}, epu_{i,t})'$ be the k_i-dimensional vector of endogenous variables for country i. We include as regressors the country's own lagged variables and a corresponding vector of "foreign" (global) variables $x^*_{i,t}$, which are constructed as weighted averages of other countries' variables. Formally,

$$x_{i,t} = c_i + \sum_{\ell=1}^{4} A_{i,\ell}\, x_{i,t-\ell} + \sum_{\ell=0}^{4} D_{i,\ell}\, x^*_{i,t-\ell} + \varepsilon_{i,t},$$

where c_i is a constant, and $x^*_{i,t} = \sum_{j \neq i} w_{ij}\, x_{j,t}$. The weights w_{ij} (with $\sum_j w_{ij} = 1$) are pre-specified (we use bilateral trade shares) so that $x^*_{i,t}$ represents the trade-weighted aggregate of foreign variables impacting country i. In practice we include four lags of both domestic and foreign variables, selecting lag length by information criteria and by checking for residual autocorrelation. All error terms $\varepsilon_{i,t}$ are assumed mean-zero with covariance Σ_i. As shown in the BGVAR literature, these country models are then combined into a global system by stacking the N equations and imposing the cross-section through W. The result is a large VAR of dimension $\sum_i k_i$, which we estimate in Bayesian form. In this way each country's dynamics can depend on other countries' dynamics through the weakly exogenous foreign blocks constructed with W.

The matrix $W = [w_{ij}]$ collects row-normalized bilateral trade weights used to construct each country's foreign block: $x^*_{i,t} = \sum_{j \neq i} w_{ij} x_{j,t}$ with $w_{ij} \geq 0$ and $\sum_{j \neq i} w_{ij} = 1$. We compute w_{ij} as the row-country share of bilateral trade (FOB exports + CIF imports) averaged annually over 2003–2024 and then averaged across years, the data used is presented in Table A2. Diagonal elements w_{ii} are set to zero.

4.2 Prior Specification and Estimation

The BGVAR involves a very large number of coefficients, so we employ Bayesian shrinkage to avoid overfitting. Following George and McCulloch (1995) and Koop, León□González, and Strachan (2012) and Koop and Korobilis (2013), we use a Stochastic Search Variable Selection (SSVS) prior on the VAR coefficients. Under SSVS, each coefficient β has a mixture prior $(1-\gamma)\, N(0, \tau_0^2) + \gamma\, N(0, \tau_1^2)$ where $\gamma \sim$ Bernoulli$(1/2)$ selects between a "narrow" variance τ_0^2 and a "wide" variance τ_1^2. In effect, many coefficients are shrunk toward zero unless the data strongly support a nonzero value. This prior formulation has been used in recent BGVAR applications (for example, Onipede, Bashir, and Abubakar (2023) implement exactly the SSVS of George and McCulloch (1995) and Koop, León□González, and Strachan (2012) and Koop and Korobilis (2013) in a GVAR context). We set tight prior variances for most coefficients and allow a small probability of large deviation.

Estimation proceeds by Markov-chain Monte Carlo. We use the BGVAR R package (Böck, Feldkircher, and Huber, 2022), which implements these priors and allows for diagnostic checking. We run the MCMC with 5,000 burn-in draws and 2,500 retained draws, which results indicates is sufficient for convergence. We test convergence diagnostics through Geweke's CD, a procedure that assesses equality of the sample means from the beginning and end of a Markov chain, by default the first 10% and the final 50% of iterations. When the chain is sampling from its stationary distribution the two segment means are equal, and the resulting CD statistic converges in distribution to $\mathcal{N}(0, 1)$. Our baseline lag order is 4, but we also estimated models with higher lags to ensure residual autocorrelation was negligible. Importantly, Cuaresma, Feldkircher, and Huber (2016) show that Bayesian shrinkage priors can substantially improve GVAR forecast accuracy, so we adopt their recommended approach here.

4.3 Spillover Computation

After estimating the BGVAR, we trace out the dynamic response of each variable to shocks via generalized impulse response functions (GIRFs). We then compute the *generalized* forecast error variance decomposition (GFEVD) following Pesaran and Shin (1998), which accommodates non-orthogonalized shocks. Specifically, we use the BGVAR toolkit to obtain the fraction of the 12-step-ahead forecast error variance of each variable that is attributable to each structural shock. As discussed in the BGVAR documentation, this generalized FEVD does not depend on variable ordering but can yield shares exceeding 100% in aggregate due to residual correlation. To summarize the influence of U.S. and Chinese uncertainty, we extract the entries of the GFEVD corresponding to shocks in U.S. EPU and China EPU affecting each Central American country's EPU. In other words, for each country i, we compute the fraction of $epu_{i,t}$'s forecast variance explained by innovations in U.S. and China epu_t. These bilateral contributions are then normalized by the row (total variance of country i's EPU) and converted to percentages, as in Diebold and Yilmaz (2012) and Diebold and Yilmaz (2014). We also compute the total spillover index (sum of off-diagonal contributions) to quantify overall connectedness. This approach parallels the Diebold-Yilmaz spillover index methodology, but here we focus specifically on the cross-border transmission of EPU shocks from two large economies into the Central American block.

5 Results

5.1 Generalized Impulse Response Analysis

Figure 1 plots the generalized impulse responses (GIRFs) of each country's EPU index to a one-standard-deviation shock in China's EPU and US EPU. As expected, China's own EPU index jumps immediately and then gradually decays, reflecting a strong and persistent uncertainty shock within China. Several Central American economies exhibit significant positive responses as well, for example, Nicaragua's EPU rises by roughly 0.3–0.4 (in index units) one quarter after the shock, and Panama's EPU by about 0.25, before slowly reverting toward zero. In contrast, some countries show smaller or even slightly negative responses, the Dominican Republic's EPU, for instance, falls on impact and then returns toward baseline (Figure A4). In all cases the blue shaded bands (90% credible intervals) exclude zero for several periods, indicating that the spillovers are statistically robust. These results suggest that a surge in Chinese policy uncertainty elevates uncertainty in most CAPRD economies (Costa Rica, Guatemala, etc.), albeit with modest magnitude relative to China. Such increased uncertainty typically portends declines in real activity and investment, implying that Chinese uncertainty shocks likely have adverse effects on the region.

The immediate effect on US EPU is large and then slowly decays, as expected. Notably, the spillover responses in CAPRD countries are generally larger than in the Chinese-shock scenario. For example, Nicaragua's EPU jumps by nearly 0.6 on impact and remains elevated (about 0.25) after one year; Guatemala and Costa Rica also display peak responses on the order of 0.3, followed by gradual mean reversion. El Salvador and Honduras have smaller but still positive responses (on the order of 0.1). Again the credible bands exclude zero for many horizons, indicating statistical significance. The Dominican Republic's EPU, as before, shows a negative response (falling by roughly 0.3 at its trough), consistent with an offsetting reaction pattern. Overall, the US shock induces systematically higher EPU spillovers in Central America than does the China shock. This reflects the region's closer economic integration with the US. Indeed, many Central American and Latin economies export primarily to the United States, so US policy uncertainty transmits more strongly to local uncertainty. The pattern accords with the findings of Onipede, Bashir, and Abubakar (2023), who report that in small open-economy panels the influence of US shocks is at least as large as (and often larger than) the impact of Chinese shocks. Likewise, our results are consistent with Kose et al. (2017), who emphasize that many smaller EMDEs rely heavily on exports to the US, implying stronger US shock transmission.

Across the Central American and Dominican Republic group, the generalized impulse response functions exhibit clear heterogeneity in both magnitude and persistence when exposed to external policy uncertainty originating in the United States and in China. In particular, responses to US EPU shocks tend to be larger at the contemporaneous horizon in Costa Rica, Guatemala and Nicaragua, indicating stronger immediate amplification through financial and trade channels in these small open economies. By contrast, China EPU shocks generate comparatively more persistent responses in Panama, suggesting slower unfolding channels that may operate through commodity prices, supply chain linkages and trade patterns. These comparative patterns imply that the country level exposure to global policy uncertainty is not uniform; the dominant external transmitter varies across CAPRD countries according to differences in bilateral trade shares.

Where 90% credible intervals for the US- and China-origin GIRFs overlap for most of the countries, we cannot reject the hypothesis that the two impulse responses are equal at conventional levels for the given horizon. In our sample, overlap often occurs at longer horizons and for several CAPRD members, indicating that while the pointwise peak responses differ, the associated posterior uncertainty implies caution in declaring statistically distinct long-run dynamics. Where the credible bands do not overlap (notably major economies with more trade dependence to the US, in the short-to-medium run), the posterior evidence supports materially different transmission from the two source economies.

Economically, the impulse responses indicate that heightened US uncertainty significantly raises policy uncertainty in the CAPRD countries, whereas Chinese uncertainty has a smaller and more heterogeneous effect. The strong positive responses imply that external policy uncertainty events propagate to domestic uncertainty in Central America, which may then depress investment and consumption (as in *e.g.* Diakonova, Ghirelli, and Quiñónez (2025)). The larger magnitude from the US shock suggests that bilateral economic linkages (trade, remittances, financial flows, and even dollarized economies like Panama) amplify US uncertainty transmission. By contrast, although China's growing trade ties to Central America do generate spillovers, they are more muted. We note also the exception of the Dominican Republic, whose EPU moves inversely; this idiosyncrasy could reflect country-specific policies or commodity links that mitigate uncertainty from abroad. In summary, the GIRFs reveal clear directional asymmetry, US-origin policy uncertainty shocks impose more persistent uncertainty on the CAPRD region than do comparable Chinese shocks, consistent with their relative trade and financial ties.

5.2 Forecast Error Variance Decomposition and Spillover Matrix

We next examine the Diebold–Yilmaz method of the forecast error variance decomposition (GFEVD) of the BGVAR, which quantifies the contribution of each country's EPU shock to the forecast error variance of every other country's EPU. Table 3 presents the full 19×19 spillover matrix (at the 12 month forecast horizon). The diagonal entries are the shares due to own-country shocks; off-diagonals are contributions from each foreign source. Many entries are nonzero, reflecting interconnectedness in policy uncertainty.

Table 3 reports the 12-month generalized forecast-error variance shares attributable to shocks originating in each source country. The vertical column labeled "US" shows the contribution of a United States EPU shock to each recipient country's 12-month-ahead EPU forecast-error variance. The results indicate that a US EPU innovation accounts for nonzero but generally modest shares of individual countries' EPU variances at the 12-month horizon, with the largest bilateral impacts observed for Canada, Mexico, the Euro area and the United Kingdom. Focusing on the CAPRD group, the US shock implies the following direct contributions, Costa Rica 0.1608, Dominican Republic 0.0846, El Salvador 0.0033, Guatemala 0.1219, Honduras 0.0018, Nicaragua 0.0772 and Panama 0.0812. Thus, within the CAPRD block the United States has heterogeneous direct effects, with Costa Rica and Guatemala among the more exposed and El Salvador and Honduras among the least exposed in the 12-month GFEVDs. Finally, the bottom rows of the table show that, when contributions are aggregated across recipients, the United States is the second largest external transmitter in the panel, the "Contribution TO others" entry for the US equals 4.349 and the "Contribution incl. own" equals 7.392, confirming that US EPU is the principal source of cross-country connectedness in our sample for the western hemisphere countries and CAPRD countries.

Analogous to the US column, the vertical column labeled "CN" in Table 3 reports the contribution of a China EPU shock to each recipient country's 12-month-ahead EPU forecast-error variance. Focusing on the CAPRD group, the China column implies the following direct 12-month GFEVD contributions, Costa Rica 0.1346, Dominican Republic 0.0384, El Salvador 0.0018, Guatemala 0.1011, Honduras 0.0011, Nicaragua 0.0623 and Panama 0.2011. These cell-level values indicate that China's direct bilateral impacts on Central American EPU are present but smaller in absolute terms relative to the US contributions. By contrast, several non-CAPRD recipients exhibit substantially larger direct shares from China, notably Korea 0.9386, Euro area 0.9838, the United States 0.8293, Japan 0.5414 and Canada 0.4673.

The summary rows at the bottom of the table put the cell-level results into aggregate perspective. The entry "Contribution TO others" for China equals 6.289, while "Contribution incl. own" equals 10.804. Thus China is an important external transmitter in the full panel once cross-country contributions are aggregated. The results shows that China exerts sizable aggregate connectedness across the 19-country system, while its direct bilateral shares for most CAPRD recipients remain small compared with US contributions. This pattern is consistent with the interpretation that China is a major global source of EPU transmission overall, but that the strength of bilateral spillovers varies sharply with the economic and trade exposure of each recipient.

Viewed in aggregate, however, the table highlights that China and the United States are the principal global transmitters in the panel. The row "Contribution TO others" places China at 6.289 and the United States at 4.349, and the row "Contribution incl. own" reports China 10.804 and the United States 7.392 on the 100-unit scale. Thus the apparent smallness of any single bilateral cell coexists with substantial system-wide influence once contributions are summed across recipients. This pattern implies that domestic persistence governs country-level EPU variation while external connectedness matters at the system level, and that the relative importance of a given source for any particular recipient depends on the cross-country exposure profile. These results are consistent with the GVAR intuition that trade-weighted linkages mediate cross-border transmission and with prior evidence on asymmetric EPU spillovers from large economies. (Pesaran, Schuermann, and Weiner, 2004; Diebold and Yilmaz, 2012; Onipede, Bashir, and Abubakar, 2023; Diakonova, Ghirelli, and Quiñónez, 2025)

Using the CAPRD data from the Table 3 the intra-regional spillovers are clearly asymmetric. El Salvador emerges as the principal regional transmitter to CAPRD peers, with an outbound contribution of 0.094 percentage points to others and a positive net outward balance of +0.091 percentage points of 12-month forecast-error variance. Honduras is the second largest net transmitter, contributing 0.068

percentage points to peers and registering a net outward balance of $+0.067$ percentage points. The Dominican Republic is effectively neutral to marginally positive as a transmitter with a very small net outward balance of $+0.001$ percentage points. By contrast, Guatemala is the largest net receiver within the block, absorbing 0.107 percentage points from CAPRD peers while contributing only 0.022 percentage points, yielding a net inward balance of -0.085 percentage points. Nicaragua and Costa Rica are also net receivers with net balances of -0.048 and -0.019 percentage points respectively, and Panama is a slight net receiver with a net balance of -0.006 percentage points.

These patterns indicate that policy uncertainty does not diffuse uniformly across the CAPRD region; rather, a small set of countries, notably El Salvador and Honduras, act as regional amplifiers of EPU shocks while others, especially Guatemala and Nicaragua, function as absorbers.

