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Quantifying the spillover effects of U.S. economic policy uncertainty on emerging market economies using GMM-PVAR model

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Abstract

This paper quantifies the spillover effects of economic policy uncertainty (EPU) in the United States on emerging market economies (EMEs). Using a generalized method of moments (GMM) estimation of a panel vector autoregression (PVAR) model on a dataset of 39 EMEs from 2005 to 2019, we find that increased U.S. EPU significantly raises the consumer price index (CPI) and negatively impacts the real GDP of these economies. Additionally, heightened U.S. EPU leads to a depreciation of emerging market currencies and a reduction in short-term interest rates. We employ a news-based EPU index developed by Baker et al. (2016) and conduct robustness checks using forward orthogonal transformation, an alternative EPU index, and by addressing the potential endogeneity of the oil price uncertainty (OPU) index. Our findings highlight the adverse effects of U.S. economic policy uncertainty on key macroeconomic variables in emerging markets, underscoring the importance of stable economic policies and robust institutions to mitigate these impacts.

Keywords: economic policy uncertainty, GMM-PVAR, spillover effects, emerging markets.
JEL classification: C33, E44, E58, F42, G01.

1. Introduction

Uncertainty is widely recognized for its adverse effects on economic activity. Since the global financial crisis (GFC), global economic uncertainties have significantly risen, impacting both advanced and emerging markets. The adoption of unconventional monetary policies by the U.S. has particularly affected emerging markets, which are already characterized by inherent instabilities.

Economic literature identifies uncertainty as a factor that exacerbates economic contractions and delays recoveries (Bloom, 2014). High uncertainty can

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lead firms to postpone irreversible investment decisions (Bernanke, 1983; Bloom, 2007; Bloom, 2009) and influence consumer behavior, reducing the consumption of durable goods (Parker and Preston, 2005). Empirical evidence supports the hypothesis that monetary policy may have reduced effects during periods of significant instability, depending on the prevailing uncertainty regime.

The COVID-19 pandemic further elevated uncertainty to unprecedented levels, prompting economic agents to defer crucial decisions. This heightened uncertainty motivates individuals to postpone choices, anticipating more precise information, which diminishes their responsiveness to interest rate fluctuations. These concerns underscore the necessity for policymakers to adopt assertive measures to stabilize the economy during macroeconomic crises.

Emerging markets, often characterized by pre-existing instabilities, are particularly susceptible to external shocks from economic policy uncertainty (EPU) generated in the U.S. These markets face unique challenges in their pursuit of stability, growth, and inflation control, exacerbated by uncertain economic policies in major economies like the U.S. Understanding the nature and magnitude of U.S. EPU spillovers is crucial for effective policy formulation in these regions. A growing body of literature examines the international spillovers of uncertainty (Berger et al., 2017; Carrière-Swallow and Céspedes, 2013; Gabauer and Gupta, 2018; Gupta et al., 2016; Kamber et al., 2016; Trung, 2019; Yin and Han, 2014). Colombo (2013) and Alam (2015) demonstrate that disturbances in U.S. policy and uncertainty exert a more pronounced influence on the euro area and Canada compared to the reverse.

This study employs a generalized method of moments (GMM) extension of the panel vector autoregression (PVAR) model. The GMM-PVAR approach is particularly suitable for understanding dynamic spillover effects, as it effectively addresses endogeneity issues and captures interdependencies among variables over time. By using a news-based proxy of uncertainty (Baker et al., 2016), this research provides new insights into the transmission mechanisms of U.S. EPU and its impact on emerging markets. The robustness of the findings is ensured through various checks, including forward orthogonal difference transformation, alternative measures of U.S. EPU, and addressing the potential endogeneity of the oil price uncertainty (OPU) index by treating both U.S. EPU and OPU as predetermined variables.

The paper is structured as follows: Section 2 reviews relevant literature on EPU and its spillover effects. Section 3 describes the data and methodology. Section 4 presents the GMM-PVAR analysis results, and Section 5 discusses the robustness of these findings. Finally, Section 6 concludes the paper.

2. Literature review

Economic uncertainty has long been recognized as a significant factor influencing economic activity, prompting economic agents to postpone decisions until more accurate information becomes available. Research by Bernanke (1983), Dixit and Pindyck (1994), and Bloom (2014) emphasizes that this cautious behavior reduces responsiveness to interest rate fluctuations. Empirical studies support these theoretical claims, with Bloom (2009) employing a vector autoregression (VAR) model to identify uncertainty shocks. His findings indicate that volatility shocks cause a short-term decline in industrial production of approximately 1%, followed by a prolonged recovery phase. Various studies using diverse proxies for uncertainty, including news-based indices, corroborate these results, highlighting the detrimental effects of economic uncertainty on both general economic performance and asset values (Baker et al., 2016; Bachmann et al., 2013; Caggiano et al., 2017).

