Uncertainty shocks in emerging economies: a global to local approach for identification*

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Abstract

The paper investigates the effects of uncertainty shocks in emerging economies (EMEs). I construct novel measures of uncertainty for fifteen small EMEs and to address endogeneity I instrument them with fluctuations in global uncertainty. My results show that uncertainty shocks have substantial contractionary effects on GDP, stock prices and local currencies and the recessionary effect is much stronger in EMEs compared to advanced economies (AEs). I also estimate a negative co-movement between prices and output which triggers a delayed monetary tightening in correspondence to the inflationary peak. Counterfactual scenarios reveal that in the absence of uncertainty shocks, the fall in GDP recorded in EMEs during the 2008-2009 crisis would have been attenuated by around 2%.

JEL Classification: C3, C11, E3

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1 Introduction

There is a large literature analyzing the effects of uncertainty shocks in advanced economies (AEs) which attests the existence of a negative relationship between uncertainty and economic growth. Much less evidence is available for emerging markets (EMEs), with the few existing empirical investigations focusing on the spillover effects of global uncertainty on the economy of these countries (see Carrière-Swallow and Céspedes, 2013, Bhattarai et al., 2019 and Bonciani and Ricci, 2020). However, the spillover approach has one important limitation, it fails to account for the dynamics of domestic uncertainty. This omission is unfortunate since EMEs are particularly exposed to political instabilities and natural disasters, all events that are associated with both heightened domestic uncertainty and recessionary effects (see Baker et al., 2022). On these grounds, the main objective of this paper is to extend our understanding of the role of uncertainty shocks in EMEs, by looking at shocks that move domestic uncertainty, and are allowed to be driven by both local and global factors.

My paper contributes to the literature on two fronts. First, I construct measures of uncertainty for fifteen small EMEs and I provide new insights on the causal link between *country-level* uncertainty and the macroeconomy in emerging markets. Second, to address potential endogeneity between uncertainty and economic growth, I extend to a panel VAR framework the identification approach proposed by Nakamura and Steinsson (2014), Bonfiglioli et al. (2022) and Alfaro et al. (2021) in the context of a classical panel model analysis. Thus, I instrument local uncertainty shocks with fluctuations in global uncertainty. This is different from analyzing the spillover effects of global uncertainty. Specifically, my empirical model includes the domestic uncertainty index as an endogenous variable, while global uncertainty is used to detect exogenous fluctuations in this index. The uncertainty shocks obtained this way capture changes in the *country-level* uncertainty that are exogenous to the local economic conditions. These changes can be driven either by domestic or by foreign factors, hence they reflect a combination of country-specific and global events. In fact, in Section 4.1.2, I show that the uncertainty shocks series of Chile captures both global events such as the GFC, as well as country-specific events, such as the 2010 and 2015 earthquakes and the elections in 2000. On the other side, spillover studies focus on the effects of global uncertainty per se, and do not account for the dynamics of domestic uncertainty neither for the locally driven shocks, which can be of high relevance in emerging countries. In this sense, I view my analysis as complementary to the spillover literature.

Results show that uncertainty shocks have substantial effects on emerging markets. A one-standard-deviation uncertainty shock leads to a persistent and substantial decline in the level of real GDP (-1%). The shock sharply decreases the stock prices with a peak effect of 7% and leads to a depreciation of the local currency by 0.6%. Heightened uncertainty generates a negative co-movement between GDP and CPI, with an estimated increase in the price level of around 0.3%. The central bank reaction is neutral right after the shock, but it tightens in correspondence to the inflationary peak. A counterfactual analysis shows that in the absence of uncertainty shocks, the recessionary effects experienced by EMEs during the GFC and the European debt crisis would have been substantially lower. Finally, if endogeneity is left untreated my results indicate that the effects of uncertainty shocks in EMEs can be largely underestimated by models that take the exogeneity of uncertainty for granted (e.g. VAR models identified with a recursive scheme).

My findings have important implications. I show that in EMEs uncertainty shocks have powerful recessionary effects to the extent that around 2% of their GDP fall recorded during the GFC could be attributed to these shocks. The magnitude of the recessionary effect is more than double compared to what has been reported for advanced economies (see Redl, 2020). The reaction of financial variables suggests that uncertainty shocks trigger a "flight to quality" effect which materializes in the depreciation of the local currency combined with a severe drop in asset prices. But importantly, if most of the previous empirical studies favor a demand-side explanation for uncertainty disturbances, my estimates show that in EMEs these shocks trigger a negative co-movement in prices and output, in line with supply-side disturbances. This finding is consistent with theoretical frameworks featuring monopolistic competition in labor and goods markets, which gives rise to time-varying markups (see Fernández-Villaverde et al., 2015, Born and Pfeifer, 2014 and Born and Pfeifer, 2021) and is appealing for two main reasons. First, it offers a plausible explanation to the stagflation periods often observed in emerging countries. Second, it suggests that uncertainty shocks in these countries cannot be easily mitigated by the central banker intervention due to the negative trade-off between prices and output.

To carry out this investigation, there are three main challenges that need to be addressed. The most important challenge is related to the identification of uncertainty shocks. While uncertainty may affect the economy (see Bloom, 2009, Fernández-Villaverde et al., 2011, Leduc and Liu, 2016, Basu and Bundick, 2017), the reverse is also true (see Van Nieuwerburgh and Veldkamp, 2006, Bachmann et al., 2013, and Gourio, 2013). Thus, it is hard to interpret any correlation between the two. This requires moving away from the recursive identification scheme, which is by construction ill-suited to deal with reverse causality. To identify the effect of economic uncertainty on the business cycle in EMEs, I develop an Instrumental Variables (IV) strategy that builds on two premises. The first is the well-known result that there is significant commonality between country and global uncertainty measures, as reported by Mumtaz and Theodoridis (2015), Mumtaz and Musso (2019), Cesa-Bianchi et al. (2020) and Carriero et al. (2020). The second premise is that shocks occurring in small EMEs are unlikely to affect global uncertainty. Based on this, I use global uncertainty shocks as an IV to disentangle changes in the country uncertainty index that are exogenous to the domestic economic conditions.

This is not the first paper to use global variables as instruments to identify local shocks. Nakamura and Steinsson (2014) exploit variation in military buildups at the US country level as an instrument for regional government spending shocks. Alfaro et al. (2021) exploit differential exposure of US firms to aggregate volatility to detect exogenous changes in firm-level volatility. Even closer to my identification approach, Bonfiglioli et al. (2022) use global volatility as an instrument for country-level volatility shocks and examine the effect of uncertainty shocks on structural reforms. Importantly, as in these studies, the focus of my analysis is not on the impact of global uncertainty per se, but I exploit its fluctuations as a useful source of exogenous variation in national uncertainty, a variation that proves key to my identification. [1]

[1] My results identify a classic local average treatment (LATE) effect in that the identification is driven by the exposure of national uncertainty to variation in the global uncertainty instrument (see Angrist and Imbens, 1994 for details).

The second challenge faced in this analysis is the absence of an objective measure of uncertainty for EMEs which makes difficult the empirical analysis of the adverse effects of uncertainty in these countries. Thus, I construct global and country-specific uncertainty measures for fifteen EMEs using the widely-employed methodology of Jurado et al. (2015) (JLN). The uncertainty measure proposed by JLN relies on the unforecastable components of a broad set of economic variables. Thus, it captures whether the economy as a whole has become more or less predictable, i.e., less or more uncertain, while controlling for a large information set.

Finally, the limited data availability for EMEs can make inference hard in standard VAR models. To address this, I estimate an extended version of the panel VAR model proposed by Jarociński (2010) that accommodates for external instruments identification, known as Proxy VAR, as in Caldara and Herbst (2019) and Rogers et al. (2018).[2] This empirical framework is particularly suited for the current application since it makes efficient use of the limited data, accommodates unbalanced panel data, and allows for instrumental variable identification.

The credibility of my identification strategy depends on the validity of the instrument which requires that: i) the IV is relevant, meaning that fluctuations in global uncertainty are correlated with the domestic uncertainty shock; and ii) the IV is exogenous, meaning that the instrument is uncorrelated with any other shock in the model. While the relevance condition is testable, the exogeneity condition is based on the identifying assumptions. The first identifying assumption builds on a small open economy argument and it states that shocks in small EMEs are unlikely to cause global uncertainty. To preclude the direction of causality that could run from EMEs to the instrument, big emerging economies and major oil exporters are deliberately excluded from the sample. The second assumption is related to the exclusion restriction condition. Such a condition requires that *conditional on the observables*, the only channel through which global uncertainty affects domestic economies is via its impact on the country uncertainty index. The exclusion restriction fails if, for example, the instrument correlates with other contemporaneous variables which also affect the EMEs, say global demand and global supply, and such variables are not

[2]The term Proxy VAR was introduced by Mertens and Ravn (2013) and describes a VAR model identified with instruments.

controlled for. I control for these potential global channels by including in the country VAR global variables that enter the model contemporaneously.