The generalized FEVD reported in Table 4 shows a striking regularity, the EPU series is dominated by its own shocks. On average, about 90.6% of the 12-step-ahead forecast error variance of a country's EPU is attributable to its own EPU innovations (domestic and foreign), leaving only modest shares to other variables in the system. Cross-country heterogeneity is, however, informative. Exchange-rate movements account for measurable shares of EPU variance in a few economies (notably China 10.3%, Brazil 6.8%, Mexico 6.3%, and Korea 5.2%), indicating a currency channel through which external developments can amplify domestic policy uncertainty. Commodity- and price-related variables (columns labelled 'pal' and 'poil') contribute non-negligible shares in commodity-exposed countries (for Brazil and Mexico), while trade flow variables (exports 'x' and imports 'm') and inflation 'p' generally explain only small fractions of EPU variance across the panel. At the extremes, small states such as Honduras and El Salvador display almost entirely idiosyncratic EPU dynamics (own-shares $\approx$99% and $\approx$98.6%, respectively), which is consistent with the problem of serial correlation of the EPU index for this two countries. Taken together, the table implies that EPU is largely self-exciting at monthly horizons, but that specific transmission channels, most prominently exchange-rate and commodity-price channels are important in a subset of countries and therefore warrant targeted attention when interpreting cross-border EPU spillovers.

Table 3: Spillover matrix (Diebold-Yilmaz methodology) from the BGVAR model based on the GFEVD 12 months ahead for bilateral EPU shocks

Country	BR	CA	CH	CN	CO	CR	DR	EA	GT	HN	IN	JP	KO	MX	NI	PA	SL	UK	US	From Others
BR	4.9331	0.0123	0.0011	0.1422	0.0003	0.0000	0.0001	0.0392	0.0001	0.0001	0.0049	0.0055	0.0061	0.0242	0.0000	0.0000	0.0001	0.0136	0.0802	0.330
CA	0.0163	3.3791	0.0016	0.4673	0.0006	0.0003	0.0006	0.1690	0.0006	0.0010	0.0214	0.0423	0.0280	0.2035	0.0002	0.0000	0.0009	0.0781	0.8524	1.884
CH	0.0408	0.0327	4.3271	0.4336	0.0008	0.0002	0.0002	0.0993	0.0003	0.0004	0.0142	0.0168	0.0230	0.0612	0.0001	0.0000	0.0004	0.0375	0.1746	0.936
CN	0.0208	0.0527	0.0024	4.5150	0.0004	0.0001	0.0003	0.1627	0.0003	0.0006	0.0256	0.0551	0.0460	0.0881	0.0001	0.0000	0.0005	0.0638	0.2285	0.748
CO	0.0331	0.0582	0.0038	0.3668	4.0343	0.0005	0.0018	0.1329	0.0016	0.0015	0.0224	0.0192	0.0197	0.1369	0.0003	0.0002	0.0010	0.0502	0.3786	1.229
CR	0.0062	0.0254	0.0007	**0.1346**	0.0004	4.7490	0.0007	0.0524	0.0066	0.0067	0.0054	0.0077	0.0070	0.0624	0.0065	0.0007	0.0050	0.0249	**0.1608**	**0.514**
DR	0.0028	0.0096	0.0001	**0.0384**	0.0003	0.0002	5.0809	0.0137	0.0004	0.0002	0.0020	0.0028	0.0023	0.0203	0.0000	0.0000	0.0001	0.0042	**0.0846**	**0.182**
EA	0.0476	0.1091	0.0031	0.9838	0.0010	0.0004	0.0008	2.7768	0.0007	0.0010	0.0527	0.0555	0.0527	0.1781	0.0002	0.0001	0.0008	0.3931	0.6057	2.486
GT	0.0037	0.0209	0.0005	**0.1011**	0.0004	0.0023	0.0004	0.0322	4.7883	0.0413	0.0045	0.0095	0.0059	0.0553	0.0056	0.0002	0.0566	0.0124	**0.1219**	**0.475**
HN	0.0001	0.0003	0.0000	**0.0011**	0.0000	0.0000	0.0000	0.0005	0.0002	5.2575	0.0001	0.0001	0.0001	0.0006	0.0000	0.0000	0.0006	0.0002	**0.0018**	**0.006**
IN	0.0077	0.0161	0.0005	0.2160	0.0002	0.0000	0.0002	0.0642	0.0001	0.0001	4.7702	0.0137	0.0124	0.0299	0.0000	0.0000	0.0001	0.0228	0.1088	0.493
JP	0.0115	0.0421	0.0015	0.5414	0.0003	0.0001	0.0002	0.1078	0.0002	0.0004	0.0147	4.1680	0.0416	0.0682	0.0001	0.0000	0.0003	0.0415	0.2233	1.095
KO	0.0192	0.0527	0.0024	0.9386	0.0004	0.0001	0.0003	0.1520	0.0004	0.0005	0.0271	0.0584	3.5785	0.0990	0.0001	0.0000	0.0005	0.0588	0.2741	1.685
MX	0.0121	0.0850	0.0013	0.2829	0.0006	0.0002	0.0005	0.1049	0.0008	0.0010	0.0137	0.0218	0.0184	4.1538	0.0002	0.0000	0.0009	0.0417	0.5234	1.109
NI	0.0021	0.0150	0.0002	**0.0623**	0.0001	0.0035	0.0002	0.0199	0.0108	0.0162	0.0028	0.0075	0.0038	0.0435	4.9594	0.0001	0.0307	0.0080	**0.0772**	**0.304**
PA	0.0059	0.0155	0.0006	**0.2011**	0.0024	0.0009	0.0002	0.0425	0.0027	0.0022	0.0058	0.0321	0.0153	0.0310	0.0002	4.8062	0.0012	0.0163	**0.0812**	v0.457
SL	0.0001	0.0005	0.0000	**0.0018**	0.0000	0.0001	0.0000	0.0007	0.0011	0.0010	0.0001	0.0002	0.0001	0.0012	0.0004	0.0000	5.2523	0.0003	**0.0033**	**0.011**
UK	0.0218	0.0730	0.0015	0.5461	0.0005	0.0002	0.0004	0.6638	0.0004	0.0005	0.0308	0.0363	0.0287	0.0982	0.0001	0.0000	0.0004	3.3921	0.3682	1.871
US	0.0300	0.2937	0.0028	0.8293	0.0014	0.0007	0.0017	0.2904	0.0016	0.0021	0.0379	0.0736	0.0503	0.4842	0.0004	0.0001	0.0018	0.1180	3.0432	2.220
Contribution TO others	0.282	0.915	0.024	**6.289**	0.010	0.010	0.009	2.148	0.029	0.077	0.286	0.458	0.361	1.686	0.015	0.002	0.102	0.985	**4.349**	**18.035**
Contribution incl. own	5.215	4.294	4.351	10.804	4.044	4.759	5.090	4.925	4.817	5.334	5.056	4.626	3.940	5.840	4.974	4.808	5.354	4.378	7.392	100

Source: author's elaboration

Notes: The rows represent the source of shocks, while the columns capture the share of forecast error variance in each country explained by shocks originating in other countries. Diagonal elements indicate own-country contributions.

Table 4: Generalized Forecast Error Variance Decomposition of the EPU Index for every country by variable participation

Country	e	epu	m	p	pal	poil	x	y	Total
AVG	3.1	90.6	0.9	1.5	1.1	0.9	1.0	0.8	100.0
BR	6.8	83.5	1.0	1.7	1.2	3.8	0.9	1.2	100.0
CA	3.4	87.0	1.0	2.2	2.0	1.2	1.1	2.1	100.0
CH	10.3	82.4	1.0	2.7	1.0	0.5	1.5	0.6	100.0
CN	1.8	91.0	0.7	2.2	1.4	0.7	1.5	0.6	100.0
CO	2.9	89.6	1.0	2.0	1.3	1.3	1.0	0.9	100.0
CR	2.4	91.7	1.3	1.2	0.6	1.1	0.9	0.8	100.0
DR	0.7	93.4	1.3	1.0	0.5	0.6	1.1	1.5	100.0
EA	4.8	87.6	0.9	1.6	2.0	0.8	1.4	1.0	100.0
GT	0.7	95.9	0.6	0.6	0.7	0.2	0.8	0.5	100.0
HN	0.1	99.2	0.1	0.2	0.1	0.0	0.1	0.2	100.0
IN	3.5	90.7	0.9	1.6	1.0	0.8	1.1	0.5	100.0
JP	3.8	89.8	0.9	1.6	0.7	1.0	1.1	1.0	100.0
KO	5.2	87.6	0.8	3.0	1.0	0.6	1.0	0.9	100.0
MX	6.3	84.0	1.5	2.3	3.0	0.9	1.4	0.6	100.0
NI	1.0	92.9	0.9	1.6	0.7	1.1	1.4	0.5	100.0
PA	0.9	94.5	1.8	0.8	0.5	0.3	0.6	0.5	100.0
SL	0.3	98.6	0.1	0.2	0.3	0.1	0.2	0.2	100.0
UK	1.9	93.1	0.8	1.0	0.9	0.5	0.8	0.9	100.0
US	2.2	89.4	1.0	1.6	1.5	2.1	1.1	1.1	100.0

5.3 Trade Linkages and Spillover Channels

Figure 2 explores the cross-sectional relationship between bilateral trade integration and EPU spillovers. We plot each country pair's estimated spillover magnitude (from the GFEVD) against their bilateral trade weight. The points show a clear positive correlation, countries with a higher share of trade with a given shock-origin tend to experience stronger spillovers. The fitted lines indicate this pattern quantitatively. Overall (solid line) a higher trade weight predicts proportionally larger spillovers ($R^2 \approx 0.43$, slope ≈ 0.82). Notably, the relationship is steeper for Chinese shocks (blue circles, slope ≈ 0.91) than for US shocks (orange diamonds, slope ≈ 0.43), implying that increases in trade share with China lead to especially large additional uncertainty spillover from Chinese shocks. This finding is in line with intuition from gravity models, stronger trade linkages transmit policy uncertainty more intensely. It also complements the regional results, Central American countries trade a greater fraction of their output with the United States than with China, hence they lie above the US fit line and acquire larger spillovers from US EPU shocks. As Rojas-Suárez and Albe (2025) emphasize, export dependence on the US among Central America (e.g. through CAFTA) is high, so our plot confirms that their volatility is closely tied to the United States. In sum, Figure 2 shows that trade is a key channel, pairs with roughly 10% bilateral trade see spillovers on the order of 0.8–9% for Chinese shocks (and 0.4–5% for US shocks), whereas a 20% trade share corresponds to spillovers above 0.16% (China) or 0.08% (US). This evidence strongly supports the economic interpretation that interconnected markets amplify uncertainty transmission.

The spillover–trade analysis reinforces the conclusion that US shocks dominate uncertainty transmission to Central America. Countries with larger US trade shares (e.g. Mexico, Panama) lie furthest to the right and exhibit the strongest US-induced spillovers. Conversely, China's influence is significant mainly where China–CAPRD trade is relatively high (e.g. Panama has grown closely tied to Chinese trade and shows correspondingly elevated Chinese EPU spillover). The linear trends capture about 42% of the cross-country variation in spillover magnitude. This pattern matches prior findings that trade integration amplifies volatility linkages (Giovanni and Levchenko, 2006). In short, geographic and economic proximity to the US explains why US EPU shocks have a larger footprint in our region.

The patterns we observe are economically meaningful. The fact that positive EPU shocks raise local uncertainty (and thus lower real economic activity) is consistent with the evidence of Diakonova, Ghirelli, and Quiñónez (2025) that uncertainty shocks in Central America lead to declines in output and investment. Similarly, our findings echo those of Ghirelli et al. (2019) for Latin America, who document that unexpected EPU shocks significantly dampen trade and FDI flows between countries. By revealing sizable cross-border uncertainty channels from the US and China to Central America, our results underscore the vulnerability of these small economies to fluctuations in global policy environments. The formal quantification provided by the BGVAR thus yields new insight into how much and how quickly US and Chinese policy jitters can permeate the region's economic sentiment.

5.4 Model Estimation and Diagnostic Checks

Finally, we summarize estimation details and diagnostic checks to confirm the robustness of the results. The BGVAR was estimated with 4 domestic and foreign lags and SSVS priors as described above. We ran 5,000 MCMC draws and discarded the first 2,500 as burn-in, leaving 2,496 posterior draws for inference. Convergence of the chains was assessed via Geweke statistics indicating good convergence rate. We also monitored effective sample sizes and observed that all key coefficients had ample effective draws. Posteriors of the EPU-response coefficients (used in Figures A4–A5) showed clear convergence to well-defined distributions.

We applied standard residual diagnostics to check model adequacy. The test revealed no significant serial autocorrelation up to lag 6. Likewise, formal tests for normality of the residuals did not reject the null of Gaussianity at conventional significance levels. These findings suggest that the BGVAR residuals behave as white noise, so that the variance decomposition results and impulse responses are not driven by misspecification. The background summary statistics (Table A1) indicate substantial heterogeneity in baseline EPU volatilities, CAPRD indices have modest means and variances compared to global averages, but with nontrivial skewness and kurtosis. None of these diagnostics undermines our substantive results. A more detail model diagnostic is presented in Appendix 8.1.

5.5 Posterior Inclusion Probabilities for Average Model

The SSVS-derived posterior inclusion probabilities (PIPs) plotted in Figure 3 reveal a clear and economically intuitive selection pattern. First, persistence dominates, own first lags receive very high PIPs (e.g. y_{t-1} for y: 0.906; epu_{t-1} for epu: 0.974; x_{t-1} for x: 0.925; m_{t-1} for m: 0.963; and e_{t-1} for e:

1.00), indicating that month-to-month dynamics are largely driven by strong within-variable autoregression. Second, the BGVAR also selects key cross-variable and cross-border predictors, several foreign-aggregate lags (marked with '*' in the table) and first lags of exchange-rate and trade variables show elevated PIPs (for example, $e^*_{\ell=1}$ and $m^*_{\ell=1}$ exceed conventional significance thresholds), underscoring the role of trade-weighted foreign blocks as relevant predictors for domestic EPU and related macro-variables. Third, commodity-related predictors (oil and 'pal' series and their lags) display moderate inclusion probabilities for price and policy-related equations, signalling that external commodity-price information partially explains domestic inflationary and uncertainty dynamics in the sample. Finally, most cross-equation PIPs outside the strong own-lag band are moderate (roughly 0.2–0.4), which is consistent with the SSVS mechanism. The prior shrinks weak predictors while retaining important channels. These PIP patterns support the use of an SSVS prior in a high-dimensional BGVAR because they concentrate posterior mass on persistent own dynamics and a relatively small set of economically interpretable cross-variable and foreign predictors, thereby improving identification and interpretability of the GIRFs and GFEVD spillover measures (George and McCulloch, 1995; Böck, Feldkircher, and Huber, 2022).

6 Discussion

The empirical evidence presented in the previous section establishes a clear and coherent picture, economic policy uncertainty (EPU) shocks originating in large advanced economies, most notably the United States, transmit materially to the policy uncertainty of Central American and Caribbean (CAPRD) economies, while analogous shocks from China produce more heterogeneous and, on average, smaller effects. The generalized impulse responses and the GFEVD-based Diebold and Yilmaz (2012) spillover matrix jointly show that roughly one fifth to one quarter of short- to medium-run EPU variability in many CAPRD countries can be attributed to foreign policy-uncertainty shocks, with the U.S. channel typically dominant. Below we interpret these results in light of the theoretical and empirical literature, discuss the transmission channels and cross-country heterogeneity, explore policy implications, and consider robustness and limitations.