Focusing on the United States, several studies demonstrate that elevated EPU dampens investment, output, and employment (Baker et al., 2016; Bachmann et al., 2013). Caggiano et al. (2017) utilize a nonlinear Interacted VAR (IVAR) model to show that the contractionary effects of uncertainty are amplified when monetary policy is constrained by the zero lower bound. Further, Aastveit et al. (2013) and Pellegrino (2021) illustrate that monetary policy shocks have diminished effects during periods of high uncertainty. These findings underscore the significant impact of uncertainty on macroeconomic variables in the U.S. context.

In the euro area and Canada, research by Colombo (2013) and Alam (2015) indicates that disturbances in U.S. policy and uncertainty exert a more pronounced influence compared to the reverse. This highlights the significant cross-border impacts of U.S. EPU, reflecting the interconnectedness of global economies. These studies emphasize the need to understand how uncertainties in one major economy can spill over and affect others, particularly those closely tied through trade and financial links.

The literature identifies several channels through which uncertainty affects economic activity. The “wait-and-see” effect suggests that under high uncertainty, firms and households delay investment and consumption decisions, thereby reducing output (Bernanke, 1983; Bloom, 2009). Additionally, elevated uncertainty can lead households to increase precautionary savings, temporarily reducing consumption but potentially spurring future investments and long-term economic growth (Bloom, 2014). Another critical channel is the “risk premium,” where elevated uncertainty raises borrowing costs due to increased risk perception, especially impacting financially constrained economies (Arellano et al., 2012; Christiano et al., 2014). These effects are particularly pronounced in developing and emerging economies, which often face greater financial constraints.

Research on international spillovers of uncertainty has predominantly focused on individual countries or small groups of economies. Carrière-Swallow and Céspedes (2013) and Colombo (2013) find that U.S. uncertainty shocks negatively impact investment and consumption in both developed and emerging markets. Moreover, uncertainty can affect capital flows, with some studies suggesting a reduction in flows to emerging markets (Gauvin et al., 2014), while others indicate that it may spur capital flows into these economies (Gourio et al., 2015). This duality highlights the complexity of these interactions and the need for a more nuanced understanding.

The response to external shocks is significantly influenced by trade and financial openness, as well as the quality of institutions. Trade openness can increase an economy’s vulnerability to external shocks due to its reliance on exports, but it can also promote risk diversification (Calderón and Schmidt-Hebbel, 2008; Georgiadis, 2016; Giovanni and Levchenko, 2009). Similarly, financial openness can amplify the adverse effects of external shocks by allowing rapid transmission of financial disturbances, although it may also improve risk-sharing possibilities (Mishkin, 2006). Institutional quality, including governance and regulatory frameworks, plays a crucial role in shaping how economies respond to external shocks (Acemoglu et al., 2003).

Despite the extensive research on the impacts of EPU, most studies focus on developed economies or small groups of countries. Comprehensive studies examining the spillover effects of U.S. EPU on a large panel of emerging markets are limited. Furthermore, previous research often fails to adequately address the dynamic interactions and endogeneity issues inherent in such analyses. This study addresses these gaps by employing a robust GMM-based PVAR model, providing a more comprehensive understanding of the spillover effects across a diverse set of emerging economies.

3. Data and methodology

3.1. Data

This study uses a comprehensive panel dataset comprising 39 emerging market economies over the period from 2005 to 2019 (a list of countries incorporated in the model is provided in Appendix A). The chosen timeframe captures the effects of EPU during significant global economic events, including the GFC. The key economic indicators included in our analysis are real gross domestic product (GDP), consumer price index (CPI), short-term interest rates, and nominal effective exchange rate (NEER). To capture the impact of uncertainties, we incorporate the U.S. EPU index and the oil price uncertainty (OPU) index. The interest rates are expressed as percentages, while other variables are presented in their natural logarithmic form to ensure consistency in variance and a normalized distribution. The economic data is sourced from the International Financial Statistics of the International Monetary Fund, and the uncertainty indices are retrieved from economicpolicyuncertainty.com.

The U.S. EPU index, developed by Baker et al. (2016), is based on a daily count of newspaper articles from the NewsBank Access World News service that mention terms related to the economy, uncertainty, and policy actions. This index captures a wide array of publications, ranging from national to regional newspapers. To account for the growing number of newspapers over time — from 18 in 1985 to more than 1800 by 2008 — a normalization procedure is applied. This standardizes the daily counts of EPU-related articles against the total number of articles published, ensuring the index reflects relative changes in uncertainty rather than absolute increases in news volume. This news-based measure is preferred for its broad reflection of public perception, as newspapers serve as a mirror to the educated populace involved in business decision-making, offering a comprehensive view of economic uncertainty.

The OPU index, incorporated in our analysis, follows the methodology outlined by Baker et al. (2016) and operationalized by Abiad and Qureshi (2023). This monthly index spans from January 1969 to December 2019 and is constructed by analyzing English-language news articles from an international selection of newspapers. The selection process focuses on articles that mention oil-related terms in proximity to expressions of price and uncertainty. Raw counts of such articles are standardized against the total number of articles for the respective newspapers and months, ensuring uniform deviation across the index's timespan. The normalized OPU index averages the figures to a baseline mean of 100 for the years 1969 to 2019, providing a consistent measure of OPU over time.