To address potential remaining threats to the identification I conduct an extensive sensitivity analysis. Importantly, I show that my results hold if I use a range of alternative instruments, which include the uncertainty shock series from i) the disaster events study of Baker et al. (2022); ii) the monthly VAR model proposed by JLN, identified with timing restrictions; and iii) the monthly VAR model of JLN, identified with the penalty function approach of Caldara et al. (2016). Moreover, my results are robust if I further control for time fixed effects, lags of the instrument and lags of the global variables or if I add squared values of the global variables. Finally, in a counterfactual analysis, I study how potential violations of the exclusion restriction would affect the baseline results. I find that even substantial relaxations of the exclusion restriction would leave inference informative about the effects of uncertainty shocks on output in emerging markets. This increases further my confidence in the strength of the results.

Relation to the literature. This study builds on the extensive literature that aims to explain the business cycle in EMEs. For example, Aguiar and Gopinath (2007) suggest that an RBC model driven primarily by permanent shocks to productivity can explain well business cycles in developing countries, while Chang and Fernández (2013) find that conventional productivity shocks combined with financial frictions explain a large fraction of output fluctuations in EMEs. Hale and Arteta (2009) highlight the importance of balance-sheet effects of large devaluations in emerging markets. Mora and Siotis (2005) focus on the effect of growth in large economies on the prospects for recovery in emerging market economies experiencing recessions. Garcia-Cicco et al. (2010) show that models featuring preference and country-premium shocks perform better in capturing long-time series data in EMEs. Other sources of business cycle fluctuations in EMEs are attributed to country-spreads shocks (Neumeyer and Perri, 2005 and Uribe and Yue, 2006), terms-of-trade shocks (Mendoza, 1995 and Mendoza, 1997 and Schmitt-Grohé and Uribe, 2018), commodity shocks (Agénor, 2016) and interest rate shocks (Rothert, 2020 and Shapiro, 2018).

I contribute to this literature by assessing the role of uncertainty shocks in explaining output fluctuations in EMEs. In that, my study is related to Carrière-Swallow and Céspedes (2013), Bhattarai et al. (2019) and Bonciani and Ricci (2020) who analyze the spillover effects of global uncertainty on emerging markets.[3] I view my work as complementary to this literature since my focus is not on the effects of global uncertainty per se. I instead exploit its fluctuations to detect exogenous variation in the national uncertainty measures in EMEs. As discussed in Section 4.1.2, the structural uncertainty shocks in my analysis reflect many country-specific events, such as elections, political instabilities, or natural disasters, which are not accounted for by spillover analyses. Unsurprisingly, the two approaches lead to differences in the results as well. I find that uncertainty shocks in EMEs are inflationary and contractionary, while Bonciani and Ricci (2020) and Bhattarai et al. (2019) suggest that the shock is contractionary but might cause either inflation or deflation depending on some group characteristics. In line with Carrière-Swallow and Céspedes (2013), I show that the contractionary effect of uncertainty shocks is stronger in EMEs compared to AEs, while Bonciani and Ricci (2020) suggest the opposite.

This paper is also related to the recent literature that empirically addresses the endogeneity of uncertainty by means of novel identification procedures. Specifically, Piffer and Podstawski (2017), Mumtaz (2018) and Redl (2020) rely on external instruments to identify uncertainty shocks showing that such shocks are an important source of economic fluctuations. Caldara et al. (2016) find similar results adopting a penalty function approach within a VAR framework. Carriero et al. (2018b) and Angelini et al. (2019) instead, exploit the heteroskedasticity of macroeconomic variables to relax the timing restrictions embedded in the Cholesky identification; they show that macroeconomic uncertainty can be considered exogenous while the financial uncertainty is more an endogenous response to macroeconomic conditions. In contrast, Ludvigson et al. (2021) mix event constraints with correlation constraints in a set identified framework to achieve identification for uncertainty shocks. They claim that macro uncertainty is endogenous while financial markets

[3]The international transmission of uncertainty shocks has been widely assessed in advanced economies as well, see Mumtaz and Theodoridis (2015), Mumtaz and Musso (2019), Cuaresma et al. (2020) and Pfarrhofer (2022) and citations therein.

are a source of output fluctuations. Baker et al. (2022) use disaster events to construct instruments for first and second-moment shocks in a large panel of data and find that uncertainty shocks have substantial detrimental effects on output growth. Cesa-Bianchi et al. (2020) propose a common factor approach in a multi-country setting, placing restrictions on cross-country correlations, and argue that country-specific volatility shocks play a negligible role in determining the business cycle.

Finally, my paper is linked to the strand of the literature that focuses on measuring economic uncertainty. For example, Bloom (2009) proposes the stock market volatility as a measure of uncertainty, Baker et al. (2016) and Scotti (2016) use news-based indicators, Bachmann et al. (2013), Jo and Sekkel (2019) and Ozturk and Sheng (2018) rely on survey data to obtain uncertainty measures. Fernández-Villaverde et al. (2011), Carriero et al. (2018a), Clark et al. (2018), Mumtaz et al. (2018), Alessandri and Mumtaz (2019) and Mumtaz and Musso (2019) construct proxies of uncertainty based on the time-varying volatility of errors while Chan and Song (2018) employ high-frequency data in an unobserved components model to produce a measure of inflation expectation uncertainty. JLN measure uncertainty as the unforecastable component of large sets of macro and financial variables, while Rossi and Sekhposyan (2015) infer uncertainty by means of forecast errors. I contribute to this literature by constructing novel uncertainty measures for fifteen EMEs using the JLN approach.

The remainder of the paper is structured as follows. Section 2 describes the model specification and estimation. Section 3 presents the data and the uncertainty measures. In section 4 I discuss the results obtained from both the VAR model and the regression analysis. In section 5 I run additional robustness checks while section 6 concludes.

2 Empirical model

This section presents the empirical model highlighting the key points of the prior distributions and MCMC algorithm; more details are available in Appendix A.

2.1 The Panel Proxy VAR with hierarchical structure

I assume that each country can be modeled as an individual structural (S)VAR and information from all countries in the sample is then used to perform the estimation.

Consider a set of countries c= 1,....,C, l = 1 . . . L denotes lags, t = 1 . . . T denotes time periods, i= 1,.....N, represents the number of endogenous variables per country.

For each country I define the following SVAR model:

$$Y_{tc} = X_{tc}\beta_c + Z_t\theta_c + u_{tc} \tag{1}$$

$$u_{tc} = R_c\varepsilon_{tc} \tag{2}$$

Y_{tc} is a $1 \times N$ matrix of endogenous variables for country c, X_{tc} is a $1 \times (N \times L + 1)$ matrix of regressors specific to country c, including an intercept which accounts for the country c fixed effects. Z_t is the matrix of W exogenous variables common to all countries which enter the VAR equation at time t. In the "small-open economy" SVAR it is crucial to accommodate contemporaneous values of foreign variables to control for global shocks. $u_{tc} \sim$ N(0,Σ_c) is the vector of N reduced form residuals for country c. For simplicity define the matrix of coefficients $\Phi_c = \{\beta_c, \theta_c\}$ with dimension $(N \times L + 1 + W) \times N$ and $G_{tc} = \{X_{tc}, Z_t\}$ as the matrix of regressors with dimension $(N \times L + 1 + W)$ that is the same across each equation of the VAR model.

The reduced form shocks can be related to the underlying structural shocks as per equation 2; for convenience, I call ε_{t1} the vector of the structural shock of interest and ε_{t2} the vector of the remaining shocks. The goal is to identify the column of the $N \times N$ matrix R of country c, corresponding to the structural shock of interest.[4]

In a proxy (IV) SVAR framework the standard VAR model described by equations 1 and 2 is augmented by a measurement equation that links the reduced form residuals to the instrument for

[4] The order of the column is arbitrary in a proxy SVAR framework, but for simplicity, it is normalized to be the first.

the targeted structural shock. I define the measurement equation in reduced form, as in equation 3.[5]

$$u_{tc} = \gamma_c M_t + \eta_{tc} \tag{3}$$

$\eta_{ct} \sim$ N $(0,\omega_c^2)$ is the vector of the residuals of the measurement equation, u_{tc} is the vector containing the country-specific VAR model residuals, and M is the instrument for the structural shock ε_{t1}.

The instrument validity assumptions require that:

$$E(\varepsilon_{t1c}M_t) = \alpha_c \text{ (Relevance condition)}$$

$$E(\varepsilon_{t2c}M_t) = 0 \text{ (Exogeneity condition)}$$

If the instrument is valid, it can be shown that R_{1c} is identified up to a scale and sign. In particular, the first column of R_c, assuming a unit shock, can be estimated as follows:

$$R_{1c} = E(u_{tc}M_t)/E(u_{t1c}M_t) \tag{4}$$

With the estimates of R_{1c} in hand, the impulse responses that increase the uncertainty index by one standard deviation are retrieved following the derivation provided by Mertens and Ravn (2013)

Alternative ways of specifying a proxy SVAR model from a Bayesian perspective have been proposed by Caldara and Herbst (2019), who work with the model expressed in structural form, and by Drautzburg (2016) who performs inference analogous to inference in a SUR model transformed to obtained independently normally distributed errors.