6.1 Synthesis with existing theory and empirical work

The finding that uncertainty shocks propagate internationally is consistent with a large macroeconomic literature demonstrating the real effects of uncertainty and the potential for cross-border spillovers. At the macro level, uncertainty shocks reduce investment and employment through postponement and option-value channels; seminal work by Bloom (2009) formalizes how increases in uncertainty depress real activity and amplify business-cycle fluctuations. Our demonstration that U.S. uncertainty causes persistent increases in CAPRD EPU accords with these mechanisms, higher domestic uncertainty in small open economies is plausibly the first-order channel through which external policy noise shrinks domestic investment and output (and thereby raises local uncertainty further). This two-way interaction between uncertainty and the real economy is emphasized by Jurado, Ludvigson, and Ng (2015) and Caldara and Iacoviello (2022), who document that uncertainty measures are both endogenous to and causal for macroeconomic fluctuations; our results complement these findings by quantifying how much of the CAPRD uncertainty is exogenous (coming from the U.S. and China) versus domestic.

The dominance of the U.S. channel is also consistent with the literature on international shock transmission and the special global role of the United States. Diebold and Yilmaz (2012) and Diebold and Yilmaz (2014) formalize connectedness measures derived from variance decompositions and show that large financial actors and systemically important economies exert outsized influence on global variance networks; our GFEVD matrix reproduces this pattern in the domain of policy uncertainty. Similarly, Feldkircher and Huber (2016) and Cuaresma, Feldkircher, and Huber (2016) find that U.S. shocks are often the primary drivers of international spillovers in BGVAR frameworks; these studies support the empirical plausibility and interpretation of our estimates. The asymmetric strength of U.S. versus Chinese transmission that we find, stronger, more uniform effects from the U.S.; weaker and more heterogeneous effects from China, matches recent cross-country evidence on the differing global footprints of the two economies (in particular with respect to the Americas) and complements analyses that document country-specific patterns of sensitivity to major partners (Feldkircher and Huber, 2016; Cuaresma, Feldkircher, and Huber, 2016; Diebold and Yilmaz, 2014; Giraldo et al., 2025).

Trade exposure and dollar financial linkages provide a natural explanation for the asymmetric transmission. The positive, economically meaningful correlation between bilateral trade weights and spillover magnitudes (Figure 2) aligns with a body of work showing that trade networks are important vectors for shock transmission (Pesaran, Schuermann, and Weiner, 2004; Georgiadis, 2016; Tran, Tran, and Vu, 2021; Onipede, Bashir, and Abubakar, 2023). In practice, Central American countries trade a large fraction of their goods with the United States (through CAFTA-DR and other trade relationships), and several CAPRD economies (notably Panama) are tightly integrated with U.S.-dominated financial channels; these structural ties make CAPRD EPU especially sensitive to U.S. policy uncertainty. The stronger slope of the spillover–trade relationship for China (conditional on trade weights) is noteworthy, although most CAPRD economies have smaller trade exposure to China than to the U.S., those countries that do trade relatively heavily with China show large sensitivity to Chinese EPU. This observation mirrors results in the trade-and-spillover literature that emphasize how both direction and intensity of trade links condition the magnitude of cross-border propagation (Pesaran, Schuermann, and Weiner, 2004; Onipede, Bashir, and Abubakar, 2023; Georgiadis, 2016; Tran, Tran, and Vu, 2021).

Our results also speak to the literature on heterogeneity of uncertainty spillovers. Several recent studies find country-specific responses that depend on structural characteristics (exchange-rate regime, openness, remittance dependence, debt vulnerability, and financial openness). For instance, Caggiano, Castelnuovo, and Figueres (2019) and Salisu, Gupta, and Demirer (2022) document nonlinear and state-dependent effects of policy uncertainty, with greater real impacts during downturns or financial stress. In our sample, the heterogeneity across CAPRD countries (e.g., the contrasting negative response of the Dominican Republic in the GIRFs) plausibly reflects differences in economic structure, policy regimes, and crisis exposure. Countries with larger fiscal buffers, more flexible exchange rates, or less trade concentration are better able to absorb foreign uncertainty shocks; those with concentrated trade patterns are more exposed, consistent with the evidence presented in related working papers on U.S. uncertainty effects in Latin America (Giraldo et al., 2025). Thus our empirical patterns harmonize with a view of spillovers that is both network- and country-structure dependent.

6.2 Mechanisms: trade, financial channels, remittances and commodity exposures

The BGVAR decomposition and the trade–spillover correlation together point toward multiple channels, (i) trade channel, (ii) financial channel (including interest rates and global financial cycle effects), (iii) remittances and migration-linked channels, and (iv) commodity and supply-chain linkages. When a large partner experiences policy uncertainty, it can reduce demand for imports, disrupt supply chains, and alter expectations about future exchange rates and trade policy—these real effects transmit directly through trade flows and indirectly through expectations and financial markets (Forbes and Rigobon, 2002; Pesaran, Schuermann, and Weiner, 2004). Our results suggest trade is quantitatively significant in the EPU transmission, bilateral trade weight explains a substantial portion of cross-sectional variation in spillovers (Figure 2), which is consistent with trade-based GVAR literature (Pesaran, Schuermann, and Weiner, 2004; Onipede, Bashir, and Abubakar, 2023).

Financial linkages matter as well. The global financial cycle and cross-border credit conditions amplify uncertainty shocks (via exchange-rate pressures, capital-flow reversals, and risk-premium adjustments). Salisu, Gupta, and Demirer (2022) show that U.S. uncertainty propagation is modulated by the state of the global financial cycle; in our BGVAR, countries with tighter financial integration to U.S. markets (or with large external liabilities priced in dollars) display larger EPU spillovers and more persistent GIRFs, this speaks to the financial amplification channel documented in the international macro-finance literature. Remittances, an especially important income channel for several Central American economies, offer another conduit, U.S. uncertainty that weakens U.S. labor demand or raises exchange-rate volatility can reduce remittance flows or increase their variance, which in turn raises domestic uncertainty and consumption volatility. Although remittances are not directly modeled in the current BGVAR, the observed patterns (larger U.S. spillovers for remittance-dependent economies) are consistent with this mechanism (Giraldo et al., 2025).

Commodity and supply-chain exposures are a final plausible channel. For commodity exporters, uncertainty about policy (trade, tariffs, or geopolitics) in major markets can change commodity price expectations and disrupt export revenues; this channel is particularly relevant for countries with concentrated export baskets (Caldara and Iacoviello, 2022; Li et al., 2023). In our sample, commodity-linked Latin economies (e.g., some Central American exporters) experience pronounced EPU responses to partner shocks, consistent with prior findings that commodity price channels amplify external shocks.

6.3 Heterogeneity across CAPRD economies and notable exceptions

Although CAPRD countries share geography and some institutional features, their responses to foreign EPU are far from uniform. The GFEVD matrix shows that own-country EPU typically explains 85–95%

of variance, leaving a large minority attributable to foreign shocks; but the identity of the dominant foreign source differs across countries. Nicaragua, Panama, and Guatemala receive the largest combined shares from U.S. and Chinese EPU, whereas El Salvador and Honduras are somewhat less exposed. These differences align with structural factors, Panama's sizable Chinese trade share (and its role as a regional logistics hub) and its dollarized or quasi-dollarized financial arrangements raise its exposure to both trade and financial shocks. Nicaragua's higher sensitivity fits with the literature documenting that highly indebted emerging economies are particularly vulnerable to external policy noise (Giraldo et al., 2025; Onipede, Bashir, and Abubakar, 2023). The Dominican Republic's idiosyncratic negative impulse-response to some shocks suggests country-specific offsetting policies or commodity-price dynamics that moderate domestic uncertainty when partner uncertainty rises; similar idiosyncratic responses have been documented in other regional studies (see Caggiano, Castelnuovo, and Figueres (2019) for nonlinearity and state dependence).

We emphasize that heterogeneity is economically meaningful, policy prescriptions cannot be uniform across the CAPRD region. Countries with high external vulnerability (debt, narrow export base, shallow financial systems) should prioritize buffers and contingency planning, while those with greater policy flexibility can rely on conventional monetary and fiscal stabilization tools to a larger extent. This policy heterogeneity complements empirical findings in the BGVAR literature showing that country-specific characteristics condition both the magnitude and persistence of spillovers (Cuaresma, Feldkircher, and Huber, 2016; Feldkircher and Huber, 2016).

6.4 Policy implications

The results carry immediate policy relevance. First, policymakers in CAPRD economies should monitor major-country policy uncertainty indices (particularly U.S. EPU) as part of systemic risk surveillance, a material fraction of domestic uncertainty originates abroad, and pre-emptive communication and contingency planning can reduce second-round effects on investment and credit. This recommendation echoes broader calls in the literature for integrating international uncertainty indicators into domestic macroprudential and fiscal frameworks (Diebold and Yilmaz, 2014; Caldara and Iacoviello, 2022). Second, the trade–spillover linkage suggests that diversification strategies (export market diversification and product diversification) can mitigate vulnerability to any single partner's policy instability. While diversification is a long-term strategy, targeted trade facilitation and export promotion policies may attenuate immediate exposure. Third, countries that are heavily dollarized or rely on U.S. financial markets should strengthen foreign-exchange reserves, develop local-currency financing, or implement flexible policies to dampen exchange-rate-induced uncertainty. This suite of recommendations follows directly from the channels identified in Sections 3 and 4 and is consistent with policy-oriented contributions that stress the importance of buffer-building when external uncertainty is likely to transmit (e.g., Salisu, Gupta, and Demirer (2022) and Onipede, Bashir, and Abubakar (2023)).

6.5 Spillover matrix excluding the COVID period

The Table A6 shows the Spillover Matrix estimated from the BGVAR excluding the pandemic period. Estimating the BGVAR over the pre-pandemic window January 2003 to December 2019 and using the corrected spillover matrix produces two clear messages. First, at the system level China and the United States remain the principal transmitters of EPU, with China exhibiting the larger aggregate footprint. The row summary statistics report that China accounts for 6.79 units of contribution to others and 11.35 units when own-country shares are included on the 100 unit scale, while the United States accounts for 4.08 units contributed to others and 7.02 units including own contributions. Relative to the full-sample decomposition the United States' aggregate outward share is somewhat lower, while China's aggregated influence is slightly higher. This pattern shows that excluding the pandemic years does not eliminate China's system-wide role and that measured global connectedness is shaped by both enduring structural linkages and by episode-specific dynamics (Pesaran, Schuermann, and Weiner, 2004; Diebold and Yilmaz, 2012; Caldara and Iacoviello, 2022).

Second, at the bilateral and regional level the corrected matrix confirms the earlier finding that CAPRD economies are heterogeneous in their exposure to external EPU. For most Central American recipients the United States remains the larger bilateral source of EPU relative to China. For example Costa Rica records a larger 12 month GFEVD share from the United States than from China, Guatemala and Nicaragua display substantially larger bilateral shares attributable to the United States than to China, and the Dominican Republic follows the same pattern. Panama is the notable exception, where the bilateral share from China exceeds that from the United States. These cell-level asymmetries are consistent with trade and financial linkages that differ across CAPRD members and with the trade-weighted foreign aggregates that underpin the GVAR construction (Pesaran, Schuermann, and Weiner, 2004; Feldkircher and Huber, 2016).

Within the CAPRD block internal asymmetries persist. El Salvador continues to act as a relatively important regional transmitter in the pre-pandemic sample, as reflected by its comparatively large contribution to others among the CAPRD group. Guatemala remains a net receiver within the block. The overall magnitudes of intra-regional transfers are smaller than the largest cross-border bilateral cells involving global powers, but the rank ordering of net transmitters and net receivers is stable relative to the full-sample results. This stability implies that country-specific propagation mechanisms and domestic amplification of uncertainty are persistent features of the region rather than transient artifacts of the pandemic period (Böck, Feldkircher, and Huber, 2022; George and McCulloch, 1995).

From an interpretative perspective the corrected no-COVID results support two conclusions. The first is that country-level exposure to foreign EPU is conditional on observable economic links, most notably trade intensity and financial interdependence, so that the GVAR decomposition yields economically meaningful bilateral measures of transmission (Pesaran, Schuermann, and Weiner, 2004). The second conclusion is that extreme global episodes can reshape but do not completely determine the network of uncertainty transmission. In this sample excluding the pandemic reduces the overall contribution of external shocks to some recipient variances and slightly alters the relative magnitudes of major transmitters, but it does not overturn the principal empirical finding that the United States is the dominant external source for most CAPRD economies while China is the largest aggregated transmitter at the system level. The corrected results therefore strengthen the robustness of the paper's substantive claims about asymmetric EPU spillovers and their dependence on the pattern of bilateral economic exposure (Jurado, Ludvigson, and Ng, 2015; Baker, Bloom, and Davis, 2016).

6.6 Robustness: twelve-country specification (CAPRD plus main partners)

Estimating the BGVAR on the restricted twelve-country panel that retains the CAPRD economies and their principal trading partners produces a compact but informative picture of bilateral EPU transmission, the results are presented in Table A7. China remains the largest aggregated transmitter in this reduced system while the United States is also a major source. The row summaries show that China contributes 5.07 units to other countries and the United States contributes 4.09 units on the 100-unit scale. At the country level most CAPRD members continue to register larger bilateral shares from the United States than from China. Costa Rica, the Dominican Republic, Guatemala, Nicaragua and El Salvador all display larger 12-month GFEVD shares associated with U.S. EPU innovations than with Chinese innovations. Panama is the principal exception where the China-origin share exceeds the U.S.-origin share. These cell-level patterns mirror the trade-exposure logic embedded in the GVAR construction and the earlier full-sample and no-COVID findings. Bilateral spillovers align with the strength and direction of observable economic linkages rather than with a uniform global influence (Pesaran, Schuermann, and Weiner, 2004; Diebold and Yilmaz, 2012).

The twelve-country exercise helps to conclude with the claims because the principal qualitative conclusions are invariant to a substantial reduction in the cross-sectional set. Restricting the system reduces noise coming from peripheral linkages while preserving the essential transmission channels. The relative magnitudes of China and the United States as aggregated transmitters shift only modestly compared with the full-sample estimates, indicating that our main inference about asymmetric EPU spillovers is not driven by outlier countries or by the inclusion of a large number of peripheral units. This stability accords with prior work that interprets GFEVD-based connectedness as a function of structural exposure captured by trade weights and country-specific dynamics (Diebold and Yilmaz, 2012; Böck, Feldkircher, and Huber, 2022).

6.7 Methodological considerations and limitations

Several methodological points deserve emphasis. First, our BGVAR estimation uses SSVS shrinkage priors and stochastic volatility, which mitigate the curse of dimensionality and permit robust inference in large multi-country systems; this is consistent with best-practice recommendations in the BGVAR literature (George and McCulloch, 1995; Koop and Korobilis, 2013; Cuaresma, Feldkircher, and Huber, 2016). The diagnostic checks reported earlier indicate adequate mixing and stable posterior draws, while residual tests suggest limited serial correlation; these diagnostics increase confidence in the substantive conclusions. Second, the use of generalized impulse responses and generalized FEVD (following Pesaran and Shin (1998)) avoids ordering sensitivity and provides a transparent decomposition of forecast-variance contributions as in Diebold and Yilmaz (2012). Third, we explicitly used trade-weighted foreign variables in the country-block specification, which is the standard approach in GVAR applications and aligns with the structural rationale in Pesaran, Schuermann, and Weiner (2004).