3.2. Econometric methodology

3.2.1. Preliminary analysis

Before estimating our model, we conduct stationarity tests to ensure that our panel data does not contain unit roots, which could lead to spurious regression results. Specifically, we use the Augmented Dickey–Fuller (ADF) Fisher test and the Im, Pesaran, and Shin (IPS) test, incorporating trends to account for deterministic components in the data. The ADF Fisher test combines individual ADF tests applied to each cross-section unit, aggregating the *p*-values from these individual tests into a single test statistic. This approach allows us to assess the overall stationarity of the panel dataset. The IPS test allows for heterogeneity in the autoregressive root across cross-sections. It provides a Z-t-tilde-bar statistic that adjusts for cross-sectional dependence and aggregates the unit root tests of individual time series. Both tests help us confirm that our data series are stationary, ensuring the validity of our subsequent econometric analysis.

3.2.2. GMM estimation of PVAR model

We employ a PVAR model integrated with the GMM approach to analyze the dynamic interactions among multiple endogenous variables while addressing potential endogeneity issues. The PVAR model, extending the vector autoregressive panel model proposed by Holtz-Eakin et al. (1988) and further developed by Sigmund and Ferstl (2021), allows for a system of equations treating all variables as endogenous. The model is specified as follows:

$$y_{i,t} = \mu_i + \sum_{l=1}^{p} A_l y_{i,t-1} + Bx_{i,t} + Cs_{i,t} + \epsilon_{i,t}, \quad (1)$$

where $y_{i,t}$ represents the $m \times 1$ vector of endogenous variables for the i^{th} cross-sectional unit at time t, with lagged endogenous variables $y_{i,t-1}$, a $k \times 1$ vector of predetermined variables $x_{i,t}$, and an $n \times 1$ vector of strictly exogenous variables $s_{i,t}$; $\epsilon_{i,t}$ is assumed to be independently and identically distributed for all i and t.

To estimate this model, we utilize the first difference GMM estimator, which is particularly suitable for handling the potential endogeneity of the regressors and the dynamic nature of the panel data. The first difference GMM estimator, as proposed by Arellano and Bond (1991), employs lags of endogenous variables as instruments and extends this framework to incorporate additional lags, predetermined, and strictly exogenous variables. The first difference transformation is applied to eliminate fixed effects, resulting in the following transformed model:

$$\Delta^* y_{i,t} = \sum_{l=2}^{p} A_l \Delta^* y_{i,t-1} + B\Delta^* x_{i,t} + C\Delta^* s_{i,t} + \Delta^* \epsilon_{i,t}, \quad (2)$$

where Δ^* signifies the first difference or forward orthogonal transformation, enabling the utilization of lagged levels of endogenous variables as instruments for GMM estimation. This transformation helps mitigate any bias arising from time-invariant unobserved heterogeneity. The first difference transformation subtracts the value of a variable at time $t-1$ from its value at time t, effectively removing time-invariant individual effects and mitigating any bias arising from unobserved heterogeneity.

Alternatively, the forward orthogonal deviation transformation can be used, which is defined as:

$$\Delta^* y_{i,t} = y_{i,t} - \frac{1}{T-t+1}\sum\nolimits_{s=t+1}^{T} y_{i,s}. \quad (3)$$

This transformation subtracts the average of all future observations of a variable from its current value. Unlike the first difference transformation, the forward orthogonal transformation preserves more information by minimizing data loss due to differencing and can be particularly advantageous when dealing with unbalanced panels. Both transformations serve to eliminate fixed effects but differ in their approach to handling the data.

In our GMM framework, we use lagged values of the endogenous variables and strictly exogenous variables as instruments. These instruments help address the endogeneity problem by providing valid instruments that are correlated with the endogenous regressors but uncorrelated with the error term. Our model includes the natural logarithms of U.S. EPU, GDP, CPI, NEER, and short-term interest rates in percentage form as endogenous variables. The natural logarithm of OPU is treated as a strictly exogenous variable.

Including U.S. EPU in the vector of endogenous variables allows us to capture the dynamic interactions and feedback mechanisms between EPU and the macroeconomic variables in emerging markets. This is particularly important for generating impulse response functions (IRFs), which trace the effects of a one-time shock to one of the endogenous variables on the future values of all endogenous variables in the model. By treating U.S. EPU as endogenous, we can accurately assess how shocks to EPU propagate through the system and affect GDP, CPI, NEER, and interest rates in emerging markets over time. The rationale for treating OPU as a strictly exogenous variable is based on the assumption that while OPU can influence the macroeconomic environment, it is not contemporaneously affected by the economic conditions in the emerging markets within the model's timeframe. This assumption simplifies the model and allows us to isolate the effects of external oil price shocks on the endogenous variables.