The model described by equations 1-3 exploits the cross section dimension of the data. This occurs through the hierarchical prior specified for Φ_c and γ_{ic} coefficients as follows:

[5] An alternative would be to express the measurement equation in structural form as per Caldara and Herbst (2019) which would require an additional MH step in the Bayesian algorithm.

$$p\left(\Phi_c \mid \bar{\Phi}, O_c, \tau\right) = N\left(\bar{\Phi}, \tau O_c\right) \tag{5}$$

$$p\left(\gamma_{1c} \mid \bar{\gamma}, \Xi_c, \lambda\right) = N\left(\bar{\gamma}, \lambda \Xi_c\right) \tag{6}$$

O_c and Ξ_c are standard Minnesota priors and reflect the scale of the data, $\bar{\Phi}$ and $\bar{\gamma}$ are cross-sectional average coefficients that are treated as random variables and their posterior distribution is endogenously determined in the model. The crucial parameters in this setting are τ and λ which control the degree of heterogeneity in the model. As τ and $\lambda \to \infty$ the coefficients collapse to the country-specific VAR values while for τ and λ close to 0, the model is equivalent to the pooled estimator. In the current model, τ and λ should reflect a good balance between individual and pooled estimates. In a standard Bayesian framework $\bar{\Phi}$, $\bar{\gamma}$, τ and λ are parameters to be calibrated while in the current context they are treated as random variables and have their own distribution. This gives the hierarchical structure to the model.

In brief, equations 5 and 6 reveal that country coefficients are drawn from a common distribution centered around the cross-sectional mean (endogenously estimated), but are allowed to deviate from this mean at a higher or lower degree dictated by the value of the endogenously determined parameters τ and λ. Therefore, the posterior of Φ_c and γ_{ic} are weighted averages of the country-specific OLS estimates and the cross-sectional means for the VAR and IV coefficients defined in equations 5 and 6.

The hierarchical structure of the model offers several advantages that are relevant to the current study. First, the model delivers both country-specific and average-country estimates.[6] Moreover, the average-country impulse response functions are computed using the mean model coefficients $\bar{\Phi}$ and $\bar{\gamma}$ which are endogenously estimated. As opposed to the classical pooled panel approach, this model precludes the use of averages across country-level results, which are often hard to justify in practice.

[6]The country-specific estimates are employed in Sections 4.1.2 and 4.4 to compute country-specific structural shocks and counterfactual scenarios.

Moreover, $\bar{\Phi}$ and $\bar{\gamma}$ contain information from the whole panel and are updated at each draw of the algorithm. This feature of the model should improve the estimation precision. Finally, since each country is modeled as an individual VAR, the framework accommodates (time) unbalanced data.

2.2 Prior specification and posterior sampler

2.2.1 Priors

Following Jarociński (2010) and Dieppe et al. (2016) I assume diffuse priors for $\bar{\Phi}$, $\bar{\gamma}$, Σ_c and ω_c^2 and Minnesota type priors for O_c while Ξ_c is an identity matrix. Regarding τ and λ a common prior choice is an inverse Gamma distribution with shape parameter $s_0/2$ and scale $v_0/2$. Gelman et al. (2006) shows that results can be sensitive to the choice of the values for s_0 and v_0 and suggest instead the use of a non-informative prior (obtained by setting $s_0 =$ -1 and $v_0 = 0$) for models where the number of units is greater than 5 which is the strategy adopted in this paper.

2.2.2 Algorithm

This section provides a summary description of the algorithm. Details about the specific distributions employed are available in the Appendix A. The algorithm builds on Caldara and Herbst (2019) and Rogers et al. (2018) for the instrumental variable identification, while the hierarchical structure of the model is taken from Jarociński (2010). The algorithm combines a Gibbs sampler with an Independent Metropolis Hastings (MH) step to draw from the posterior distributions.

For ease of exposition the parameters Θ are split in two groups, the VAR parameters Θ_{VAR} and the IV parameters Θ_{IV} :

$$\Theta_{VAR} = \left\{\Phi_c, \Sigma_c, \tau, \bar{\Phi}, \right\} \text{ and } \Theta_{IV} = \left\{\gamma_{1c}, \bar{\gamma}, \lambda, \omega_c^2, R_c\right\}.$$

The joint likelihood of the VAR data (G) and the instrument data (M) is defined as follows:

$$P(G,M \mid \Theta) = P(G \mid \Theta_{VAR}) P(M \mid G, \Theta_{IV}, \Theta_{VAR}) \tag{7}$$

Combining the priors with the likelihood and collecting the VAR data (G) and the instrument data (M) in matrix D, the posterior can be written as :

$$P(\Theta \mid D) = P(\Theta_{VAR} \mid D) P(\Theta_{IV} \mid \Theta_{VAR}, D) \tag{8}$$

As shown in Caldara and Herbst (2019) and Rogers et al. (2018), the addition of the IV equation to the model leads to non-closed forms conditional posteriors for Φ_c and Σ_c which requires the use of an Independent MH step instead of a Gibbs sampler step.

The algorithm can be summarized thus:

1. Draw Φ_c^{new} and Σ_c^{new} using an Independence MH step. The proposal density $q(\Phi_c^{new} \mid \Phi_c^{old})$ for the VAR coefficients is normally distributed and takes the form of the conditional posterior distribution for the case of a Panel VAR with hierarchical prior, as derived in Jarociński (2010). The proposal density $q(\Sigma_c^{new} \mid \Sigma_c^{new})$ for Σ_c takes the form of the known inverse-Wishart distribution when classical diffuse prior is assumed. Accept the proposal with probability:

$$\alpha = min\left(\frac{P(\Phi_c^{new}, \Sigma_c^{new}, \tau, \bar{\Phi}, \gamma_{1c}, \bar{\gamma}, \lambda, \omega_c \mid \ D)}{P(\Phi_c^{old}, \Sigma_c^{old}, \tau, \bar{\Phi}, \gamma_{1c}, \bar{\gamma}, \lambda, \omega_c \mid \ D)} \times q\frac{(\Phi_c^{old} \mid \Phi_c^{new})}{(\Phi_c^{new} \mid \Phi_c^{old})} \times q\frac{(\Sigma_c^{old} \mid \Sigma_c^{new})}{(\Sigma_c^{new} \mid \Sigma_c^{old})}, 1\right)$$

where P denotes the posterior distribution of the VAR coefficients and variance evaluated at the new draw (the numerator of the first term) and the old draws (the denominator of the first term), while q represents the two candidate proposal distributions for the VAR coefficients and the variance evaluated at the new and the old draws.

2. Conditional on the VAR coefficients and variance, draw γ_{ic}, ω_c^2 and R_{ic} from known conditional posterior distributions using a Gibbs sampler, as derived by Rogers et al. (2018).

Run Steps (1)-(2) for each country c=1....N

3. Conditional on the parameters drawn in steps (1) and (2), $\bar{\Phi}$, $\bar{\gamma}$, τ and λ have known conditional posterior distributions (as derived in Jarociński, 2010) and are drawn using a Gibbs sampler. This step exploits the information from all the countries in the sample.

Note that the execution of steps (1) and (2) is based on an internal loop which scrolls across countries. Once completed the internal loop, the parameters specific to the hierarchical structure are drawn in Step 3 using information from the whole sample of countries.

I use 35,000 replications and base the inference on the last 15,000 replications saving one every 5 draws. A Monte-Carlo experiment indicating that the proposed algorithm performs well and evidence in favor of convergence are presented in the Appendix A.

3 Data

3.1 VAR analysis data

The empirical exercise focuses on fifteen relatively small EMEs, namely Argentina (ARG), Chile (CH), Colombia (COL), Croatia (CR), Czech Republic (CZE), Hungary (HUN), Peru (PE), Philippines (PHI), Poland (POL), Romania (ROM), Singapore (SGP), Slovenia (SLO), South Africa (SAF), Thailand (THA), and Turkey (TUR). Big emerging economies such as China, India, Brazil and the oil exporter countries are deliberately excluded from the sample to avoid that domestic fluctuations might affect the global uncertainty indicator. For each country, I construct a VAR described by equations 1-2. The matrix of endogenous variables for country c includes the measure of domestic uncertainty, real GDP, CPI, central bank interest rate (R), real exchange rate (REER), and a composite stock price index. To account for the world developments which can potentially affect the business cycle of EMEs, a vector of exogenous variables, Z_t, common to all countries, is included in the model. Following previous studies, Z_t contains a commodity price index, the OECD industrial production index to capture world demand shocks, and the US Federal Fund Rate which captures the risk appetite, a constant and a linear trend. The variables are at a quarterly frequency and run from 1998q2 to 2016q4 for nine countries. The sample stops in 2016 due to the availability of the Mumtaz and Musso (2019) dataset employed in the construction of the uncertainty measures. The sample span varies for six EMEs due to constraints arising from data availability and quality, as described in Appendix E. The variables enter the model in log levels (apart from the interest rate which is in levels) and the data is not per-processed before estimation except for the seasonal adjustment; the uncertainty measures are standardized.