Nonetheless, limitations remain. The EPU indices themselves, though widely used (Baker, Bloom, and Davis, 2016), are imperfect proxies, they capture media-based and policy-announcement-related uncertainty but may omit other forms of uncertainty (e.g., firm-level or micro-level uncertainty captured by firm surveys). Alternative uncertainty metrics (Jurado–Ludvigson–Ng measures, Caldara–Iacoviello GPR index) may deliver somewhat different quantitative magnitudes; future robustness checks could re-estimate the BGVAR using those alternative indicators to assess sensitivity (Jurado, Ludvigson, and Ng, 2015; Caldara and Iacoviello, 2022). Another limitation is that our BGVAR is estimated with fixed parameter dynamics (albeit with stochastic volatility); time-varying parameter models might capture evolving transmission mechanisms (e.g., structural breaks associated with the global financial crisis or the COVID-19 pandemic). Several authors have shown that allowing for time variation can be informative for dynamic spillover assessment (Onipede, Bashir, and Abubakar, 2023; Koop and Korobilis, 2013). Finally, while trade weights explain a substantial share of cross-sectional variation in spillovers, omitted channels (financial network centrality, policy synchrony, and institutional similarity) may also matter; incorporating these dimensions could enrich causal interpretation.

6.8 Connections to recent and region-specific studies

Our work dovetails with a growing set of studies focusing specifically on Latin America and Central America. The working paper by Giraldo et al. (2025) documents that U.S. uncertainty shocks materially depress credit and production in a broad set of Latin American countries, particularly those with high external vulnerabilities; this complements our finding of large U.S.-origin EPU spillovers to Nicaragua, Panama, and Guatemala. Similarly, Li et al. (2023), Gao, Qin, and Zhou (2025) and Tran, Tran, and Vu (2021) document how EPU and monetary-policy shocks propagate along trade and financial linkages, lending further empirical weight to our trade-based interpretation. The BGVAR applications documented in Feldkircher and Huber (2016), Cuaresma, Feldkircher, and Huber (2016) and the BGVAR software documentation (Böck, Feldkircher, and Huber, 2022) support both our modeling choices (SSVS, stochastic volatility) and our inferential strategy (GIRFs and GFEVD). At the same time, our evidence extends the literature by providing detailed bilateral estimates of EPU transmission specifically for CAPRD economies over the 2003–2024 horizon, which includes the global financial crisis, the commodity cycle, and the COVID-19 era, periods during which the international propagation of policy, and geopolitical-related uncertainty was especially salient.

6.9 Directions for future research

Several extensions would usefully build on the current results. First, a time-varying parameter BGVAR with stochastic volatility would identify whether the strength and direction of uncertainty spillovers change across regimes (e.g., pre- and post-2008, or before and after major policy events). Second, incorporating alternative uncertainty measures (Jurado–Ludvigson–Ng, Caldara–Iacoviello GPR, and sectoral EPUs) would test robustness and might reveal sectorally-specific spillovers. Third, micro-level evidence, firm or bank-level responses to partner-policy uncertainty, would clarify the transmission from elevated EPU to real activity and financial strain at the firm/financial-institution level. Fourth, causal identification strategies (external instruments, narrative shocks, or high-frequency identification around policy announcements) could strengthen causal claims about the directionality of transmission between the U.S./China and CAPRD economies (Forbes and Rigobon, 2002; Diebold and Yilmaz, 2014). Finally, policy simulations (conditional forecasts under alternative U.S. policy scenarios) would translate the connectedness statistics into welfare-relevant metrics for policymakers.

In sum, the empirical results demonstrate that the EPU of large economies, mainly the United States, constitutes a quantitatively important source of uncertainty for Central American economies. The BGVAR estimates indicate that external uncertainty accounts for a meaningful share of domestic EPU fluctuations; trade and financial linkages amplify this transmission; and country-specific features determine the size and persistence of responses. These findings reinforce the view that small open economies cannot insulate themselves fully from global policy noise and should incorporate international uncertainty indicators and shock–response planning into macroeconomic policy frameworks. Future research that allows for time variation, employs alternative uncertainty measures, or exploits causal identification will further refine the quantitative assessment and help tailor policy responses for the heterogeneous group of CAPRD economies.

7 Conclusion

This paper set out to quantify the cross border transmission of economic policy uncertainty shocks from the United States and from China to Central American economies using a Bayesian Global Vector Autoregression. The principal research question asked whether uncertainty originating in the two largest global economies propagates heterogeneously across the CAPRD block and whether those transmissions are robust to alternative sample windows and to changes in the country set. To answer this question we estimated a 19 country BGVAR with six domestic variables per country and trade weighted foreign aggregates, using a Stochastic Search Variable Selection prior together with stochastic volatility to improve estimation in the high dimensional system. The BGVAR framework permits direct calculation of generalized forecast error variance decompositions and bilateral spillover matrices in the spirit of Diebold and Yilmaz (2012) and Diebold and Yilmaz (2014) while accounting for each country's heterogeneous exposure through measured trade links as proposed by Pesaran, Schuermann, and Weiner (2004). The economic policy uncertainty indices we employ follow the widely used news based construction of Baker, Bloom, and Davis (2016) and related extensions for trade and geopolitical uncertainty (Caldara et al., 2019; Caldara and Iacoviello, 2022).

The evidence in the full sample indicates a clear asymmetry in transmission. United States uncertainty dominates as a bilateral source of EPU variance for most Central American recipients. The 12 month GFEVD cells reported in Table 3 show that the United States accounts for non trivial shares of forecast error variance in several CAPRD economies, with particularly notable direct impacts on Costa Rica and Guatemala. China on the other hand appears as an important aggregate transmitter in the global system. When contributions are summed across all recipients China typically registers the largest contribution to others while United States contributions are somewhat smaller at the system level. Taken together these two facts imply a dual message. On a country by country basis the United States matters more for most Central American EPU responses whereas China plays a larger role in global connectedness because its uncertainty disperses across a broader group of countries and sectors. This pattern is consistent with the trade weighted transmission mechanism of the BGVAR and with prior empirical findings on asymmetric uncertainty spillovers (Pesaran, Schuermann, and Weiner, 2004; Diebold and Yilmaz, 2014; Caldara et al., 2019).

Two robustness exercises support the main interpretation and sharpen its nuance. First we re estimated the BGVAR restricting the sample to January 2003 through December 2019 and thereby excluded the COVID 19 pandemic era. The no COVID results preserve the qualitative asymmetry. China remains the largest aggregate transmitter in the panel while the United States continues to produce the larger bilateral shares into the CAPRD countries. Excluding the pandemic reduces the absolute magnitude of several bilateral cells and lowers the overall cross border contributions, suggesting that the exceptional global volatility during 2020 to 2024 amplified cross border EPU propagation in some channels. Nevertheless the cross sectional pattern of stronger US bilateral impacts on Central America and wide reach of Chinese uncertainty is robust across both samples. Second we estimated a reduced 12 country BGVAR that retains only the CAPRD group and the principal trading partners. The 12 country specification yields the same qualitative conclusions while producing modest quantitative differences. In particular China remains an important systemic transmitter and the United States retains a prominent role in bilateral transmission to CAPRD. The reduced sample confirms that the main finding is not driven by a specific peripheral country and that trade oriented exposures are central for explaining heterogeneity in recipient responses.

The internal mechanics of the model also help to interpret the results. The GFEVD based decomposition of the EPU variable indicates that EPU is highly persistent at the country level and that own country EPU explains the vast majority of short to medium term forecast variance. On average the EPU variable contributes over ninety percent of its own variance across countries, a result that highlights strong domestic persistence in policy uncertainty. Nevertheless the non zero off diagonal entries are economically meaningful. They reveal systematic heterogeneity that is well aligned with trade exposure and with the PIP evidence from the SSVS estimation which shows that lagged foreign EPU and specific external variables receive substantial posterior inclusion probabilities in many country equations. This combination of high own persistence and economically relevant foreign transmission accords with the intuition that domestic political and policy dynamics dominate, while external policy noise nevertheless operates as a measurable amplifier through trade and financial channels (Baker, Bloom, and Davis, 2016; Caldara et al., 2019).

Methodologically the evidence attests to the value of the BGVAR with Bayesian shrinkage. The SSVS prior concentrates mass on parsimonious lag structures and produces interpretable posterior inclusion probabilities that complement the GFEVD interpretation. The stochastic volatility component improves fit in turbulent subperiods and reduces spuriously large cross country correlations that can arise under constant variance assumptions (George and McCulloch, 1995; Cuaresma, Feldkircher, and Huber, 2016; Böck, Feldkircher, and Huber, 2022). The convergence diagnostics and residual serial correlation tests reported in the main text indicate acceptable sampling performance and only limited residual cross unit serial dependence after controlling for endogenous and weakly exogenous dynamics. These diagnostics lend credibility to the quantitative magnitudes presented for bilateral spillovers.

The empirical pattern has clear policy implications. Central American authorities should recognise that a substantial fraction of their domestic uncertainty originates abroad and that this exposure is heterogeneous across countries. Because United States EPU produces comparatively larger direct bilateral effects on most CAPRD economies, monitoring US policy noise is especially important for near term volatility assessment and crisis preparedness. At the same time the system wide influence of Chinese uncertainty underlines that policymakers must not ignore global sources beyond the immediate geographic neighbourhood. The two tier insight matters for policy design. Policies that improve shock absorption at the domestic level such as strengthened fiscal buffers, targeted foreign exchange liquidity arrangements and regional coordination mechanisms will reduce the domestic amplification of foreign EPU shocks. At the same time diversification of trade partners and deeper regional integration can mitigate concentration risk associated with strong bilateral exposure to a single partner (Caldara et al., 2019; Pesaran, Schuermann, and Weiner, 2004).

The paper has limitations that also motivate future research. The EPU indexes are constructed from national media coverage and related indicators and while they are widely used they may partially reflect foreign event coverage reported in domestic press. This measurement nuance can confound identification of purely domestic versus foreign driven peaks. Robustness checks using alternative uncertainty measures and finer text filtering protocols would be valuable. In addition structural interpretation of identified EPU shocks requires caution because the BGVAR identifies statistical innovations rather than structural policy changes. Finally further work could explore non linearities in transmission and the role of financial versus trade channels in greater depth using higher frequency financial data or local credit and capital flow indicators. For now the combination of consistent bilateral asymmetry, stability of qualitative findings across the no COVID and reduced country specifications, and the alignment of the SSVS inclusion evidence with trade based exposure mechanisms provides a cogent and robust picture of how international policy noise percolates into Central American economies.

To conclude the study provides three core messages. First United States policy uncertainty is the more important bilateral driver of EPU fluctuations in Central America. Second China is a large systemic transmitter in the twenty country system and its broad reach matters for global connectedness. Third these conclusions are robust to excluding the COVID period and to restricting the set of countries. The findings quantify the channels through which foreign policy noise is transmitted to small open economies and they argue for policy frameworks that explicitly incorporate external uncertainty into macroeconomic management (Pesaran, Schuermann, and Weiner, 2004; Diebold and Yilmaz, 2014; Baker, Bloom, and Davis, 2016; Caldara et al., 2019; Böck, Feldkircher, and Huber, 2022; Giraldo et al., 2025).

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Anexos

7.1 Data summary

Table A1: Summary statistics (Mean, SD, Min, Max) for each variable and country

	BR				CA				CH				CN				CO			
Variable	Mean	SD	Min	Max	Mean	SD	Min	Max	Mean	SD	Min	Max	Mean	SD	Min	Max	Mean	SD	Min	Max
e	4.524	0.265	4.011	5.082	4.433	0.119	4.206	4.640	4.633	0.143	4.367	4.937	4.446	0.128	4.260	4.682	4.133	0.165	3.939	4.504
epu	5.002	0.523	3.104	6.518	5.138	0.635	3.700	6.520	4.778	0.581	3.453	6.119	4.863	0.712	3.166	6.495	4.677	0.712	2.310	6.100
m	0.155	1.414	-3.989	6.171	0.053	0.610	-2.813	3.520	0.147	1.264	-3.067	6.415	0.193	1.471	-5.015	9.820	0.136	1.191	-2.637	4.873
p	0.005	0.003	-0.006	0.021	0.002	0.003	-0.010	0.012	0.003	0.004	-0.013	0.017	0.002	0.004	-0.010	0.019	0.004	0.003	-0.003	0.015
x	0.143	1.357	-4.653	7.070	0.055	0.617	-3.328	2.701	0.152	1.151	-3.025	6.927	0.265	2.014	-4.689	15.801	0.150	1.390	-3.764	5.794
y	0.408	2.872	-21.137	11.664	0.491	2.303	-7.005	8.109	0.783	4.038	-21.917	15.906	1.796	4.211	-16.435	22.694	0.788	3.911	-29.467	18.309

	CR				DR				EA				GT				HN			
Variable	Mean	SD	Min	Max	Mean	SD	Min	Max	Mean	SD	Min	Max	Mean	SD	Min	Max	Mean	SD	Min	Max
e	4.444	0.125	4.258	4.662	4.654	0.129	4.477	5.096	4.376	0.120	4.109	4.627	4.133	0.165	3.939	4.504	4.392	0.097	4.297	4.592
epu	4.396	0.664	2.398	5.881	3.679	1.514	0.000	6.113	5.131	0.489	3.865	6.183	3.833	1.706	0.000	6.206	2.363	2.498	0.000	6.768
m	0.109	1.232	-4.189	5.893	0.113	1.149	-3.836	4.445	0.056	0.658	-2.210	2.126	0.109	1.066	-2.964	3.354	0.120	1.061	-2.660	4.304
p	0.004	0.005	-0.008	0.021	0.006	0.012	-0.033	0.111	0.002	0.003	-0.007	0.018	0.004	0.004	-0.008	0.018	0.005	0.003	-0.006	0.020
x	0.094	0.942	-3.553	3.710	0.125	1.291	-3.440	8.015	0.059	0.721	-2.831	2.325	0.107	1.121	-2.778	4.555	0.137	1.435	-4.485	6.588
y	0.799	4.459	-15.411	14.576	1.105	6.375	-37.057	33.775	0.222	5.317	-42.152	42.249	0.752	3.391	-14.974	11.858	1.074	6.799	-30.018	33.105