Given the specific characteristics of our dataset, with 39 cross-sectional units ($N = 39$) and 15 time periods ($T = 15$), we opted for the one-step GMM estimator. This choice was made because the two-step GMM estimator did not satisfy the stability conditions for our data, leading to unreliable estimates. The one-step estimator uses a consistent initial weighting matrix to estimate the PVAR model coefficients, ensuring robustness and compliance with the necessary stability conditions. The two-step GMM estimator, while theoretically more efficient, produced unstable results, which could lead to biased or inconsistent estimates. The one-step GMM estimator, by contrast, offers better finite sample properties and robustness against overfitting, providing more reliable and consistent results. Given these considerations, the one-step GMM estimator is the more appropriate choice for our analysis.

To ensure the validity and robustness of our model, we perform several specification tests. The Hansen over-identification test is used to validate the instruments employed in the GMM estimation. This test assesses whether the instruments are valid by checking if they are uncorrelated with the error terms and correctly specified. Additionally, we use the model selection criteria proposed by Andrews and Lu (2001), which include the Bayesian information criterion (BIC) and the Hannan–Quinn information criterion (HQIC), to choose between the models. These criteria help us determine the optimal lag length and model specification, ensuring that our model is well-specified and reliable.

3.2.3. Impulse response functions

For structural analysis, we estimate orthogonal and generalized impulse response functions (GIRFs) to analyze the dynamic effects of shocks to the endogenous variables. IRFs are used to assess how a shock to one variable propagates through the system, affecting other variables over time. In the context of the PVAR model, IRFs explain the dynamic responses of all endogenous variables to unit shocks in any variable within the system, offering insights into the transient and long-term impacts of such perturbations. The IRF is mathematically stated as:

$$IRF(k, r) = \frac{\partial y_{i,t+k}}{\partial (t)_r} = A^k e_r, \tag{4}$$

where k represents the time period after the shock; r the component of the shock, and e_r is a vector with 1 in the r^{th} column and 0 elsewhere. This formulation allows for the analysis of how shocks to the r^{th} component of $\epsilon_{i,t}$ propagate through the system over time.

Standard IRFs typically assume orthogonal shocks, applying the Cholesky decomposition to the covariance matrix of reduced-form errors. Consequently, the IRFs are influenced by the variable ordering, which is often guided by economic theory. However, there is no definitive empirical method for identifying uncertainty shocks in the existing literature (Ludvigson, 2016). Therefore, we utilize GIRFs as proposed by Pesaran and Shin (1998). GIRFs generate shock response profiles that are independent of the variable ordering. By isolating a single element of $\epsilon_{i,t}$ and considering the impacts of other shocks based on historical error distributions, GIRFs offer an alternative approach that remains unaffected by the variable ordering.

We employ bootstrap methods, as suggested by Lütkepohl (2005), to estimate confidence intervals for these impulse responses. The bootstrap method involves resampling the data with replacement to generate multiple samples, which are then used to estimate the IRFs and their confidence intervals. This approach ensures robustness in our inference by accounting for sampling variability and providing reliable estimates of the dynamic responses to shocks. We generate the bootstrapped confidence bands through 1000 draws to interpret the spillover effects of U.S. EPU shocks.

4. Empirical analysis

4.1. Pre-estimation results

4.1.1. Descriptive statistics

The descriptive statistics for the sampled emerging economies are presented in Table B1 of Appendix B. Descriptive statistics provide an overview of the variables used in the study, helping to understand the empirical data. We report summary statistics, including median, mean, standard deviation, skewness, and kurtosis. These statistics offer insights into the distribution and variability of the data. For instance, the mean and median values indicate the central tendency, while skewness and kurtosis tests help identify any asymmetry and peakedness in the data distribution.

4.1.2. Stationarity tests

To ensure the reliability of our PVAR model, we conducted unit root tests using the IPS test and the ADF Fisher test. The results, shown in Table B2 of Appendix B cover key economic variables at their original levels and their first differences. The ADF test indicates that most variables, except for interest rates, exhibit a unit root at their levels, suggesting they are non-stationary. However, when we consider the first differences, all series become stationary at the 1% significance level. Similarly, the IPS test confirms that GDP and the CPI likely have a unit root at their levels but are stationary at their first differences. Overall, both tests confirm that the series are integrated of order 1, I (1), indicating that differencing the data is necessary to achieve stationarity.

4.1.3. Lag-selection criterion

Determining the optimal lag length is crucial for accurately capturing the dynamics and interdependencies among the endogenous variables in a PVAR model. The choice of lag length affects the model's ability to reflect both contemporaneous and lagged influences. We used several lag-selection criteria based on the moment selection criteria (MMSC): the modified bayesian information criterion (MBIC), the modified Akaike information criterion (MAIC), and the modified Hannan–Quinn information criterion (MQIC). These criteria, developed by Andrews and Lu (2001), extend traditional information criteria to dynamic panel data models. The MBIC emphasizes model simplicity by imposing a heavier penalty for additional parameters. The MAIC balances goodness-of-fit with model complexity, penalizing additional parameters less heavily than the MBIC. The MQIC adapts the Hannan–Quinn criterion for panel data. For our PVAR framework, we used the MBIC to determine the lag length, which indicated a lag order of 1, as shown in Table B3 of Appendix B.