3.2 Measuring Uncertainty

The measures of uncertainty are constructed using the JLN method which captures the deterioration in the agents' ability to predict economic outcomes. In brief, the statistical measure of uncertainty is obtained by aggregating a large number of estimated uncertainties. Following Ludvigson et al. (2021) I define $y_{jt}^{C} \in Y_t^C = (y_{1t}^C, ...y_{NCt}^C)$ to be a variable in category C. Then its h-period ahead uncertainty, $U_{jt}^C(h)$ is the volatility of the purely unforcastable component of the future value of the series, conditional on all the information available. Specifically:

$$U_{jt}^{C}(h) = \sqrt{E\left[\left(y_{jt+h}^{C} - E\left[y_{jt+h}^{C} \mid I_t\right]\right)^2 \mid I_t\right]} \tag{9}$$

where I_t represents the information available. The time-varying forecast error is computed allowing the prediction error to have time varying volatility; to clean for the predictable component using information from a large dataset, the forecast $E\left[y_{jt+h}^{C} \mid I_t\right]$ is taken from a factor-augmented forecasting model. Using a stochastic volatility model, uncertainty is calculated as the conditional expectation of the time-varying squared forecast error. Finally, the uncertainty in category C is obtained as the average over the individual uncertainties of each series in the category.

In order to construct the global uncertainty measure, I employ the dataset from Mumtaz and Musso (2019) which contains quarterly financial and macroeconomic variables from the first quarter of 1960 to the fourth quarter of 2016 for 22 OECD countries, which are all AEs. For each of the OECD country considered, the dataset contains 20 variables, including real activity variables, consumer prices, labor market variables, asset prices, interest rates, credit market variables, money, trade variables, and exchange rates. In addition to the country-specific variables, the data set includes 20 more international variables referring to international prices of commodities and some emerging market indicators. There are 460 time series; the global uncertainty indicator is obtained as the average across the uncertainty measures, one year ahead, of the 460 series, as per equation 9.

The data used to construct the domestic uncertainty measures for the fifteen EMEs is unbalanced. Specifically, the sample runs from 1996Q1 to 2016Q4 for nine countries most countries; however, the sample span and number of series included for each country vary according to data availability. The dataset prepared for each EME in the VAR analysis is complemented with measures of trade (import, export), unemployment, international liquidity, international reserves, and money variables. The domestic uncertainty for each country is, thus, calculated as the average across the one year ahead uncertainty measures for the country-specific series. The dataset used to extract the factors used as controls in the construction of the domestic uncertainties, contains all EMEs data augmented by the OECD data from Mumtaz and Musso (2019).

3.3 Uncertainty estimates

Figure 1 reports the estimate of global uncertainty. The measure recorded its highest peak during the recent financial crisis emphasizing the relevance of the recent recession for the OECD countries in the sample. The other peaks signaled by this measure coincide with the fall in the Berlin Wall, the black Wednesday currency crisis, the Asian financial crisis, the recent Charlie Hebdo terrorist attack and the Greek snap election following the plummeting of the stock prices at the end of 2014.

I compare my global uncertainty index with alternative measures of global uncertainty such as the VIX index, the measure proposed by Mumtaz and Theodoridis (2017) (hereafter M&T) which consists in the common standard deviation of the shocks to the world factors obtained from a dynamic factor model with time-varying volatility, the news-based index of global economic policy uncertainty of Baker et al. (2016) (hereafter EPU) and the global geopolitical risk index of Caldara and Iacoviello (2018). As reported in Figure C7 in Appendix C, my measure displays some independent variation compared to the other indices and unsurprisingly exhibits the highest correlation of 0.72 with M&T measure (which is also the most similar conceptually to my measure), followed by VIX and EPU with recorded correlations of 0.64 and 0.45 respectively. There is no correlation (-0.07) between my global uncertainty index and the geopolitical risk index suggesting that geopolitical events do not necessarily translate into higher global macroeconomic uncertainty or the other way around.