	IN				JP				KO				MX				NI			
Variable	Mean	SD	Min	Max	Mean	SD	Min	Max	Mean	SD	Min	Max	Mean	SD	Min	Max	Mean	SD	Min	Max
e	4.358	0.108	4.162	4.634	4.916	0.223	4.566	5.482	4.559	0.111	4.367	4.851	4.765	0.136	4.543	5.123	4.633	0.058	4.510	4.727
epu	4.400	0.498	3.151	5.648	4.628	0.284	3.880	5.477	4.970	0.480	3.619	6.772	4.139	0.561	2.141	6.061	2.562	2.349	0.000	6.525
m	0.224	1.567	-5.361	8.002	0.052	0.653	-2.091	1.788	0.091	0.823	-2.580	4.665	0.088	0.915	-2.634	3.571	0.174	1.582	-4.519	7.252
p	0.005	0.006	-0.014	0.034	0.001	0.003	-0.010	0.019	0.002	0.003	-0.005	0.011	0.004	0.002	-0.008	0.015	0.016	0.172	-0.010	2.797
x	0.235	1.928	-5.725	17.669	0.041	0.581	-2.002	1.821	0.095	0.840	-2.671	2.876	0.111	1.140	-4.237	10.245	0.195	1.636	-5.547	6.917
y	1.831	14.474	-76.736	186.684	0.107	6.165	-37.834	19.153	0.873	5.706	-24.908	25.996	0.412	3.827	-40.828	33.158	0.989	6.797	-17.977	23.333

	PA				SL				UK				US			
Variable	Mean	SD	Min	Max	Mean	SD	Min	Max	Mean	SD	Min	Max	Mean	SD	Min	Max
e	4.590	0.074	4.478	4.711	4.544	0.040	4.479	4.627	4.631	0.140	4.355	4.929				
epu	3.894	1.678	0.000	5.905	2.790	2.435	0.000	6.691	4.778	0.522	3.180	6.325	4.860	0.425	3.802	6.223
m	0.338	2.630	-6.044	11.694	0.097	1.158	-3.323	5.421	0.091	1.264	-5.768	14.160	0.056	0.529	-1.944	1.879
p	0.001	0.013	-0.193	0.013	0.002	0.005	-0.014	0.030	0.015	0.213	-0.005	3.464	0.013	0.175	-0.016	2.847
x	1.335	6.623	-9.462	32.863	0.072	1.124	-4.473	5.783	0.079	1.206	-6.100	10.537	0.059	0.473	-2.732	1.675
y	2.044	12.960	-38.241	57.094	0.670	6.653	-28.670	26.218	0.034	4.538	-37.653	33.195	0.396	1.868	-23.311	8.049
pal													4.647	0.204	4.170	5.110
poil													4.168	0.361	2.832	4.898

Each country occupies four columns (Mean, SD, Min, Max). Missing entries are left blank. Variables included are: e (real exchange rate index), epu (log Economic Policy Uncertainty index), m (monthly growth, %), p (inflation rate or price change), x (exports or external variable), y (annualized monthly growth of economic activity). For the United States, additional rows "pal" and "poil" (policy / oil indices) are included where provided.

7.2 Economic Policy Uncertainty Index for CAPRD, US and China

We use monthly newspaper-based economic policy uncertainty indices for the United States and China together with the Bank of Spain CAPRD indices for Costa Rica, Guatemala, Honduras, El Salvador, Nicaragua, Panama and the Dominican Republic. For the purpose of this narrative subsection we identify "major" source-country uncertainty episodes as local maxima in the US or China index that exceed the 90th percentile of that source index. A CAPRD country is classified as displaying an immediate spillover when, within a window of plus or minus one month around the source-country peak, that country's index reaches a local maximum and attains a value above its 75th percentile. This approach is descriptive and intended to isolate prominent co-movement episodes that merit qualitative discussion and historical verification.

Figure A1 plots each CAPRD country EPU as a separate panel. Vertical dashed lines indicate major US peaks and vertical dotted lines indicate major China peaks. The visual presentation emphasizes whether elevated policy uncertainty in the source economy coincides with elevated uncertainty in individual CAPRD countries.

Table A3 summarizes selected high-impact episodes where either US or China EPU attains a major peak and where one or more CAPRD series display a contemporaneous elevated value.

The October 2008 peak coincides with the global financial crisis and the collapse of Lehman Brothers, an episode associated with a pronounced global rise in policy uncertainty. The CAPRD indices show contemporaneous elevated values consistent with the global nature of the shock. For evidence that the US EPU spiked at the 2008 crisis see Baker, Bloom and Davis and the global EPU construct.

The November 2016 spike is consistent with documented election-related uncertainty in the United States. Several CAPRD series, notably Guatemala and Nicaragua, exhibit contemporaneous increases in EPU in the dataset. The literature documents sharp EPU rises around tight presidential elections.

Episodes in 2018 and 2019 correspond to the US-China tariff announcements and retaliations that are widely reported and studied as a source of global trade and policy uncertainty. Our detection flags several CAPRD countries during these months, most often Panama and Costa Rica. The trade-war

Table A2: Trade-weight bilateral matrix (rows → columns)

Country	BR	CA	CH	CN	CO	CR	DR	SL	EA	GT	HN	IN	JP	KO	MX	NI	PA	UK	US
BR	0	2.09	3.15	30.08	1.31	0.15	0.24	0.08	23.44	0.12	0.05	2.64	4.35	3.55	3.53	0.04	0.07	2.34	22.75
CA	0.71	0.0	0.26	6.46	0.17	0.03	0.07	0.02	6.49	0.04	0.01	0.64	2.61	1.27	2.61	0.02	0.01	2.39	76.17
CH	7.88	2.08	0.0	30.22	1.53	0.25	0.08	0.09	15.72	0.22	0.05	2.05	8.00	5.54	3.18	0.04	0.07	1.40	21.60
CN	4.09	3.58	1.75	0.0	0.58	0.11	0.14	0.07	24.24	0.10	0.05	3.63	15.09	11.13	3.88	0.03	0.06	3.95	27.50
CO	5.46	2.03	2.75	14.69	0.0	0.58	0.84	0.21	15.83	0.68	0.25	3.04	2.41	2.14	6.43	0.12	0.47	1.83	40.22
CR	1.89	1.89	0.83	11.31	1.17	0.0	0.82	1.62	13.06	3.29	1.58	0.61	2.81	1.26	7.38	1.74	1.55	4.18	43.01
DR	2.37	2.84	0.42	8.96	2.37	1.25	0.0	0.43	11.08	0.83	0.41	1.84	0.93	1.38	4.14	0.11	0.15	1.40	59.10
SL	1.23	1.05	0.60	6.18	1.00	3.82	0.78	0.0	6.14	15.97	6.13	0.50	1.17	1.22	7.03	4.50	0.82	0.38	41.48
EA	3.36	2.94	0.85	21.96	0.54	0.16	0.13	0.04	0.0	0.10	0.07	3.73	6.32	4.06	2.73	0.02	0.05	24.74	28.20
GT	1.42	2.39	1.04	8.85	1.59	3.79	0.77	7.47	7.51	0.0	4.79	1.08	1.89	2.05	9.72	1.88	0.81	0.57	42.37
HN	0.77	1.63	0.28	4.80	0.75	2.67	0.61	7.00	7.83	7.44	0.0	0.86	0.86	1.08	5.90	1.34	0.25	0.76	55.15
IN	2.70	2.04	0.79	25.60	0.67	0.05	0.16	0.04	25.01	0.10	0.04	0.0	5.05	5.97	2.19	0.03	0.04	5.26	24.24
JP	1.37	2.92	1.10	35.98	0.21	0.08	0.05	0.03	15.04	0.06	0.02	1.84	0.0	10.34	2.54	0.02	0.04	2.54	25.81
KO	1.59	1.87	1.03	40.85	0.22	0.05	0.05	0.04	13.17	0.08	0.02	2.77	13.78	0.0	3.02	0.02	0.05	1.88	19.51
MX	1.25	4.25	0.50	6.42	0.66	0.18	0.14	0.14	7.38	0.34	0.10	0.72	2.07	1.84	0.0	0.08	0.07	0.54	73.31
NI	0.97	2.48	0.33	5.43	0.37	6.32	0.50	6.29	4.96	6.80	3.22	0.73	1.14	1.71	12.01	0.0	0.38	0.57	45.78
PA	2.09	0.48	0.63	23.20	5.88	1.93	0.39	0.46	9.22	2.14	0.64	0.95	21.44	7.62	2.70	0.16	0.0	0.80	19.25
UK	0.80	2.85	0.18	8.82	0.14	0.04	0.04	0.01	65.61	0.01	0.01	1.87	2.71	1.41	0.59	0.01	0.01	0.0	14.91
US	2.06	20.78	0.79	17.43	0.92	0.41	0.48	0.21	19.72	0.37	0.18	2.39	7.61	4.23	18.04	0.08	0.10	4.22	0.0

Notes: Entries are bilateral trade weights computed from the IMF Trade Statistics database using FOB exports plus CIF imports and averaged annually over 2003–2024. The matrix reports the average share of bilateral trade (unitless) for each row country with each column country.. Matrix values are trade weights constructed from IMF Trade Statistics (FOB exports + CIF imports), averaged annually for each year 2003–2024 and then averaged across years. Each entry shows the average bilateral trade weight between the row and column country used for constructing trade-weighted aggregates and spatial weighting in the BGVAR. Source: IMF Trade Statistics; author calculations.

Date	Source	CAPRD countries flagged as elevated
2008-10	United States	Guatemala, El Salvador, Nicaragua, Dominican Republic
2016-11	United States	Guatemala, Honduras, Nicaragua
2018-03	China	Costa Rica, Panama
2019-01	United States	Honduras, Panama, Dominican Republic
2020-05	United States / China	Costa Rica, Guatemala, El Salvador, Nicaragua, Panama
2022-03	United States	Costa Rica, Guatemala, Honduras, El Salvador, Nicaragua

Table A3: Representative high-impact policy-uncertainty episodes and the CAPRD countries that show contemporaneous elevated EPU in the dataset.

literature documents both the tariff chronology and associated uncertainty and trade disruptions.

The large uncertainty jumps in 2020 are contemporaneous with the emergence of the COVID-19 pandemic. Both US and China indices show very large spikes in spring 2020 and multiple CAPRD countries also register high values in the same months. The pandemic is established as a source of record-high economic uncertainty across multiple indicators.

Finally, the March 2022 rise in uncertainty follows the Russia–Ukraine invasion and corresponds to a general surge in global uncertainty measures in March 2022. Several CAPRD countries show elevated EPU in our dataset in the same month. For discussion of the March 2022 surge in uncertainty, see the Federal Reserve note summarizing recent uncertainty metrics.

In Figure A2 we present the pairwise Pearson correlations, the results show a clear pattern of stronger co-movement between Panama, the United States and China, and generally moderate correlations across several Central American neighbors. The largest correlations are between the United States and China ($\rho \approx 0.568$, $p \approx 1.3 \times 10^{-24}$) and between Panama and the United States ($\rho \approx 0.553$, $p \approx 3.5 \times 10^{-23}$), indicating strong synchronous movements of EPU for these economies over the sample. Panama also correlates strongly with Guatemala ($\rho \approx 0.484$, $p \approx 2.1 \times 10^{-17}$), China ($\rho \approx 0.450$, $p \approx 5.9 \times 10^{-15}$) and Costa Rica ($\rho \approx 0.435$, $p \approx 5.4 \times 10^{-14}$), suggesting Panama's EPU index moves in step with both regional neighbors and major external economies. Several Central American pairs show moderate positive correlations (for example, Guatemala–United States $\rho \approx 0.457$, $p \approx 1.9 \times 10^{-15}$; El Salvador–Panama $\rho \approx 0.428$, $p \approx 1.4 \times 10^{-13}$; Nicaragua–Panama $\rho \approx 0.375$, $p \approx 1.7 \times 10^{-10}$). By contrast, Honduras and the Dominican Republic display generally low and often statistically insignificant correlations with many peers (e.g., Honduras–Costa Rica $\rho \approx 0.045$, $p \approx 0.456$; Dominican Rep.–Costa Rica $\rho \approx 0.030$, $p \approx 0.625$), indicating more idiosyncratic EPU dynamics for those series. Most of the moderate-to-strong coefficients above are highly statistically significant (many p-values $\ll 0.01$), so these co-movements are unlikely to be sampling noise.

Figura A3 shows the time-varying structure of pairwise EPU correlations estimated with a 24-month rolling window. The heatmap reveals two clear features. First, pairs that include the United States and China exhibit the strongest and most persistent positive correlations across the panel, indicating that global uncertainty episodes tend to synchronize EPU movements in the region (notably the Panama–US/China and Costa Rica–China blocks). Second, there is substantial heterogeneity across Central American countries, some pairs (e.g. involving Honduras and the Dominican Republic) show low or intermittent correlations, suggesting more idiosyncratic uncertainty dynamics. Temporally, the map displays pronounced vertical bands of elevated correlations that coincide with major global stress periods (for example the 2008–09 global financial episode and the 2020 pandemic shock), consistent with common-shock transmission. These patterns imply that much of the observed co-movement is driven by external/global factors (captured by US/China EPU) while country-specific drivers remain important for particular series.

8 Diagnostics, and Additional Results

8.1 Model Selection and Diagnostics

The BGVAR estimation reported in Section 4 was carried out with a Stochastic Search Variable Selection (SSVS) prior, four lags for both domestic and weakly exogenous blocks, stochastic volatility enabled, and an effective posterior sample of 2,496 stable draws after thinning. These modeling choices reflect standard practice in large multi-country VARs, the SSVS prior is designed to deliver aggressive regularization in high-dimensional parameter spaces (shrinking many coefficients toward zero while allowing important predictors to remain free), and stochastic volatility accommodates time-varying error variance that is endemic in panels spanning the 2003–2024 period.

A first set of diagnostics presented in Table A4 pertains to MCMC convergence. The sampler

Table A4: Model diagnostics and summary statistics for the BGVAR estimation. The table reports, (A) model information and sampling details; (B) Geweke convergence diagnostic summary; (C) F-test summary for first-order serial autocorrelation of cross-unit residuals (counts and percentages of p-value bins); and (D) Average pairwise cross-unit correlation of unit-model residuals by variable (counts and percentages).

A. Model information	
Prior:	Stochastic Search Variable Selection prior (SSVS)
Number of lags (endogenous):	4
Number of lags (weakly exogenous):	4
Number of posterior draws:	5000/2 = 2500
Number of stable posterior draws:	2496
Number of cross-sectional units:	19

B. Convergence diagnostics (Geweke)	
Geweke statistic summary:	5794 out of 53 015 variables' z-values exceed the 1.96 threshold (10.93%).

C. F-test: 1st-order serial autocorrelation of cross-unit residuals

p-value bin	Count	Percent
> 0.1	68	59.13%
0.05–0.1	14	12.17%
0.01–0.05	15	13.04%
< 0.01	18	15.65%

D. Average pairwise cross-unit correlation of unit-model residuals

Bin	y	p	e	epu	x	m
< 0.1	9 (47.37%)	19 (100%)	19 (100%)	19 (100%)	19 (100%)	18 (94.74%)
0.1–0.2	7 (36.84%)	0 (0%)	0 (0%)	0 (0%)	0 (0%)	1 (5.26%)
0.2–0.5	3 (15.79%)	0 (0%)	0 (0%)	0 (0%)	0 (0%)	0 (0%)
> 0.5	0 (0%)	0 (0%)	0 (0%)	0 (0%)	0 (0%)	0 (0%)

produced 5,000 draws with thinning equal to two, yielding 2,500 retained draws and 2,496 stable posterior draws after active trimming. Active trimming essentially removes draws that violate simple stability checks for the global companion matrix; retaining 2,496 stable draws indicates that nearly all saved draws satisfy dynamic-stability constraints. Nevertheless, the Geweke statistic reports that 5,794 out of 53,015 individual-variable z-values exceed the conventional 1.96 threshold (about 10.93%).