4.1.4. Stability test

For the PVAR model's estimation to be reliable, it must satisfy the stability criterion, ensuring that the system's dynamics do not exhibit explosive behavior over time. This criterion requires that all eigenvalues of the model's companion matrix have moduli less than one. Our stability assessment, presented in Table B4 and illustrated in Fig. B1 of Appendix B, confirms that the absolute values of all eigenvalues are less than one. This finding signifies that the PVAR model meets the stability requirement, with all eigenvalues lying strictly within the unit circle. Consequently, the PVAR system is stationary, ensuring that the IRFs can be reliably interpreted. This result assures that the variables included in the model, as well as the PVAR system as a whole, exhibit stationarity. Therefore, the estimates derived from the GMM-PVAR model are dependable and consistent.

4.2. Evidence from GMM-PVAR estimation

The GMM-PVAR coefficients, estimated using the first difference transformation, are derived by using moment conditions that exploit the time series and cross-sectional dimensions of panel data. This approach helps address endogeneity and serial correlation issues, ensuring consistent and efficient parameter estimation within the PVAR model. These coefficients describe the relationships between the current values of the endogenous variables in the system and their own past values, as well as the past values of other endogenous variables. By using lagged values as instruments, the GMM estimation controls for endogeneity and omitted variable bias. The detailed estimated results are presented in Table C1 of Appendix C.

We now turn to quantify the effects of U.S. EPU on EMEs. Our study focuses on the spillover effects of U.S. EPU on key macroeconomic variables in EMEs, interpreting the estimated coefficients to understand these relationships.

The GMM-PVAR estimates confirm a significant and negative effect of U.S. EPU on the real GDP of EMEs. Specifically, a 1% increase in the previous period's EPU is associated with a 0.0210% decrease in GDP. This finding can be explained by the "wait-and-see" effect channel, as discussed in the literature (Baker et al., 2016; Bloom, 2009; Carrière-Swallow and Céspedes, 2013; Trung, 2019). Higher uncertainty leads to reduced capital investment due to increased risk and a cautious attitude among businesses. Consumers may also delay spending and increase savings, reducing overall demand in the economy.

Additionally, a 1% increase in the previous period's EPU is associated with a 0.0194% increase in the CPI. This rise in the price index can be attributed to the increased cost of imported raw materials, driven by currency depreciation. As the domestic currency loses value, the cost of imports rises, leading to higher prices for goods and services.

Our results also show that a 1% increase in the previous period's EPU is correlated with a 0.0412% decrease in the interest rate. This suggests that policy uncertainty can prompt central banks to lower interest rates as part of an effort to stimulate the economy amidst heightened uncertainty. Central banks might reduce rates to counteract the negative impacts of uncertainty on economic activity. Furthermore, higher uncertainty can lead to a flight to safety among investors, increasing demand for bonds and thus lowering yields.

Lastly, a 1% increase in the previous period's EPU is linked with a 0.0879% depreciation of emerging-market currencies. Increased uncertainty may deter foreign investment, resulting in capital outflows and a subsequent depreciation of the domestic currency. Additionally, lower interest rates can make the currency less attractive to foreign investors, further contributing to its depreciation.

4.3. Generalized impulse response function analysis

We now examine the spillover effects of U.S. EPU shocks on the EMEs. We analyze the responses of EMEs to a one standard error positive shock to U.S. EPU. IRFs are employed to analyze the dynamic effects of a one-time shock to one of the endogenous variables on the current and future values of all endogenous variables within the PVAR system. These IRFs trace the expected values of the variables over time following the shock, providing a temporal dimension that illustrates how shocks dissipate or amplify across the system. Unlike static GMM-PVAR coefficients, IRFs offer insights into the dynamic adjustment paths of the variables. For generating the GIRFs, we bootstrapped the confidence bands with 1000 draws to ensure robust inference.

Fig. 1 illustrates the spillover effects of a U.S. EPU shock on key macroeconomic variables in EMEs. The CPI increases in response to a positive shock in U.S. EPU by one standard deviation. This inflationary pressure can be attributed to the increased cost of imported raw materials, as currency depreciation makes imports more expensive, and to capital outflows from EMEs. As investors seek safety during periods of heightened uncertainty, they tend to withdraw investments from riskier emerging markets, leading to currency depreciation. This phenomenon, known as flight-to-safety, results in outbound capital flows, depreciating emerging-market currencies against the U.S. dollar.

The NEER shows a decline, indicating that the currencies of EMEs depreciate in response to a positive U.S. EPU shock. This depreciation can be linked to the same flight-to-safety behavior where increased risk aversion among investors leads to capital outflows from EMEs to safer assets, typically denominated in U.S. dollars.

Short-term interest rates also decline following a positive U.S. EPU shock. Central banks in EMEs may respond to increased uncertainty by lowering interest rates to stimulate investment and stabilize their economies. Lower interest rates can help offset the negative impact of uncertainty on economic activity by encouraging borrowing and investment.