Figure 1: Global Uncertainty Measure

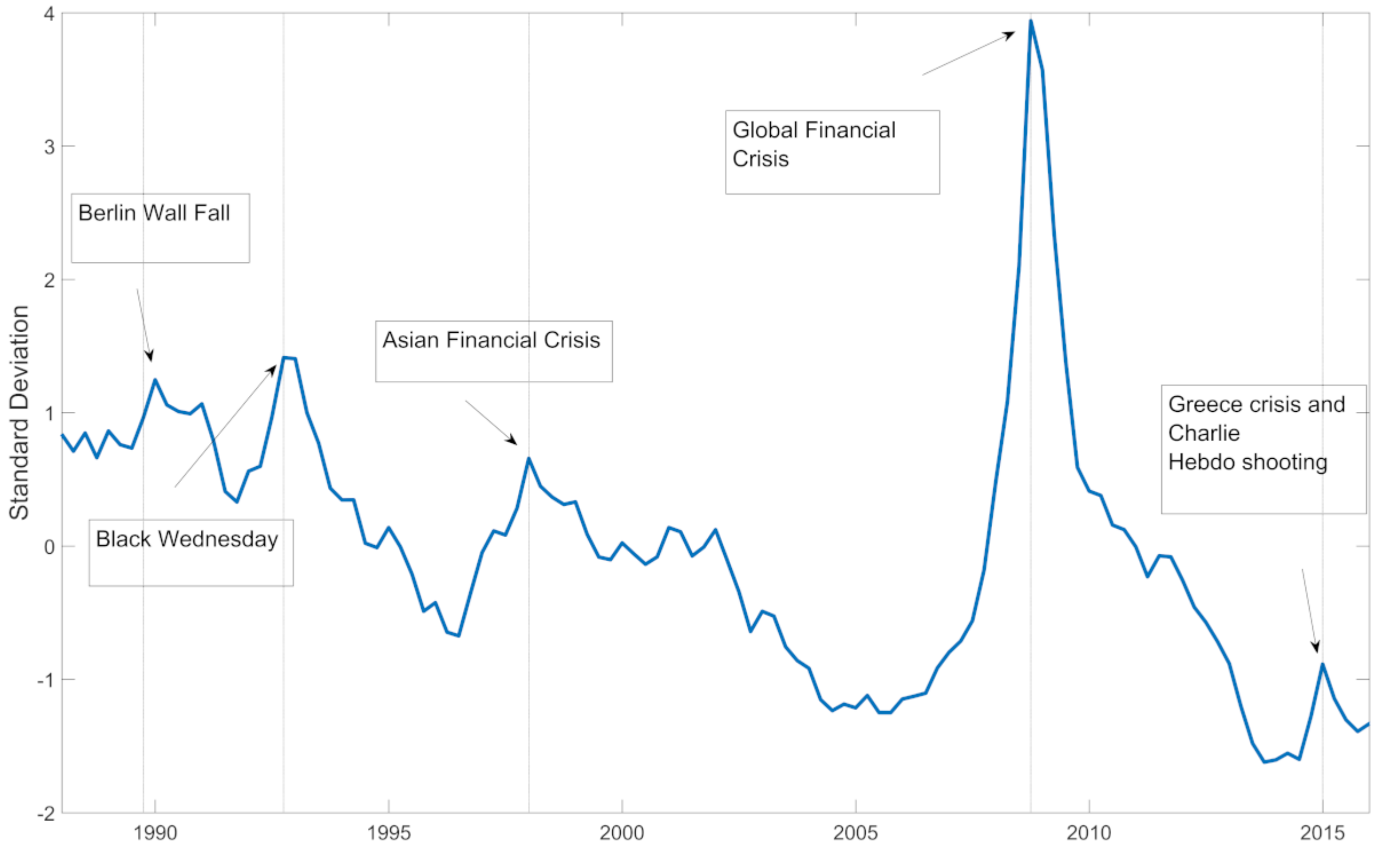


Figure 2: Domestic Uncertainty Measures

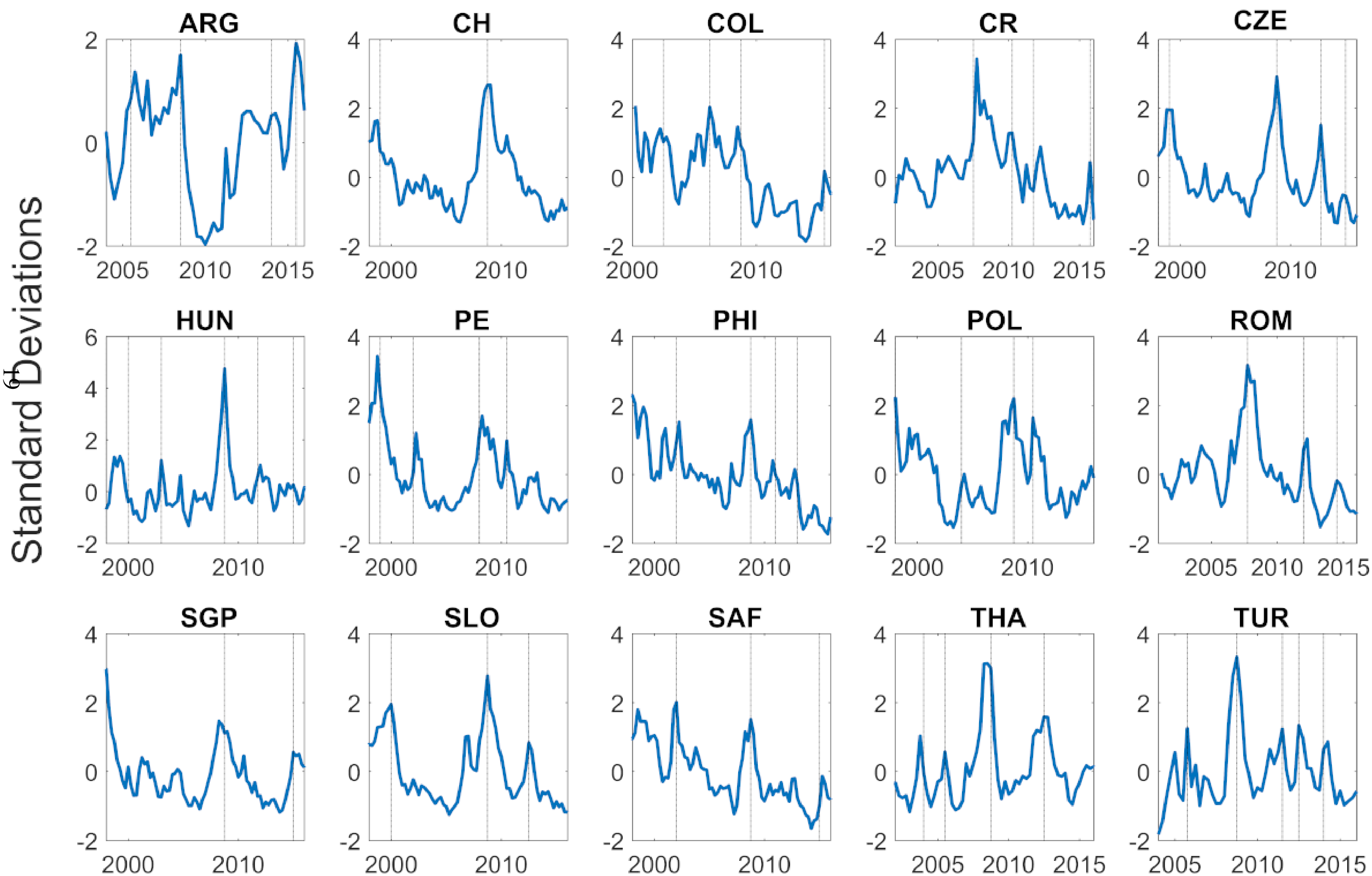


Figure 2 shows the estimated country-specific uncertainty measures for the fifteen EMEs in the sample. Note that domestic uncertainty spikes around the recent global crisis for all countries. Moreover, I detect peaks in uncertainty during country-specific events such as:

- recessions: Chile (1999), Czech Republic (1998-2000), Hungary (1998-2000 and 2003), Slovenia (1997 and 2000), South Africa (and 1997 and 2002), Poland (1998, 2000, and 2004)
- natural disasters: Philippines (typhoons 2011 and 2013), Thailand (tsunami 2004), Turkey (earthquake 2011)
- crisis: Peru (1999 credit crunch), Philippines (1997 financial crisis), Argentina (2014 sovereign default)
- political instabilities and elections: Peru (2002 violent protests), Singapore (2015 Parliament dissolved), Thailand (2012 anti-government protests), Poland (2016 anti-government protests), Romania (2012 resignation of Prime Minister and referendum for president impeachment), Romania (2014 elections), Argentina (2015 elections), Chile (1999 elections)

4 Results

4.1 Identification strategy

The identification strategy builds on previous studies that used global variables to identify local shocks (see Nakamura and Steinsson, 2014, Alfaro et al., 2021, Bonfiglioli et al., 2022). In this spirit, I use variation in global uncertainty to identify exogenous changes in the country-level uncertainty index. Specifically, as in Stock and Watson (2012), the residuals of an AR(2) regression of the global uncertainty index are employed as an instrument/proxy for country-based uncertainty shocks.[7]

[7] The length of the AR process is chosen based on the AIC test.

4.1.1 Validity of the instrument

The instrument is considered valid if it is relevant and exogenous, i.e:

$$E(\varepsilon_{1t}M_t) = \alpha \text{ (Relevance condition)}$$

$$E(\varepsilon_{2t}M_t) = 0 \text{ (Exogeneity condition)}$$

Exogeneity condition. The exogeneity of the instrument requires that M_t is contemporaneously uncorrelated with any structural shock in the model other than the shock of interest. Since this condition is not testable, it relies on identifying assumptions.

The first identifying assumption in my analysis states that business cycle fluctuations in small enough EMEs have no contemporaneous impact on the innovations in the global uncertainty index. Thus, it excludes the reverse causality between domestic variables and instrument. In other words, fluctuations in the global uncertainty are exogenous to shocks occurring in small emerging countries. The validity of this assumption is reinforced by focusing exclusively on small EMEs.

The second identifying assumption refers to the exclusion restriction condition. Such a condition requires that conditional on the observables, global uncertainty innovations affect the business cycle in EMEs only through their impact on the domestic uncertainty. The exclusion restriction is violated if the instrument is an omitted variable in the system, which implies that the VAR is not well specified. For example, if the global uncertainty fluctuations are contemporaneously correlated with some omitted global shocks, which in turn affect EMEs, then, the identification fails. To clean for such effects, I include in the system three exogenous variables that enter the model contemporaneously. In the sensitivity analysis section, I also check the robustness of my findings to a range of alternative instruments and to the inclusion in the model of lagged values of the instrument, lagged and contemporaneous values of the global variables, and squared and level values of the global variables.

Overall, the extensive sensitivity checks show that the baseline results are robust to the main confounding factors. However, this may not eliminate all concerns regarding potential violations of the exclusion restriction. Thus, in the sensitivity analysis section, I perform an additional check. I follow Conley et al. (2012) and Bonfiglioli et al. (2022) and implement a complementary exercise in which I study how my main results would change under various degrees of violation of the exclusion restriction. I show that inference about the effects of uncertainty shocks on output in EMEs would remain informative under scenarios that assume implausibly large violations of the exclusion restriction.

Relevance condition. The relevance of the instrument can be formally tested but it is a rather challenging task in SVAR models identified with IV since the instrumented structural shock is unobserved. Different methods have been proposed in the literature: some researchers approximate the relationship between the instrument and the structural shock of interest by running F tests on the measurement equation (Gertler and Karadi, 2015; Piffer and Podstawski, 2017; Rogers et al., 2018), others report a squared correlation coefficient (Mertens and Ravn, 2013; Caldara and Herbst, 2019) while Drautzburg, 2016 tests the validity of the instrument computing Bayes Factors under different scenarios.

Standard F tests are not coherent with a Bayesian framework, thus I address the relevance of my instrument as follows. I first report the posterior median estimates of γ_{1c} and 95% high probability density intervals (HPDI). Note that I use a non-informative prior for γ_c thus the relevance of the instrument should not depend on the choice of the prior. The results reported in Table 1 suggest that the hypothesis of γ_{1c} being equal to zero is rejected for each country in the sample. In addition, as shown in Figure C9 my results are little affected when using different proxies, specifically the VIX and EPU, which have a considerably lower squared ratio compared to the benchmark case (average squared ratio between median estimate of γ_{1c} and its standard error is 28.84 for the benchmark model, 7.16 for VIX and 2.51 for EPU).

Finally, I use a goodness of fit statistic to check whether the instrument data bring useful information to the model. Specifically, I compute the Deviance Information Criteria (DIC)[8] for the

[8] I rely on DIC test instead of Bayes factors since diffuse priors are assumed for several parameters which make the computation of Bayesian odds problematic (see Gelman et al. (2004)).

benchmark model, and for a scenario in which the measurement equation contains a constant only. DIC test suggests that the benchmark model is preferred to the no instrument case with an average DIC value of 3227 for the benchmark scenario vs. 3404 for the no instrument case. In light of these results, it can be assessed that the instrument performs well in terms of relevance.[9]

Table 1: Instrument relevance statistics. Benchmark case.