A second set of diagnostics concerns serial dependence in the unit-model residuals. The F-test summary for first-order serial autocorrelation across cross-unit residuals shows that a majority of p-values (59.13%) exceed 0.10, indicating no evidence for first-order serial correlation for most country–variable blocks. However, a fraction of tests fall into the ranges, about 13.04% of tests have p-values in (0.01,0.05] and 15.65% are below 0.01. The results presented in the Table A.4 indicate that the correlation levels are acceptably low.

The average pairwise cross-unit correlation of unit-model residuals provides another window into the cross-sectional dependence structure. For most variables (inflation p, real exchange rate e, EPU epu, exports x, imports m) the overwhelming majority of pairwise correlations lie below 0.1, indicating that residual comovement across countries is generally low after conditioning on the model-defined foreign aggregates. The notable exception is the activity variable y, although 47.37% of pairwise correlations for y are below 0.1, a substantial share (36.84%) lie in the 0.1–0.2 band and 15.79% in the 0.2–0.5 band. This pattern suggests moderate residual co-movement in economic activity across countries that is not fully captured by the trade-weighted foreign blocks or by the chosen lag structure. From an identification and interpretation perspective, higher residual cross-correlations for y imply that the weak-exogeneity assumption for the foreign block may be less compelling for activity than for other variables, in a GVAR framework, foreign aggregates are intended to capture common external drivers, but residual high cross-correlation indicates omitted common factors or synchronized shocks affecting activity across countries (Pesaran, Schuermann, and Weiner, 2004; Feldkircher and Huber, 2016).

The F-test Table A5 indicates that for the majority of country–variable blocks there is no evidence of first-order serial correlation (consistent with the summary statistics showing $\approx 59.1\%$ of p-values > 0.10). Nevertheless, several concentrated exceptions stand out, very large F-statistics and highly significant p-values appear for the activity equation in Colombia ($F = 23.41$, $p \approx 0.000$), India ($F = 25.65$,

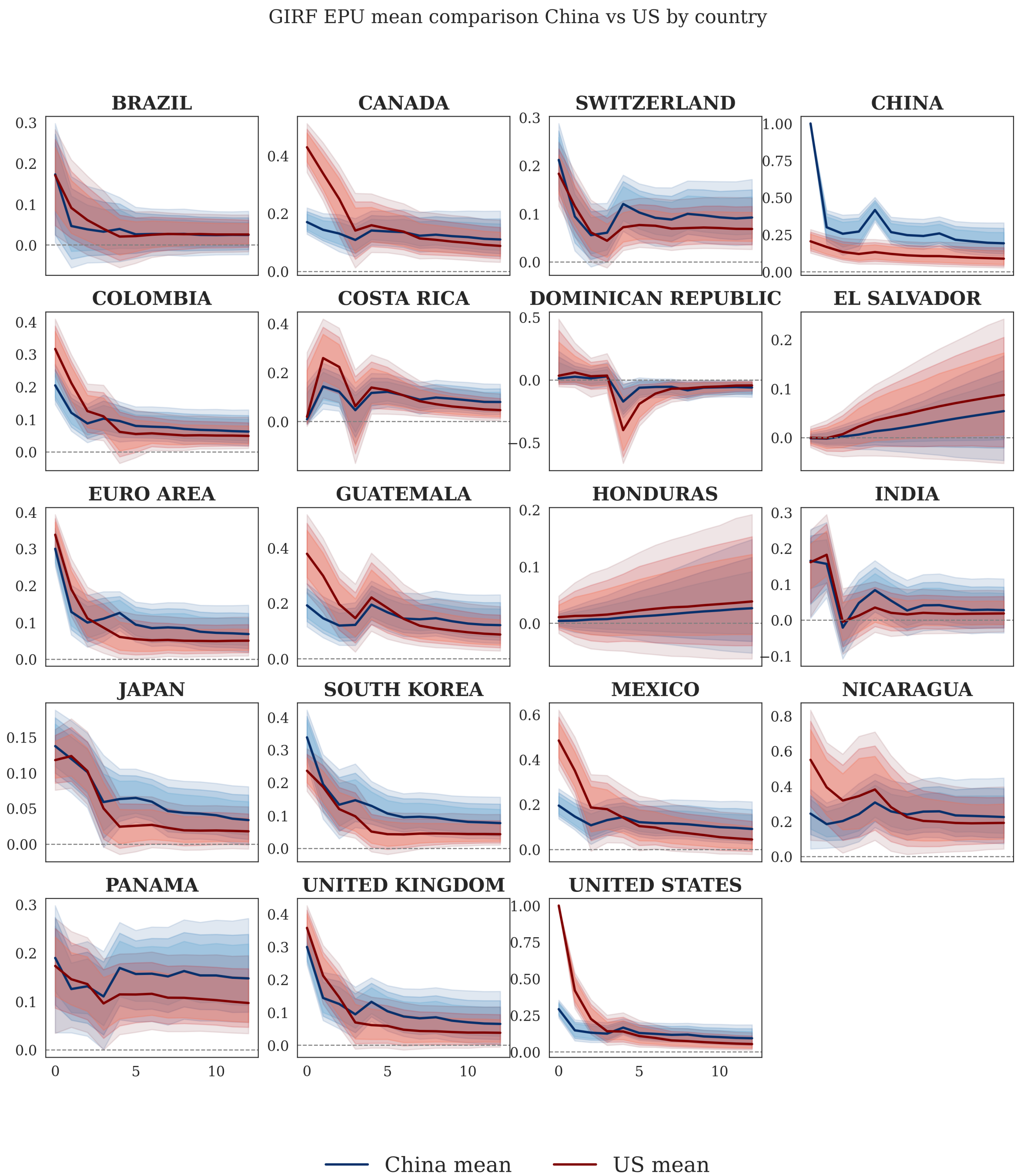
Table A5: F-test for first-order serial autocorrelation of country–variable residuals

No	Country	DoF	F-crit. (0.95)	y	p	e	epu	x	m	poil	pal
1	BR	F(1 ,253)	3.8785	0.0795	0.0487	2.2950	0.0058	6.6316	0.4620	-	-
2	-	-	-	(0.7750)	(0.8230)	(0.1280)	(0.9380)	(0.0110)	(0.4920)	-	-
3	CA	F(1 ,253)	3.8785	0.2593	0.6414	0.1147	0.0754	3.2133	0.9757	-	-
4	-	-	-	(0.6060)	(0.4180)	(0.7320)	(0.7810)	(0.0720)	(0.3190)	-	-
5	CH	F(1 ,253)	3.8785	6.4025	1.9996	1.9145	0.0445	2.3857	5.0812	-	-
6	-	-	-	(0.0120)	(0.1550)	(0.1640)	(0.8310)	(0.1200)	(0.0250)	-	-
7	CN	F(1 ,253)	3.8785	0.2926	0.8220	5.8413	0.2589	3.2502	2.9507	-	-
8	-	-	-	(0.5840)	(0.3600)	(0.0160)	(0.6070)	(0.0710)	(0.0850)	-	-
9	CO	F(1 ,253)	3.8785	23.4094	3.5564	9.1204	2.9656	4.3534	2.1314	-	-
10	-	-	-	0.0000	(0.0590)	(0.0030)	(0.0840)	(0.0370)	(0.1420)	-	-
11	CR	F(1 ,253)	3.8785	4.4789	0.8564	6.7230	0.0078	0.2255	0.0039	-	-
12	-	-	-	(0.0340)	(0.3500)	(0.0100)	(0.9290)	(0.6310)	(0.9490)	-	-
13	DR	F(1 ,253)	3.8785	2.8375	89.1274	0.0659	1.9893	9.9572	1.4794	-	-
14	-	-	-	(0.0910)	0.0000	(0.7950)	(0.1560)	(0.0020)	(0.2200)	-	-
15	SL	F(1 ,253)	3.8785	2.0531	2.9522	1.5795	63.7498	1.7410	4.3905	-	-
16	-	-	-	(0.1490)	(0.0850)	(0.2050)	0.0000	(0.1840)	(0.0360)	-	-
17	EA	F(1 ,253)	3.8785	11.6483	3.6610	1.9509	1.6083	3.4131	2.3047	-	-
18	-	-	-	(0.0010)	(0.0550)	(0.1600)	(0.2010)	(0.0640)	(0.1270)	-	-
19	GT	F(1 ,253)	3.8785	4.7758	4.9205	4.0568	1.0024	0.4468	4.8204	-	-
20	-	-	-	(0.0290)	(0.0270)	(0.0440)	(0.3120)	(0.4990)	(0.0280)	-	-
21	HN	F(1 ,253)	3.8785	11.2248	0.4195	2.6785	71.2260	1.3828	0.1403	-	-
22	-	-	-	(0.0010)	(0.5120)	(0.1000)	0.0000	(0.2360)	(0.7050)	-	-
23	IN	F(1 ,253)	3.8785	25.6502	0.5113	6.9801	0.1199	0.0615	2.5231	-	-
24	-	-	-	0.0000	(0.4700)	(0.0090)	(0.7260)	(0.8020)	(0.1100)	-	-
25	JP	F(1 ,253)	3.8785	20.0336	0.0101	3.3612	0.0025	0.0419	2.7384	-	-
26	-	-	-	0.0000	(0.9190)	(0.0660)	(0.9600)	(0.8360)	(0.0960)	-	-
27	KO	F(1 ,253)	3.8785	1.1152	1.1120	27.1114	0.4594	1.7423	3.4275	-	-
28	-	-	-	(0.2860)	(0.2870)	0.0000	(0.4930)	(0.1840)	(0.0630)	-	-
29	MX	F(1 ,253)	3.8785	20.1397	0.0529	3.4442	0.3253	0.1069	0.2000	-	-
30	-	-	-	0.0000	(0.8160)	(0.0630)	(0.5640)	(0.7410)	(0.6510)	-	-
31	NI	F(1 ,253)	3.8785	0.3262	0.0000	3.4057	0.5018	0.8922	7.8462	-	-
32	-	-	-	(0.5630)	(0.9990)	(0.0640)	(0.4740)	(0.3400)	(0.0060)	-	-
33	PA	F(1 ,253)	3.8785	0.5312	0.0132	7.9651	8.1987	1.0616	10.8636	-	-
34	-	-	-	(0.4610)	(0.9070)	(0.0050)	(0.0050)	(0.2980)	(0.0010)	-	-
35	UK	F(1 ,253)	3.8785	0.0409	0.2295	1.5313	0.0045	0.6687	5.9755	-	-
36	-	-	-	(0.8380)	(0.6280)	(0.2120)	(0.9460)	(0.4090)	(0.0150)	-	-
37	US	F(1 ,252)	3.8786	0.5407	1.1667	-	0.4467	11.3297	2.1296	5.5736	6.1822
38	-	-	-	(0.4560)	(0.2750)	-	(0.4980)	(0.0010)	(0.1410)	(0.0180)	(0.0130)

Notes: F(1,253) critical = 3.8785; significance in parentheses.

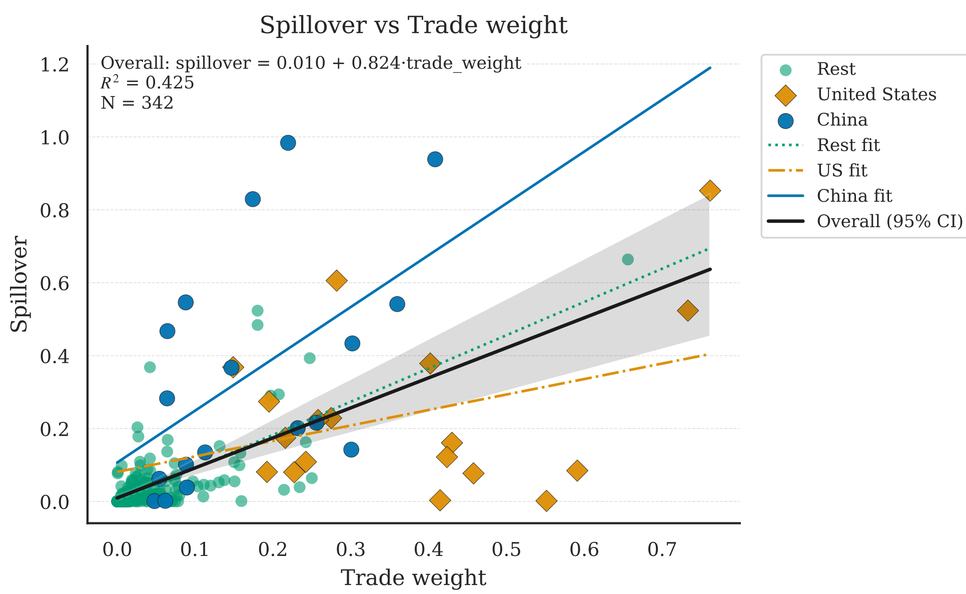
$p \approx 0.000$), Japan ($F = 20.03$, $p \approx 0.000$), Mexico ($F = 20.14$, $p \approx 0.000$) and for specific EPU entries (e.g. El Salvador and Honduras with extremely large F for *epu*, this impacts the GIRF), as well as notable significance in price or export/import equations for a few countries (e.g. China, Korea, Panama). These concentrated rejections imply that for a limited set of units the single-lag residual structure is not fully captured by the current specification and therefore the estimated dynamics for those particular country–variable pairs should be interpreted with caution; at the system level, however, the pattern is not systemic and the global connectedness and EPU spillover results remain supported by the large mass of blocks that pass the F-test.

Figure 1: GIRF of country-specific EPU indices in response to a one-standard-deviation shock in China and US



Notes: Shaded areas denote 90% posterior credible intervals. Each panel shows the impulse response of the labeled country's EPU index.

Figure 2: Spillover index (contribution of foreign shocks to forecast error variance) versus bilateral trade weight for US (orange diamonds) and China (blue circles) shocks



Notes: The overall fitted regression line (solid) and country-specific fits (dashed for US, dot-dashed for China) are shown.