The response of GDP to a U.S. EPU shock is initially positive, but it subsequently declines. This initial positive impact might reflect short-term stabilizing policies or temporary boosts in confidence. However, as uncertainty persists,

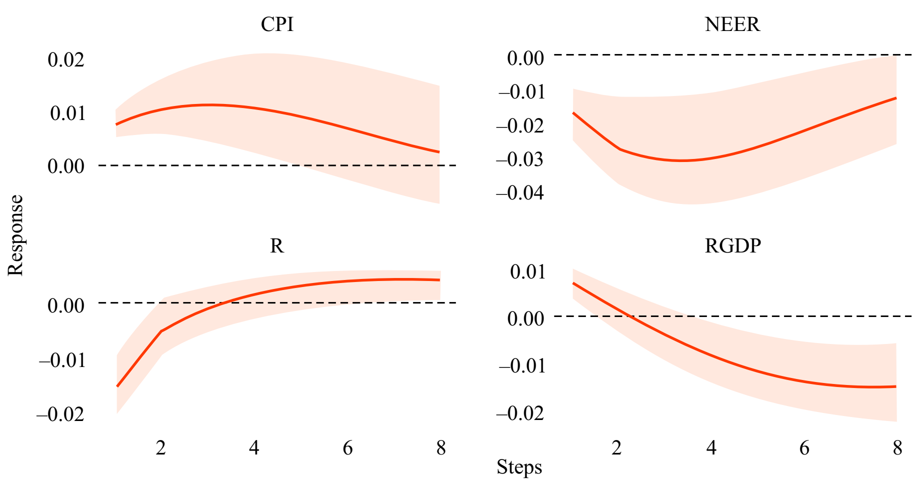

Fig. 1. The spillover effects of U.S. EPU shocks on the emerging market economies.

Note: The median estimates are presented by solid lines and the bootstrapped 95% confidence bands are presented by the shaded areas. The horizontal axis represents the time steps (in years) following the shocks, and the vertical axis represents the responses to the shocks in terms of percentage changes.
Source: Compiled by the author.

the negative effects on investment and consumption dominate, leading to a decline in output. The reduction in GDP over time underlines the adverse long-term effects of heightened U.S. EPU on economic growth in EMEs.

5. Robustness

5.1. Sensitivity to forward orthogonal transformation

In our first robustness check, we employ the forward orthogonal transformation, an alternative to the first difference transformation used in our main analysis. This method preserves the orthogonality of the error terms while accounting for changes in one period affecting future periods. The forward orthogonal transformation minimizes data loss and handles unbalanced panels more effectively compared to the first difference transformation.

In Table D1 of Appendix D, we report the estimates of the GMM-PVAR coefficients using this transformation. Consistent with our previous findings, we observe that U.S. EPU has a significant negative effect on the real GDP of emerging markets. This reaffirms our earlier conclusion that higher EPU in the U.S. leads to lower economic growth in emerging markets. Similarly, the results indicate that U.S. EPU contributes to increased inflation in emerging markets. Additionally, we find a decline in short-term interest rates and a depreciation of domestic currencies against the U.S. dollar. These results validate our primary findings, demonstrating that higher uncertainty in the U.S. has a contractionary effect on emerging markets.

5.2. Sensitivity to the alternative U.S. EPU index

To further assess the robustness of our findings, we examine the impact of U.S. EPU on emerging markets using an alternative version of the U.S. EPU index. While our main analysis utilized the news-based EPU index developed by Baker et al. (2016), this robustness check employs a three-component-based EPU index by the same authors. This index combines information from three distinct sources: news coverage, tax code provisions, and disagreement among economic forecasters, offering a more comprehensive measure of EPU.

We conduct this robustness check following the same methodology as our main model, determining the optimal lag length using the MBIC criterion to ensure comparability. The results of the GMM-PVAR estimation, presented in Table D2 of Appendix D, show that U.S. EPU has a significant negative effect on the output of emerging markets and leads to increased inflation. Furthermore, it negatively affects short-term interest rates and results in the depreciation of domestic emerging-market currencies against the U.S. dollar. These findings are consistent with our main results, highlighting that the contractionary impact of U.S. EPU on emerging markets is robust to different measures of EPU.

5.3. Addressing potential endogeneity of the oil price uncertainty index

To address the potential endogeneity of the oil price uncertainty (OPU) index, we conduct a robustness check by treating both U.S. EPU and OPU as predetermined variables. Predetermined variables are considered weakly exogenous, meaning that they may correlate with past errors but not with contemporaneous ones.

By re-specifying the model in this way, we aim to capture any feedback effects between U.S. EPU and OPU, ensuring consistent and reliable estimates. This approach accounts for the possibility that changes in U.S. EPU influence OPU, which in turn might affect the macroeconomic variables in our study.

The results of these robustness checks confirm that our main findings remain stable and consistent. The impact of U.S. EPU on CPI, GDP, interest rates, and NEER remains robust, even when accounting for potential feedback effects between U.S. EPU and OPU. The stability condition of the model is satisfied, as all eigenvalues lie within the unit circle.