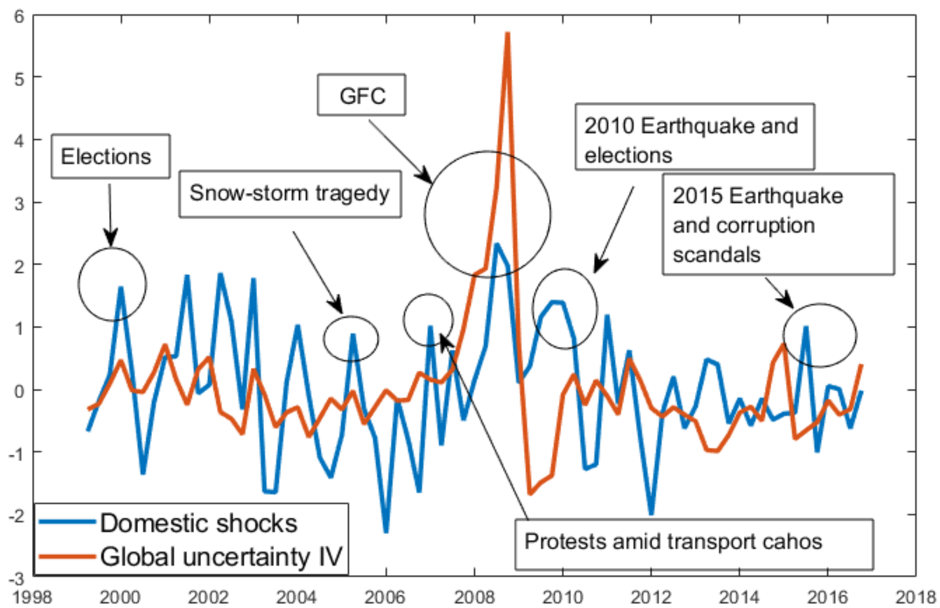
Country	Median γ_{1c}	95 HPDI	DIC benchmark	DIC No Instrument
1	0.2328	(0.1496 ; 0.3445)	3615.36	3648.88
2	0.2404	(0.1591 ; 0.3329)	2600.70	2627.92
3	0.2449	(0.1646 ; 0.3424)	3468.10	3748.32
4	0.2258	(0.1334 ; 0.3122)	3864.41	3954.84
5	0.2300	(0.1408 ; 0.3138)	4026.92	4120.37
6	0.2321	(0.1439 ; 0.3196)	3242.27	3340.16
7	0.2373	(0.1391 ; 0.3115)	3561.53	3654.09
8	0.2365	(0.1551 ; 0.3225)	2177.46	2998.72
9	0.2352	(0.1542; 0.3238)	3742.28	3830.24
10	0.2343	(0.1470; 0.3241)	3501.69	3552.24
11	0.2363	(0.1364 ; 0.3126)	2581.06	3239.13
12	0.2263	(0.1377 ; 0.3158)	2757.92	2720.93
13	0.2275	(0.1527 ; 0.3261)	3299.37	3309.32
14	0.2315	(0.1455 ; 0.3202)	2913.23	3064.44
15	0.2345	(0.0673; 0.3262)	3064.63	3255.98
Average	0.2331		3227.79	3404.37

4.1.2 The interpretation of the shock

The uncertainty shock identified in my work captures movements in the country-level uncertainty index that are exogenous to the national economic system. This shock can have either a local origin (e.g. an earthquake, elections) or a foreign origin (e.g. a global crisis, a pandemic, a war). In this sense, my identification strategy does not focus on the effects of global uncertainty per se, it just exploits its variation to detect exogenous contemporaneous changes in country-level uncertainty, i.e., to compute the impact matrix, but with no role in the estimation of the VAR dynamics.

[9] DIC test relies on the reduced form coefficients, thus the identification of the uncertainty shocks is not required for this exercise.

Figure 3: The figure reports the structural uncertainty shocks series for Chile (blue line) together with the global uncertainty instrument (orange line).



To further clarify the nature of my shocks, I compute the structural uncertainty shock series for Chile and compare it with the global uncertainty instrument.[10] Chile is an interesting laboratory for this purpose due to its exposure to natural disasters and political instabilities. This type of event is expected to trigger an increase in local uncertainty (see Baker et al., 2022) without affecting the global index, hence this effect would be most probably missed by a spillover analysis.

Figure 3 reports the uncertainty shock series for Chile together with the global IV instrument. The country-level shocks display substantial idiosyncratic variability that is unrelated to the global uncertainty fluctuations. Several of the idiosyncratic spikes in the uncertainty shocks can be linked to country-specific events, such as the 2010 and 2015 earthquakes, the 2007 March protests in the capital Santiago over chaos following the introduction of a new transport system, the snow-storm tragedy in May 2005, and the early 2000 elections. The strong idiosyncratic variation in the country-specific shocks is consistent with the labeling of the shocks as domestic uncertainty shocks.

[10]The empirical model used in this paper delivers both country-specific and average cross-sectional results.

4.2 Results for the average emerging economy

I first report the results for an average emerging economy which are computed using the posterior estimates of the mean model parameters $\bar{\Phi}$ and $\bar{\gamma}$. Note that $\bar{\Phi}$ and $\bar{\gamma}$ are endogenously estimated, thus no cross-sectional averaging is required to obtain the average country results.

Impulse responses and variance decomposition. Figure 4 presents the posterior median of the response to a one standard deviation uncertainty shock which increases the country uncertainty measure by 0.4 units. GDP does not respond to the shock on impact but it gradually falls reaching its peak of -1% after 12 quarters and the estimated effect displays high persistence. A sharp decline is observed in the stock price index of around -7% on impact. The detrimental effects of the shock on financial markets are absorbed only fifteen quarters later. The shock generates negative co-movement between CPI and GDP supporting the idea of a 'supply type' uncertainty shock in line with the conclusions reached in Fernández-Villaverde et al. (2011), Born and Pfeifer (2014), Mumtaz and Theodoridis (2015), and Bhattarai et al. (2019). The currency depreciation combined with the fall in asset prices suggests a "flight to quality" effect of the shock. The response of the monetary policy is neutral at the beginning, but it tightens in correspondence to the inflationary peak. This highlights the serious challenges posed by these shocks to the monetary authorities due to the negative trade-off between inflation and output.

Table 2 illustrates the contribution of the uncertainty shock to the forecast error variance of the endogenous variables. Unsurprisingly, the shock explains the highest share of variation (65%) of the contemporaneous forecast error variance of the domestic uncertainty index. At short horizons the shock contribution is negligible for the macro variables while it explains a share of 19% of the financial index variability on impact. However, the shock becomes more important on medium-long horizons with a contribution to GDP of 12 and 15% after 3 and respectively 5 years while the contribution to CPI, REER and the policy rate remains relatively small.

Figure 4: Impulse response to a 1 standard deviation uncertainty shock in the average emerging economy. 68 and 90 HPDI bands reported