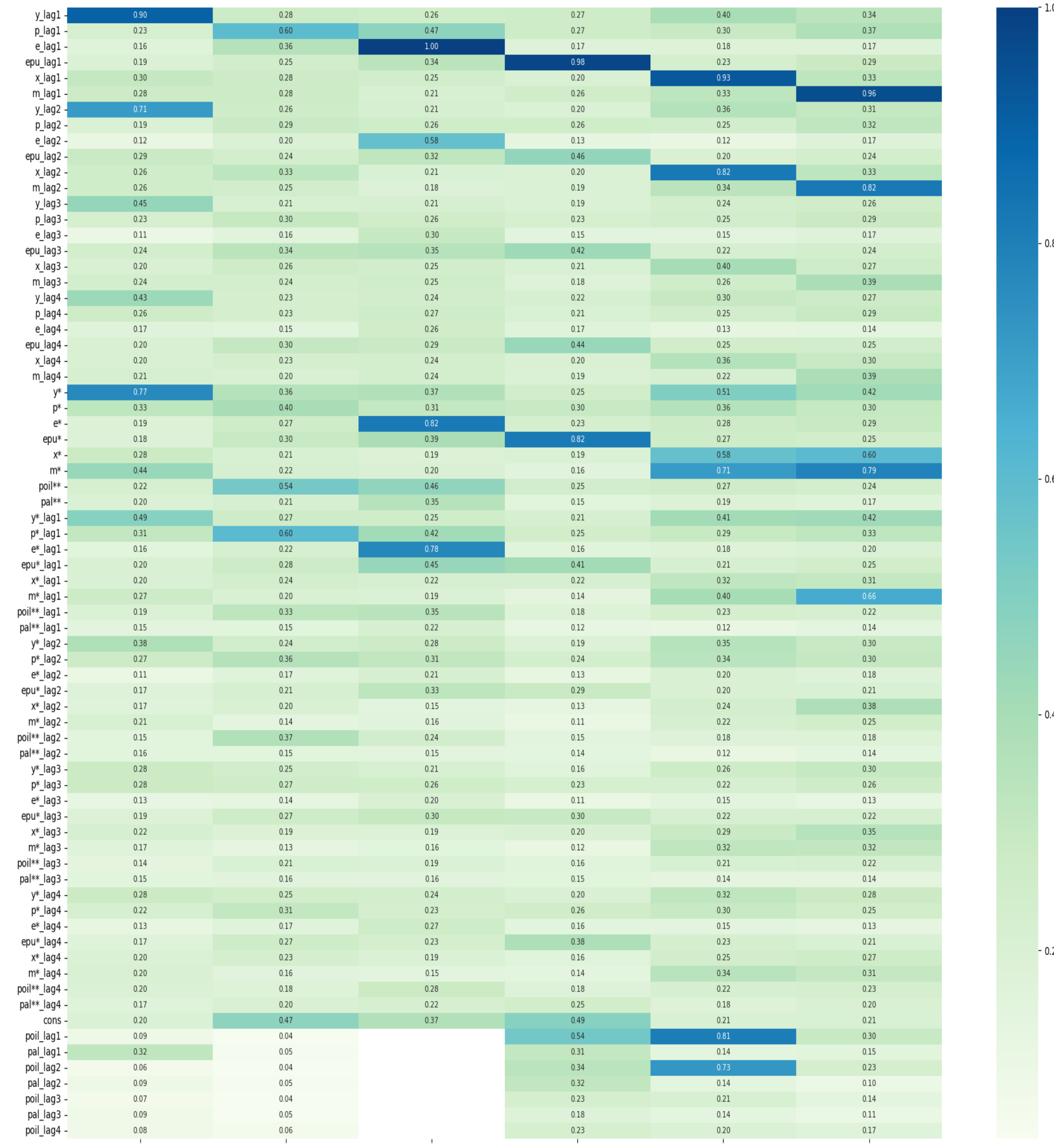
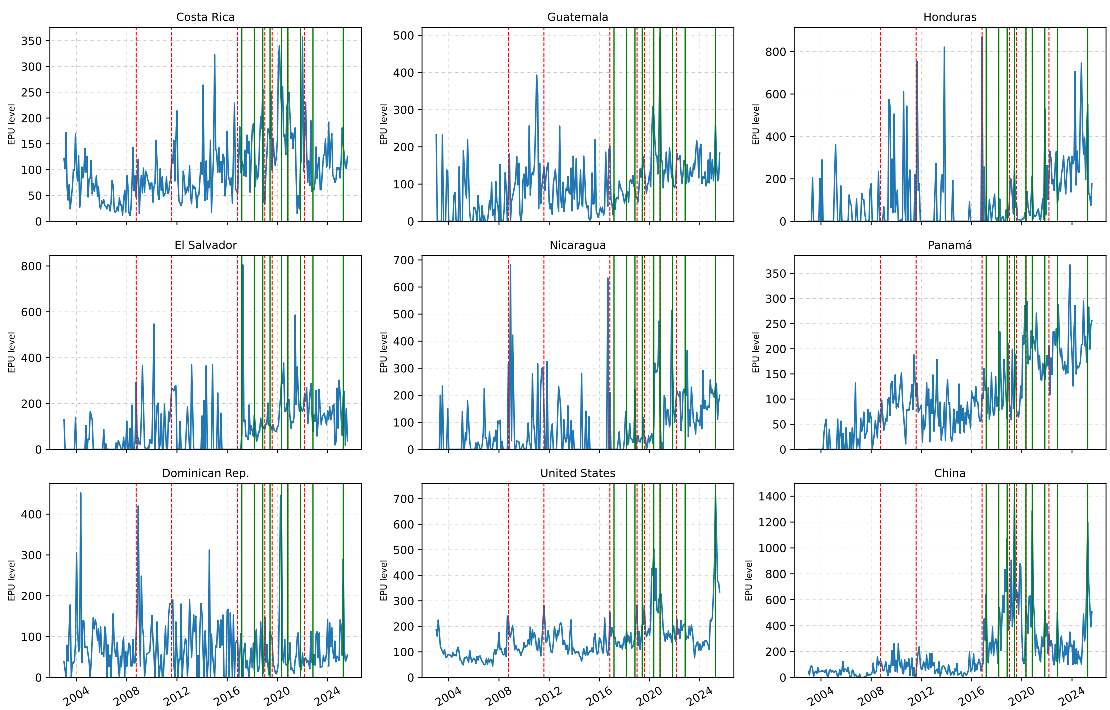


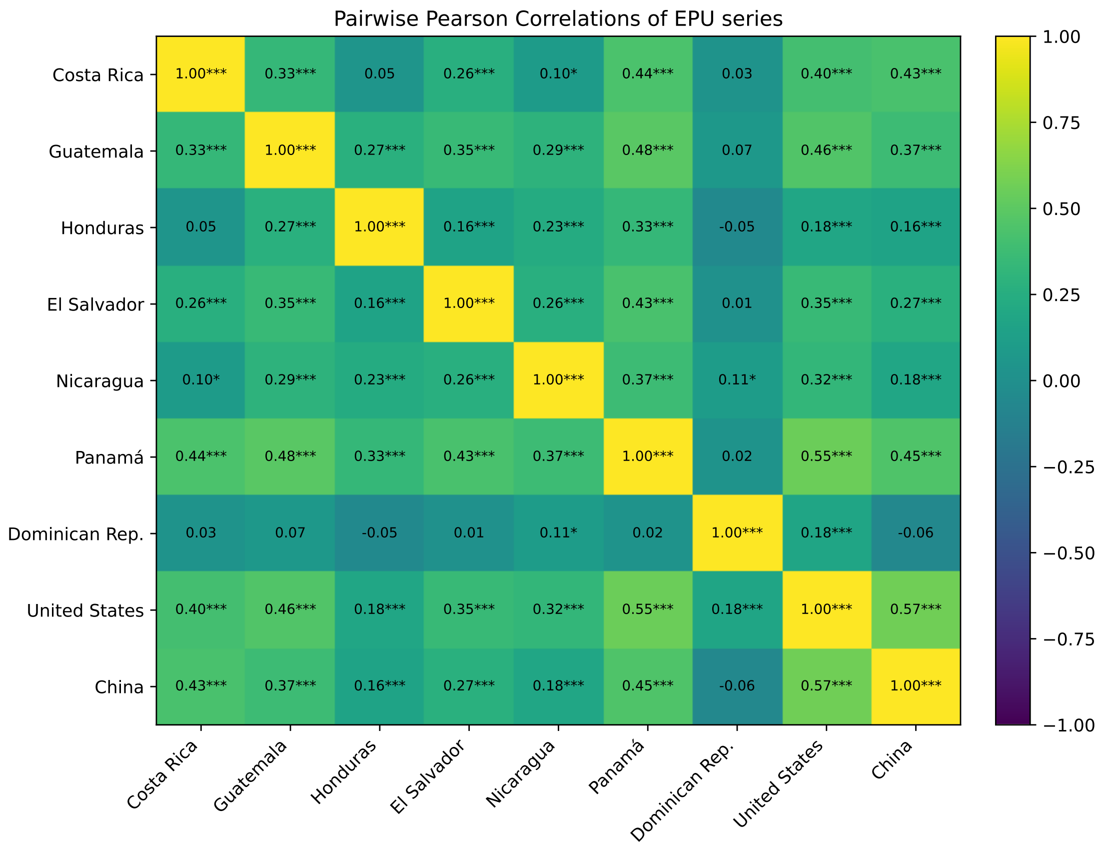
Figure 3: Posterior inclusion probabilities (PIPs) from the BGVAR with SSVS prior.
Heatmap of PIPs for candidate predictors (rows) across target variables (columns). Rows list domestic lagged predictors (lags 1–4), foreign/trade-weighted aggregates (variables with '*' and their lags), commodity-price indicators ('poil' and 'pal' and their lags), and the constant. Darker blue cells denote higher PIPs (strong evidence the coefficient belongs in the model); lighter green cells denote PIPs close to zero (weak evidence). For interpretation, PIP $\gtrsim 0.80$ indicates very strong posterior support for inclusion, PIP in $[0.50, 0.80)$ indicates moderate support, and PIP < 0.20 indicates weak/no support. The figure highlights (i) strong selection of own first lags across core variables, (ii) notable inclusion of selected foreign-aggregate lags and trade/flow predictors, and (iii) commodity-price indicators entering with nontrivial probability for price- and uncertainty-related equations, consistent with the economic channels emphasized in the main text.

Figure A1: CAPRD country monthly EPU series, 2003–2025



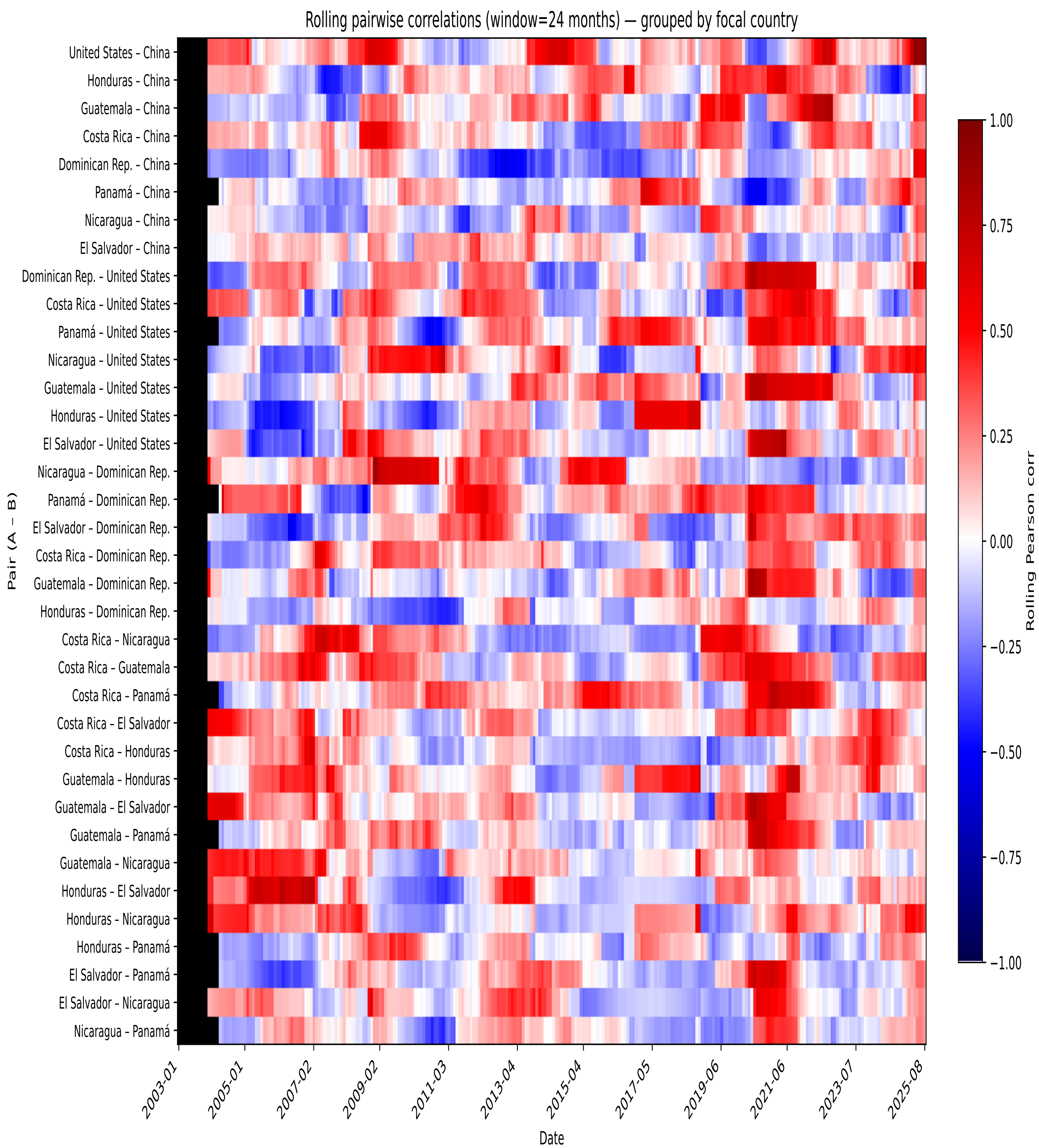
Notes: Each country occupies four columns (Mean, SD, Min, Max). Missing entries are left blank. Variables included are: e (real exchange rate index), epu (log Economic Policy Uncertainty index), m (monthly growth, %), p (inflation rate or price change), x (exports or external variable), y (annualized monthly growth of economic activity). For the United States, additional rows "pal" and "poil" (policy / oil indices) are included where provided.