The robustness check results, as presented in Table D3 of Appendix D, demonstrate that the main findings hold true even when treating U.S. EPU and OPU as predetermined variables. Specifically, U.S. EPU continues to have a significant negative effect on GDP and a significant positive effect on CPI, indicating that higher U.S. EPU leads to lower economic growth and higher inflation in emerging markets. The impact on short-term interest rates and NEER also remains significant, with higher U.S. EPU associated with lower interest rates and a depreciation of domestic currencies against the U.S. dollar. These results reaffirm that higher uncertainty in the U.S. has contractionary effects on emerging markets, validating the robustness of our findings.

6. Conclusion

In this paper, we investigated the spillover effects of U.S. EPU on the macroeconomic variables of emerging markets. Utilizing a GMM estimation of the PVAR model, we quantified the impact of U.S. EPU on domestic macroeconomic variables such as GDP, CPI, interest rates, and NEER, while treating the OPU index as a strictly exogenous variable.

Our findings reveal a statistically significant negative impact of U.S. EPU on the GDP of emerging markets, highlighting a "wait-and-see" effect among investors and businesses. This uncertainty leads to delayed decisions on investment and spending, thereby dampening economic growth. Moreover, we observe an inflationary effect, likely due to the increased costs of importing raw materials in uncertain policy environments. Additionally, the results indicate that U.S. EPU leads to a decline in short-term interest rates and a depreciation of emerging market currencies against the U.S. dollar.

To ensure the robustness of our findings, we performed additional analyses using the forward orthogonal transformation and an alternative version of the U.S. EPU index. Furthermore, we addressed potential endogeneity issues by treating both U.S. EPU and OPU as predetermined variables. This approach helps to mitigate the risk of inconsistent estimates. The consistency of results across these robustness checks reinforces the reliability of our main conclusions.

Given the observed decline in GDP due to U.S. EPU and its association with the "wait-and-see" effect, it is crucial for emerging markets to enhance the stability of their economies. This stability is essential for maintaining resilient international capital flows during periods of heightened uncertainty. Emerging markets should invest significantly in improving the quality of their institutions.

Key areas for enhancement include political stability, transparency, macroeconomic policy management, accountability, and regulatory efficiency.

Strengthening these aspects of governance and policy-making can help stabilize international capital flows and mitigate the adverse effects of U.S. EPU shocks on emerging markets. By fostering a stable and transparent economic environment, emerging markets can better withstand the challenges posed by external economic uncertainties and sustain long-term economic growth.

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Appendix A

List of countries in the model.

Albania	Mexico
Algeria	Mongolia
Azerbaijan	Montenegro
Bosnia and Herzegovina	Oman
Brazil	Pakistan
Bulgaria	Paraguay
Chile	Peru
China	Philippines
Colombia	Qatar
Egypt	Romania
Georgia	Russia
Hungary	Samoa
India	Seychelles
Indonesia	South Africa
Jamaica	Sri Lanka
Jordan	Thailand
Kuwait	Trinidad and Tobago
Malaysia	Ukraine
Maldives	Uruguay
Mauritius	

Source: Compiled by the author.

Appendix B

Table B1
Descriptive statistics.

Variable	Mean	Max	Min	St. dev.	Skewness	Kurtosis
GDP	14.273	23.117	7.404	3.502	0.123	2.439
CPI	4.664	5.665	3.936	0.251	0.236	4.376
Interest rate	0.058	0.547	–0.201	0.089	1.596	8.766
Exchange rate	2.895	9.564	–1.314	2.555	0.673	2.936
US EPU	4.808	5.240	4.207	0.306	–0.793	2.335
OPU	4.796	5.495	4.321	0.340	0.378	2.166

Note: The values except interest rates are in their natural logarithmic form.
Source: Author's calculations.

Table B2
Unit root tests.

Variable	Im-Pesaran-Shin				ADF			
	Levels		First differences		Levels		First differences	
	value	*p*-value	value	*p*-value	value	*p*-value	value	*p*-value
GDP	–1.271	0.102	–8.203	0.000	–0.181	0.428	–7.734	0.000
CPI	0.544	0.707	–8.872	0.000	3.493	0.999	–8.983	0.000
Interest rate	–9.136	0.000	–12.491	0.000	–10.090	0.000	–21.443	0.000
Exchange rate	–3.869	0.001	–8.981	0.000	2.263	0.988	–7.447	0.000
US EPU	–3.647	0.001	–9.624	0.000	2.461	0.993	–9.041	0.000
OPU	–11.544	0.000	–12.373	0.000	–14.018	0.000	–17.825	0.000

Source: Author's calculations.

Table B3
Lag selection criteria based on Moment selection criteria (MMSC).

MBIC	–14135.73
MAIC	–4529.081
MQIC	–8712.912

Source: Author's calculations.

Table B4
Eigenvalue stability condition.