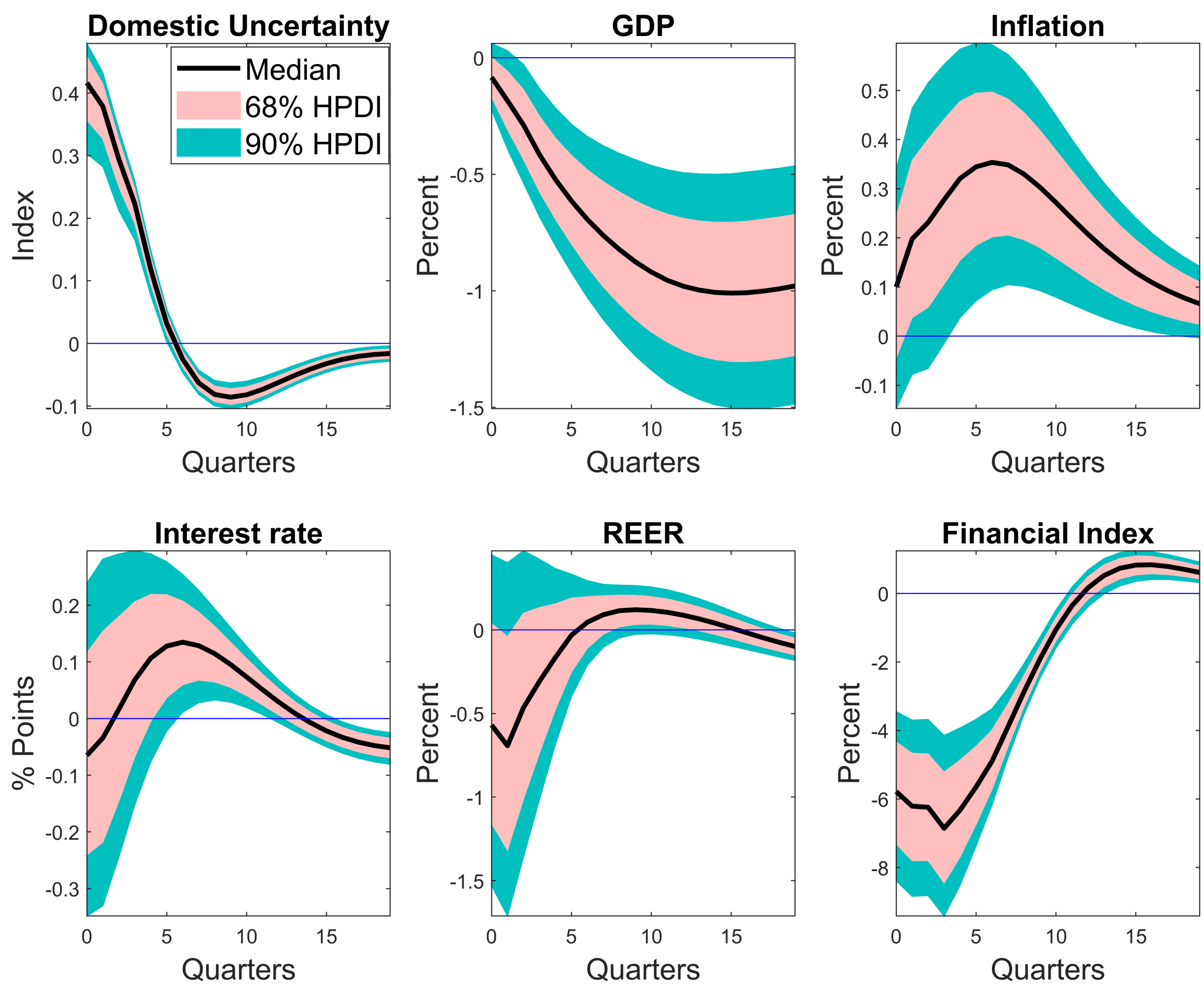


Table 2: Variance decomposition for the average country. Posterior median with 68 percent HPDI in parenthesis

Horizon	Uncertainty	GDP	CPI	R	REER	Financial index
Impact	0.65	0	0.01	0.02	0 .03	0.19
	(0.48,0.78)	(0,0.03)	(0,0.05)	(0,0.1)	(0,0.12)	(0.10,0.3)
4 Q	0.65	0.03	0.03	0.02	0 .03	0.25
	(0.49,0.78)	(0.01,0.07)	(0.01,0.09)	(0.01,0.09)	(0.01,0.12)	(0.14,0.38)
12 Q	0.61	0.12	0.07	0.04	0 .03	0.30
	(0.46,0.71)	(0.06,0.20)	(0.02,0.13)	(0.02,0.10)	(0.01,0.11)	(0.20,0.43)
20 Q	0.59	0.15	0.07	0.05	0 .03	0.30
	(0.45,0.69)	(0.07,0.25)	(0.02,0.14)	(0.03,0.1)	(0.01,0.1)	(0.19,0.44)

Quantitative magnitude of the effect on output in EMEs. In this section, I compare the magnitude of the real impact observed in my estimated EMEs panel VAR to the literature. The objective of this exercise is to understand if the shock has the same effects in EMEs vs. AEs. Because of the many differences between my study and the literature (such as different data frequency, data processing, uncertainty measures employed and empirical specifications), a direct comparison is far from trivial. Keeping that in mind, to perform the comparison between EMEs and AEs, I rely on Redl (2020) who undertakes a similar analysis for a group of AEs. He estimates panel VAR models on quarterly data and employs country-specific JLN measures to capture uncertainty, as in this paper. He reports that following an uncertainty shock that increases the domestic JLN measure by 1 unit, GDP in the average advanced economy falls by around 1%. This effect is 2.5 times smaller compared to my estimates where a shock scaled to increase the JLN measure by 0.4 units triggers a 1% fall in GDP. Thus, my results reveal a much stronger effect of uncertainty shocks in EMEs compared to the developed economies. This is consistent with Carrière-Swallow and Céspedes (2013) who detect a far stronger effect of global uncertainty on investment in EMEs vs. AEs. I extend the validity of their result to country-level uncertainty shocks.

Proxy vs. recursive identification. In this section I compare the impulse responses for the average economy identified with instruments with the ones obtained using the recursive approach with domestic uncertainty ordered first. This exercise is similar in spirit to an IV vs. OLS comparison in a uni-variate setting and is meant to signal the existence of endogeneity in the model. The impulse responses (reported in Figure C9 in Appendix) show that the IV identification gives point estimates that are of a substantially higher magnitude compared to the recursive approach. Similar findings have been reported by Carriero et al. (2015) for the US and by Baker et al. (2022) for a large panel of countries. Thus, I extend the validity of this result to EMEs and I show that failing to control for the contemporaneous endogeneity between the uncertainty and domestic conditions, leads to estimates of a significantly lower magnitude. This can be attributed either to measurement error or, for example, to contemporaneous effects that stock returns might have on uncertainty which could lead to a downward-biased estimates of the recursive approach.

Discussion. From the results reported in this section we can discern four main points. The first is that I find that uncertainty shocks are an important driver of output fluctuations in EMEs and the magnitude of the recessionary effect is substantially higher compared to what has been reported for AEs. Potential explanations for this magnified effect could be i) the stronger financial disruption triggered by the shock due to the higher instability of credit markets in EMEs; and ii) the lack of monetary support to the output recovery because of the negative co-movement between prices and output.

Second, while the majority of previous empirical studies detect a recessionary and deflationary effect of uncertainty, my estimates reveal a negative co-movement between output and prices. This result is in line with the theoretical frameworks that combine monopolistic competition with sticky prices and wages which gives rise to inverse Oi-Hartman-Abel- effects and precautionary pricing when faced with uncertainty about future economic variables (see Fernández-Villaverde et al., 2015, Born and Pfeifer, 2014, Mumtaz and Theodoridis, 2015, and Born and Pfeifer, 2021. The negative co-movement between output and inflation is particularly appealing since it is compatible with both the stagflation periods often encountered in EMEs, as well as with the existence of important downward wage rigidity in these countries, as documented by Schmitt-Grohé and Uribe (2016). In fact, Mumtaz and Theodoridis (2015) show that wage rigidity is a crucial ingredient in models featuring negative co-movement between output and inflation as a consequence of uncertainty shocks. In addition, the opposite reaction of output and prices is very important from a policy perspective because it suggests that uncertainty shocks are not easily mitigated by the central bank intervention due to the trade-off between output and prices. [11]

Third, the causal effect of uncertainty on output detected by the IV identification is substantially higher than the recursive approach suggests. This is likely due to factors such as measurement error and reverse causality bias. Thus, failing to control for endogeneity leads to potentially downward biased estimates.

Finally, the forecast error variance decomposition favors the interpretation of the shock as an uncertainty shock, with the share explained in the national uncertainty index which is by far the highest among the variables in the model.

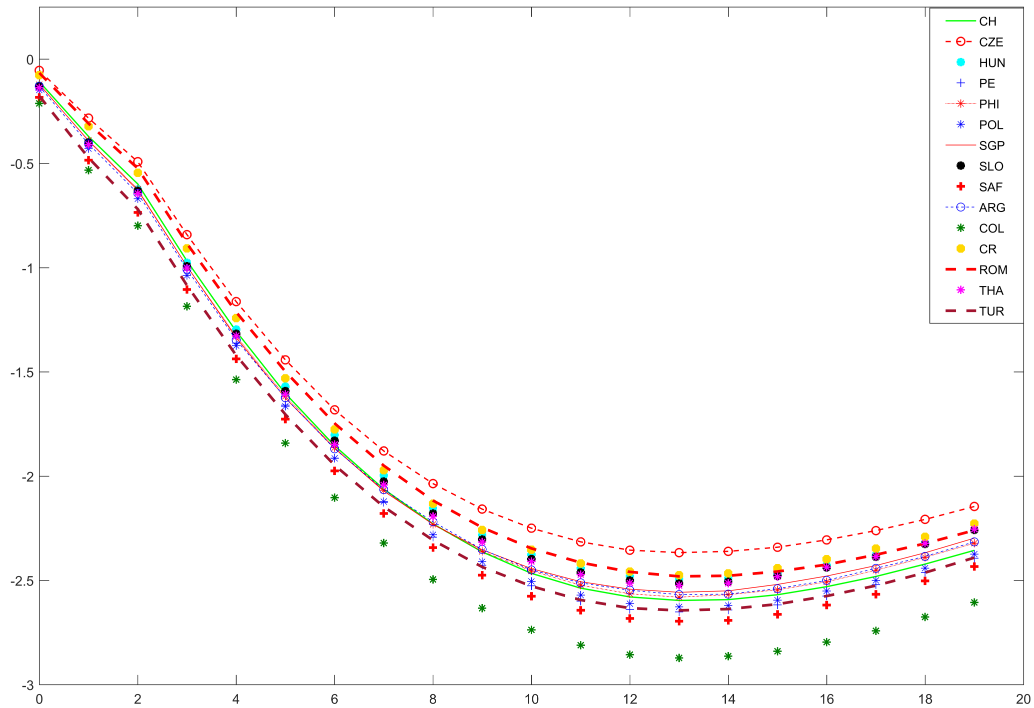
4.3 Heterogeneity across countries

The empirical framework proposed in this paper is well suited to compute country-specific results as well.[12] For ease of exposition I limit my attention to the response of GDP to uncertainty shocks. Figure 5 plots the GDP impulse responses (scaled across countries to increase the domestic uncertainty by 1 unit) for each country in the sample. Results show that the model detects a certain degree of heterogeneity which translates into a different scale of responses to shocks. The shape of the responses is similar across countries and close to the mean model response. This is a natural