Figure A2: Pairwise Pearson correlations of Economic Policy Uncertainty (EPU) series



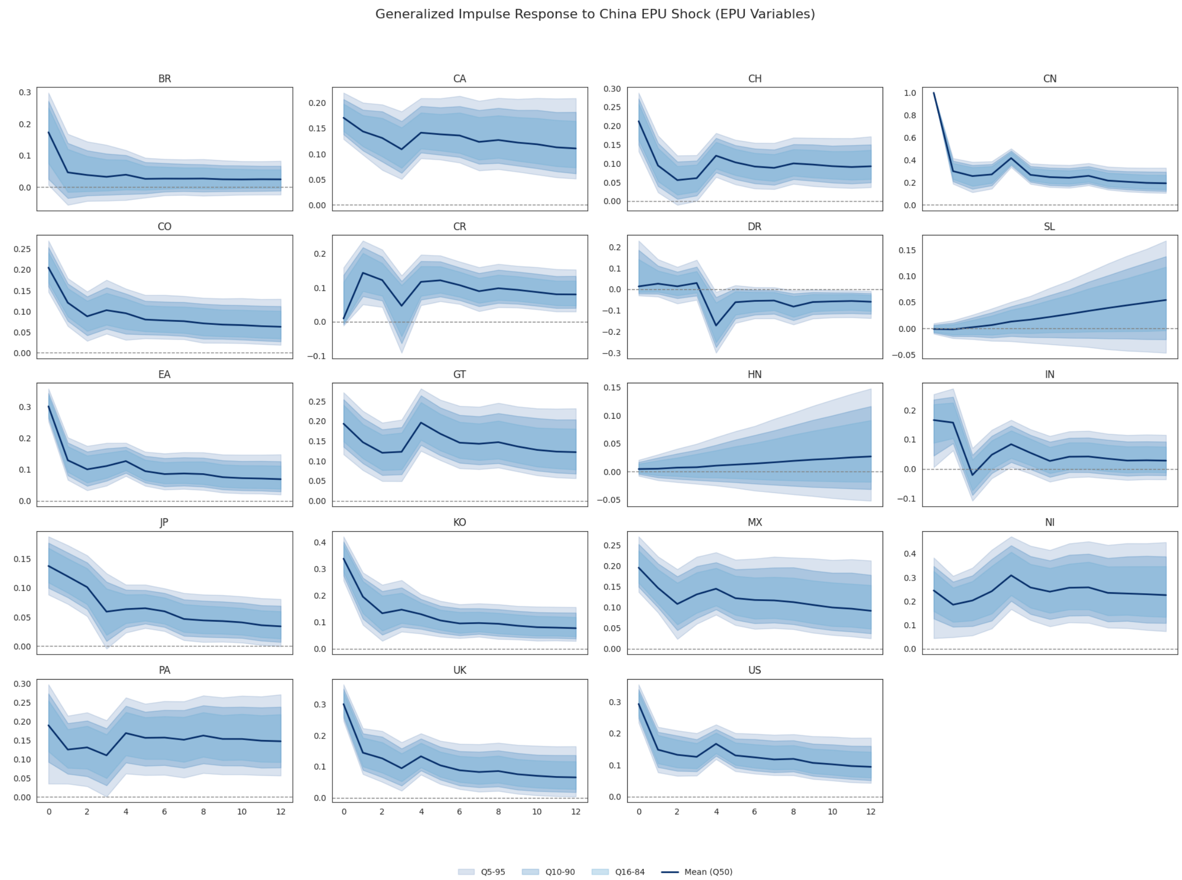
Notes: The heatmap shows Pearson correlation coefficients between monthly EPU indices for Costa Rica, Guatemala, Honduras, El Salvador, Nicaragua, Panama, the Dominican Republic, the United States and China. Each cell is annotated with the correlation coefficient and significance stars: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$.

Figure A3: Time-Varying Pairwise EPU Correlations Using a Rolling Window



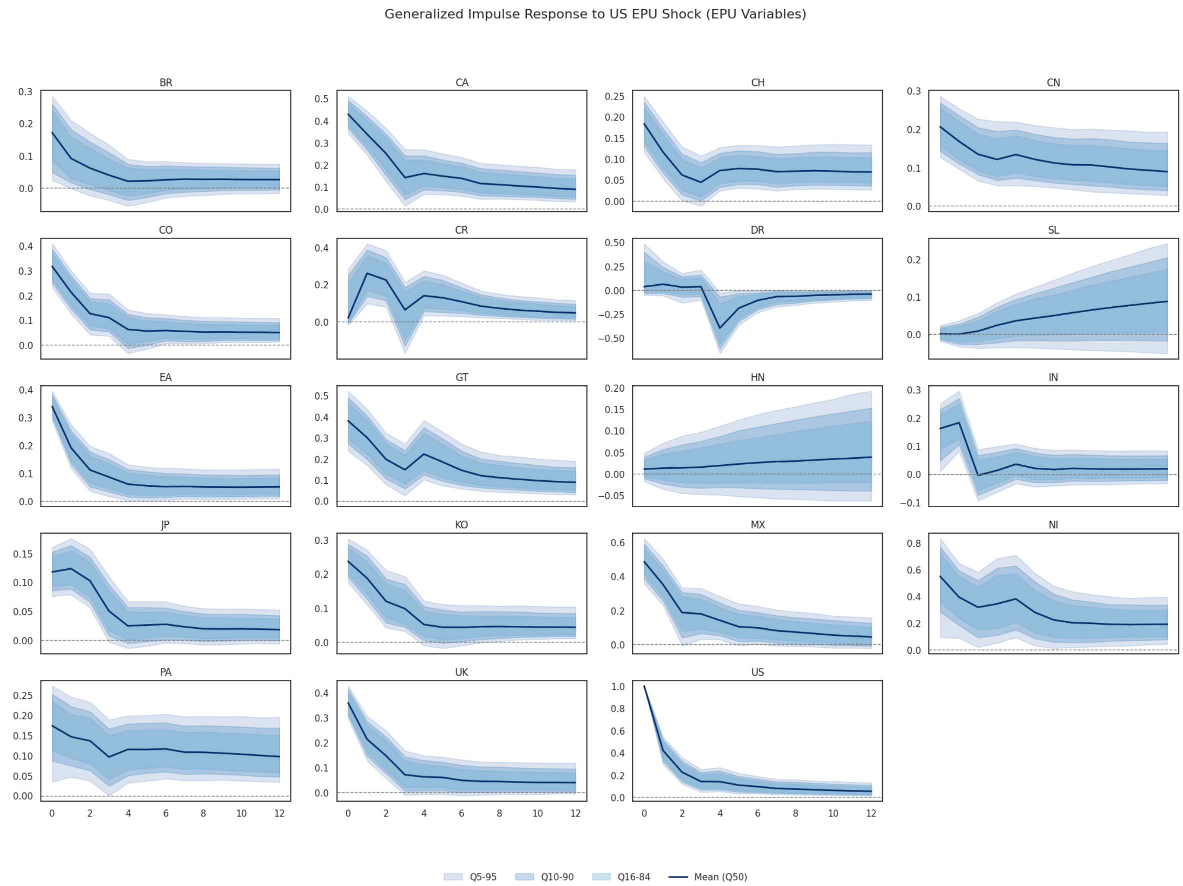
Notes: This figure presents the evolution of bilateral correlations between Economic Policy Uncertainty (EPU) indices across the sample countries using a rolling estimation window.

Figure A4: GIRFs of country-specific EPU indices in response to a one-standard-deviation shock in China's EPU



Notes: Shaded areas denote 90% posterior credible intervals. Each panel shows the impulse response of the labeled country's EPU index.

Figure A5: GIRFs of country-specific EPU indices in response to a one-standard-deviation shock in US EPU



Notes: Shaded areas denote 90% posterior credible intervals.

8.2 Additional Robustness Check

Table A6: Spillover matrix (Diebold-Yilmaz methodology) from the BGVAR model based on the GFEVD 12 months ahead for bilateral EPU shocks for the period January 2003-december 2019 (Excluding Covid-19 pandemics)

Country	BR	CA	CH	CN	CO	CR	DR	EA	GT	HN	IN	JP	KO	MX	NI	PA	SL	UK	US	From Others
BR	5.0156	0.0077	0.0008	0.1079	0.0002	0.0000	0.0002	0.0303	0.0001	0.0000	0.0032	0.0067	0.0054	0.0196	0.0000	0.0000	0.0001	0.0124	0.0529	0.248
CA	0.0274	3.1232	0.0019	0.5889	0.0009	0.0003	0.0010	0.1947	0.0012	0.0007	0.0211	0.0434	0.0415	0.2560	0.0002	0.0001	0.0011	0.1205	0.8391	2.140
CH	0.0539	0.0269	4.2489	0.4882	0.0011	0.0002	0.0003	0.0968	0.0006	0.0002	0.0118	0.0201	0.0269	0.0691	0.0001	0.0000	0.0004	0.0460	0.1715	1.014
CN	0.0277	0.0402	0.0022	4.5558	0.0005	0.0001	0.0004	0.1517	0.0005	0.0003	0.0202	0.0446	0.0531	0.0947	0.0001	0.0001	0.0005	0.0810	0.1895	0.707
CO	0.0466	0.0555	0.0042	0.4697	3.8007	0.0007	0.0029	0.1521	0.0030	0.0010	0.0215	0.0268	0.0288	0.1737	0.0004	0.0004	0.0013	0.0730	0.4009	1.462
CR	0.0089	0.0226	0.0006	**0.1630**	0.0006	4.6740	0.0012	0.0590	0.0132	0.0039	0.0048	0.0101	0.0095	0.0756	0.0108	0.0013	0.0053	0.0307	**0.1681**	**0.589**
DR	0.0021	0.0051	0.0001	**0.0264**	0.0003	0.0002	5.1489	0.0100	0.0003	0.0001	0.0011	0.0021	0.0016	0.0136	0.0000	0.0000	0.0001	0.0034	**0.0477**	**0.114**
EA	0.0545	0.0932	0.0029	1.0801	0.0013	0.0004	0.0011	2.6417	0.0013	0.0007	0.0430	0.0785	0.0677	0.2028	0.0002	0.0001	0.0010	0.4351	0.5575	2.621
GT	0.0021	0.0076	0.0002	**0.0459**	0.0002	0.0013	0.0003	0.0138	5.0475	0.0111	0.0016	0.0059	0.0036	0.0296	0.0036	0.0002	0.0290	0.0062	**0.0533**	**0.216**
HN	0.0002	0.0006	0.0000	**0.0033**	0.0000	0.0000	0.0000	0.0012	0.0008	5.2488	0.0001	0.0003	0.0002	0.0016	0.0001	0.0000	0.0017	0.0007	**0.0034**	**0.014**
IN	0.0125	0.0206	0.0007	0.2995	0.0004	0.0001	0.0003	0.0930	0.0003	0.0002	4.5686	0.0270	0.0223	0.0474	0.0001	0.0000	0.0002	0.0416	0.1284	0.695
JP	0.0119	0.0285	0.0012	0.4530	0.0003	0.0001	0.0002	0.0859	0.0003	0.0002	0.0098	4.3688	0.0407	0.0621	0.0001	0.0000	0.0003	0.0429	0.1569	0.894
KO	0.0248	0.0456	0.0023	1.0060	0.0005	0.0002	0.0004	0.1545	0.0007	0.0003	0.0230	0.0696	3.4891	0.1144	0.0001	0.0001	0.0006	0.0784	0.2525	1.774
MX	0.0199	0.0807	0.0014	0.3740	0.0009	0.0003	0.0008	0.1225	0.0016	0.0006	0.0136	0.0268	0.0277	3.9667	0.0003	0.0001	0.0011	0.0655	0.5586	1.296
NI	0.0026	0.0097	0.0002	**0.0449**	0.0001	0.0051	0.0004	0.0142	0.0236	0.0052	0.0015	0.0046	0.0034	0.0498	4.9891	0.0001	0.0197	0.0058	**0.0829**	**0.274**
PA	0.0056	0.0086	0.0004	**0.1570**	0.0033	0.0010	0.0004	0.0278	0.0048	0.0007	0.0029	0.0325	0.0144	0.0252	0.0002	4.9007	0.0007	0.0114	**0.0657**	**0.362**
SL	0.0002	0.0003	0.0000	**0.0020**	0.0000	0.0000	0.0000	0.0007	0.0014	0.0005	0.0001	0.0003	0.0001	0.0010	0.0003	0.0000	5.2540	0.0004	**0.0019**	**0.009**
UK	0.0263	0.0631	0.0015	0.5957	0.0007	0.0002	0.0006	0.6823	0.0007	0.0004	0.0250	0.0475	0.0372	0.1136	0.0001	0.0001	0.0005	3.3157	0.3520	1.947
US	0.0387	0.2483	0.0027	0.8847	0.0018	0.0008	0.0026	0.2897	0.0028	0.0012	0.0305	0.0843	0.0643	0.5360	0.0005	0.0002	0.0019	0.1403	2.9319	2.331
Contribution TO others	0.366	0.765	0.023	**6.790**	0.013	0.011	0.013	2.180	0.057	0.027	0.235	0.531	0.448	1.886	0.017	0.003	0.065	1.195	**4.083**	**18.710**
Contribution including own	5.381	3.888	4.272	11.346	3.814	4.685	5.162	4.822	5.105	5.276	4.803	4.900	3.938	5.853	5.006	4.903	5.319	4.511	7.015	100

Notes: The rows represent the source of shocks, while the columns capture the share of forecast error variance in each country explained by shocks originating in other countries. Diagonal elements indicate own-country contributions.

Table A7: Spillover matrix (Diebold-Yilmaz methodology) from the BGVAR model based on the GFEVD 12 months ahead for bilateral EPU shocks for the period January 2003-december 2023 (Including only 12 Countries - CAPRD and main trading partners)

Country	CN	CR	DR	EA	GT	HN	MX	NI	PA	SL	UK	US	From Others
CN	6.9438	0.0004	0.0007	0.4472	0.0008	0.0017	0.2408	0.0002	0.0001	0.0014	0.1703	0.5259	1.390
CR	**0.2210**	7.4664	0.0012	0.1183	0.0117	0.0133	0.1299	0.0110	0.0011	0.0100	0.0526	**0.2968**	**0.867**
DR	**0.0709**	0.0005	7.9976	0.0361	0.0008	0.0004	0.0511	0.0001	0.0000	0.0003	0.0107	**0.1648**	**0.336**
EA	1.4775	0.0007	0.0014	4.7502	0.0014	0.0024	0.3526	0.0003	0.0001	0.0018	0.7296	1.0153	3.583
GT	**0.1657**	0.0041	0.0008	0.0753	7.5258	0.0780	0.1145	0.0094	0.0004	0.1038	0.0291	**0.2264**	**0.808**
HN	**0.0015**	0.0000	0.0000	0.0009	0.0003	8.3255	0.0011	0.0000	0.0000	0.0008	0.0003	**0.0028**	**0.008**
MX	0.5028	0.0006	0.0010	0.2652	0.0017	0.0025	6.5230	0.0004	0.0001	0.0022	0.1036	0.9304	1.810
NI	**0.1279**	0.0068	0.0004	0.0599	0.0203	0.0330	0.1076	7.7286	0.0001	0.0600	0.0241	**0.1647**	**0.605**
PA	**0.2780**	0.0016	0.0004	0.0820	0.0049	0.0047	0.0605	0.0003	7.7315	0.0025	0.0306	**0.1362**	**0.602**
SL	**0.0026**	0.0001	0.0000	0.0014	0.0017	0.0016	0.0022	0.0006	0.0000	8.3173	0.0005	**0.0053**	**0.016**
UK	0.8502	0.0004	0.0008	1.3000	0.0008	0.0014	0.2059	0.0002	0.0001	0.0010	5.3476	0.6250	2.986
US	1.3713	0.0015	0.0032	0.6863	0.0035	0.0055	1.0234	0.0008	0.0002	0.0047	0.2747	4.9584	3.375
Contribution TO others	**5.069**	0.017	0.010	3.072	0.048	0.144	2.289	0.023	0.002	0.188	1.426	**4.094**	**16.384**
Contribution including own	12.013	7.483	8.008	7.823	7.574	8.470	8.813	7.752	7.734	8.506	6.774	9.052	100

Notes: The rows represent the source of shocks, while the columns capture the share of forecast error variance in each country explained by shocks originating in other countries. Diagonal elements indicate own-country contributions.