	Eigen value	Modulus
(1)	0.94030982 + 0.00000000i	0.94030982
(2)	0.81571710 + 0.1600308i	0.83126665
(3)	0.81571710 – 0.1600308i	0.83126665
(4)	0.74580474 + 0.0000000i	0.74580474
(5)	–0.04475121 + 0.0000000i	0.04475121

Source: Author's calculations.

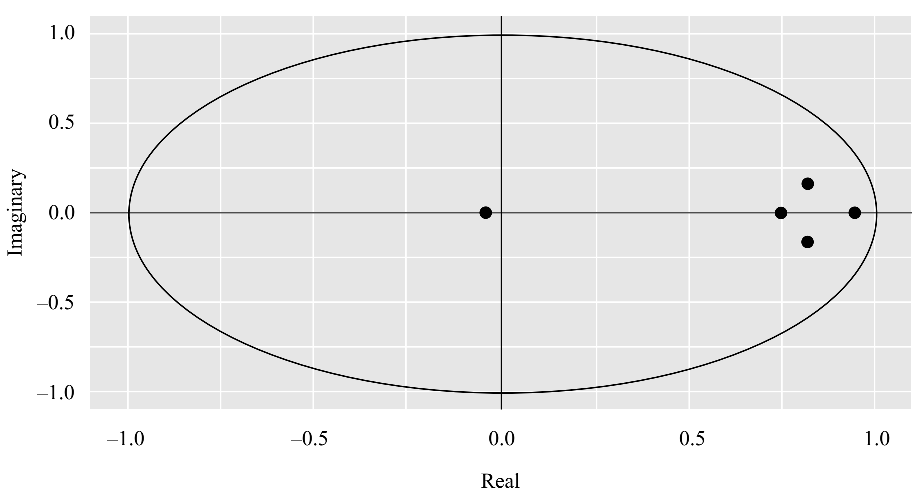

Fig. B1. Unit root stability test.

Source: Compiled by the author.

Appendix C

Table C1
GMM estimation of PVAR with first difference transformation.

	ln*USEPU*	ln*CPI*	ln*GDP*	*R*	ln*ER*
ln*USEPU* (1)	0.8995***	0.0194*	–0.0210***	–0.0412*	–0.0879***
ln*CPI* (1)	–0.4511***	0.8744***	–0.0194	0.2193***	0.3150***
ln*GDP* (1)	0.5854***	0.0554*	0.9242***	–0.0675	0.1073
R (1)	0.2717***	–0.0134	–0.0187	–0.0574	–0.0450
ln*ER* (1)	0.5985***	0.0657***	0.0467**	–0.1682**	0.6322***
ln*OPU*	0.4034***	0.0371***	–0.0088*	–0.0180	0.0098

Note: *** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$.
Source: Author's calculations.

Appendix D

Table D1
GMM estimation of PVAR with forward orthogonal transformation.

	ln*USEPU*	ln*CPI*	ln*GDP*	*R*	ln*ER*
ln*USEPU* (1)	0.8732***	0.0231*	–0.0241***	–0.0349*	–0.0666***
ln*CPI* (1)	–0.3356***	0.8788***	–0.0106	0.1840***	0.2657***
ln*GDP* (1)	0.5213***	0.0350	0.9233***	–0.0403	0.0958
R (1)	0.2591***	–0.0147	–0.0213	–0.0487	–0.0417
ln*ER* (1)	0.4831***	0.0762***	0.0334*	–0.1401**	0.7053***
ln*OPU*	0.3889***	0.0380***	–0.0106*	–0.0141	0.0173

Note: *** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$.
Source: Author's calculations.

Table D2
GMM estimation of PVAR with an alternative measure of US EPU.

	ln*USEPU*	ln*CPI*	ln*GDP*	*R*	ln*ER*
ln*USEPU* (1)	0.9755***	0.0173	–0.0070	–0.0466**	–0.1038***
ln*CPI* (1)	–0.4539***	0.8715***	–0.0346	0.2407***	0.3674***
ln*GDP* (1)	0.4476***	0.0659*	0.9204***	–0.0962*	0.0428
R (1)	–0.0253	–0.0193	–0.0089	–0.0477	–0.0256
ln*ER* (1)	0.5369***	0.0714***	0.0592***	–0.1958**	0.5667***
ln*OPU*	0.4160***	0.0360***	–0.0030	–0.0194*	0.0052

Note: *** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$.
Source: Author's calculations.

Table D3
GMM estimation of PVAR with US EPU and OPU as predetermined variables.

	ln*CPI*	ln*GDP*	*R*	ln*ER*
ln*CPI* (1)	0.8770***	–0.031	0.2052***	0.2720***
ln*GDP* (1)	0.0489*	0.9207***	–0.0655	0.0913
R (1)	–0.0175	–0.011	–0.0445	–0.0126
ln*ER* (1)	0.0703***	0.0577***	–0.1626**	0.6732***
ln*OPU*	0.0276***	0.0001	0.0006	0.0470***
ln*USEPU*	0.0222***	–0.0128*	–0.0356**	–0.0631***

Note: *** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$.
Source: Author's calculations.