[11] An alternative explanation for the inflationary and contractionary effects of foreign uncertainty shocks is provided by Bhattarai et al. (2019), who develop a two-countries theoretical model featuring nominal rigidities and forward looking behaviour of firms, while the foreign uncertainty shock triggers a "flight-to-quality" phenomenon. In their model, the inflation in the home country is determined by the marginal costs faced by home firms, which increase following an uncertainty shock due to the real exchange rate depreciation. Thus, the higher marginal costs lead to an increase in home good prices, which translates into higher inflation.

[12] Recall that unit-specific coefficients are drawn from a distribution centered around the cross-section average coefficients $\bar{\Phi}$ and $\bar{\gamma}$ with a tightness dictated by the parameters τ and λ.

Figure 5: GDP impulse responses. Posterior median estimate for each country. The shock is scaled to increase the country uncertainty by 1 unit.



consequence of the hierarchical prior specification (see the discussion in Jarociński, 2010). The most recessionary effects are experienced by Colombia, followed by South Africa, Poland, and Turkey while the less affected economies appear to be the Czech Republic, Romania, and Croatia.

I further explore the heterogeneity across countries in a regression analysis and I find that countries that are wealthier, more integrated in the global value chains and with efficient labor markets suffer less severe GDP losses from uncertainty shocks (see Appendix D for details).

4.4 Counterfactual analysis

Up to now this paper has shown that uncertainty shocks have a substantial effect on macroeconomic and financial variables. However, little has been said about the importance of such shocks from an economic perspective. I conclude this section with a counterfactual exercise aiming to provide a model-based narrative on the historical role played by uncertainty shocks in shaping GDP growth fluctuations. The question of interest is how different would have been the GDP growth in emerging markets in the absence of uncertainty shocks?[13]

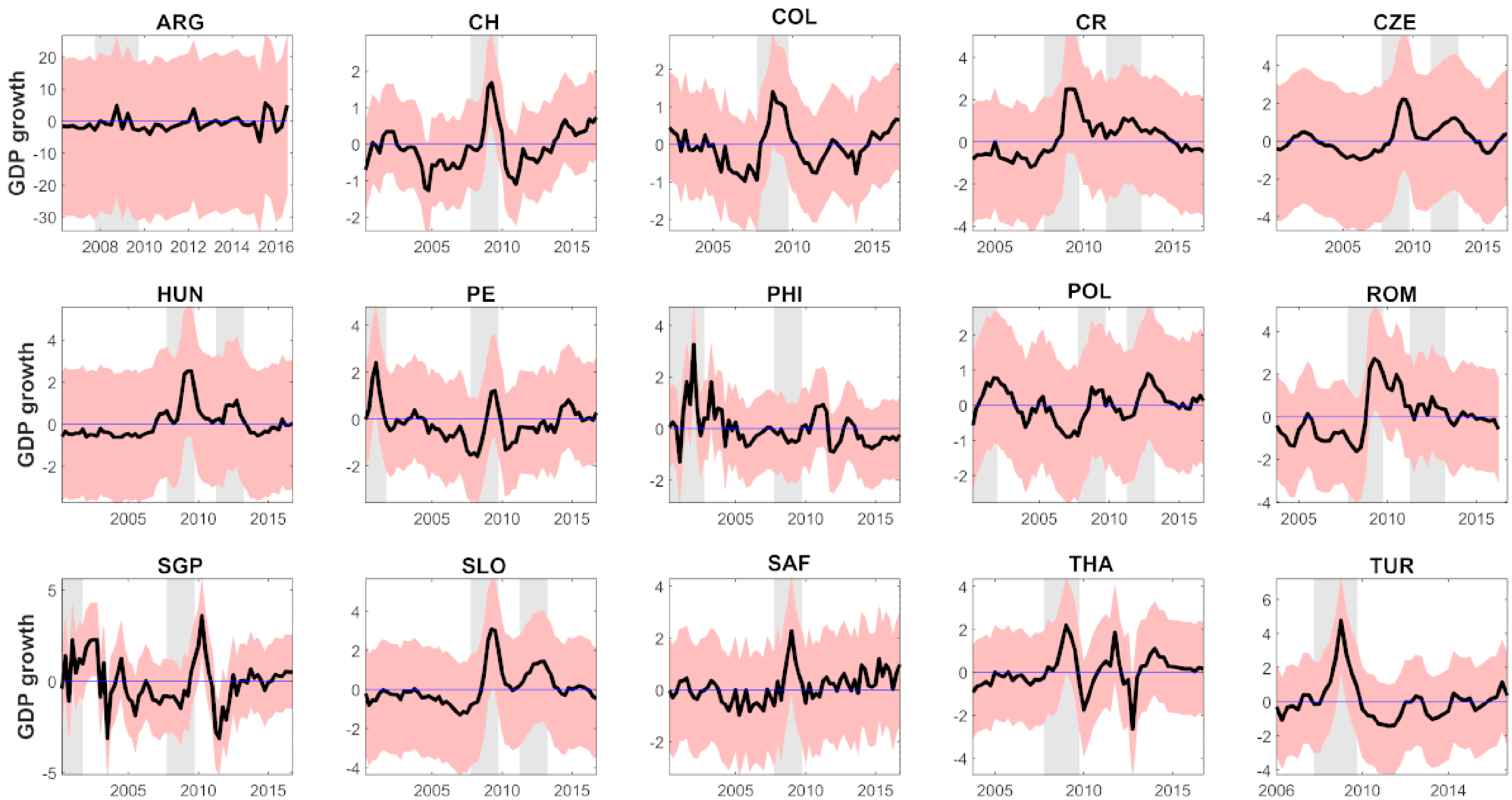
The analysis involves three steps. First, I reconstruct the historical series of structural shocks for each country, using country-specific estimates. This step involves solving numerically for the entire matrix R_c, which links the reduced form residuals to the structural shocks; I impose a recursive structure for the remaining shocks without restricting the contemporaneous response of uncertainty to the other shocks. Then, for each country, I replace the sequence of structural uncertainty shocks with zero and I recompute the reduced form residuals accordingly. Finally, I simulate the evolution of GDP growth at the country level under this scenario in which uncertainty shocks are switched off. Since no change is imposed on the values of the parameters, this exercise is not subject to Lucas' critique, as discussed in Benati (2010).

Figure 6 illustrates the results from this counterfactual exercise. For each country, I report the difference in GDP growth under the counterfactual assumption of no uncertainty shocks and the actual data. My estimates suggest that in the absence of uncertainty shocks the GDP growth would have been more than 2% higher during the Global Financial Crisis (GFC) for almost all of the countries in the sample. Moreover, it is interesting to notice that according to my results, part of the recessionary effects experienced by the European countries during the European debt crisis can be attributed to uncertainty shocks. The results also reveal that in the early 2000s when the internet bubble burst, uncertainty shocks had particularly detrimental effects in countries with pre-existing vulnerabilities, such as Singapore and the Philippines (which were recovering from the Asian crisis) and Peru (which experienced a credit crunch in 1999). Finally, I signal also the 2000-2002 recession in Poland which can be (partly) explained by uncertainty shocks.

Summing up, the counterfactual analysis shows that uncertainty shocks were an important driver of the GDP fluctuations in EMEs. The results suggest a substantial contribution of uncertainty shocks to the business cycle in emerging markets.

[13] For ease of exposition in this exercise I focus on GDP growth rather than levels.

Figure 6: Counterfactual scenario. The figure shows the difference between the GDP growth series generated under the counterfactual assumption of no uncertainty shocks and the actual data. The gray bands identify the GFC, the Euro debt crisis for European countries, and some selected recessionary episodes. 68 HPDI bands are reported.



5 Sensitivity analysis

I perform several sensitivity checks to assess the robustness of my results and the strength of the identification strategy. A summary description is provided in this section while detailed results are available in Appendices B and C.

Alternative instruments. I test the sensitivity of my findings to the instrument employed in the VAR exercise. To this end, I re-estimate the model using a range of alternative proxies. As a first check, I build on Baker et al. (2022) and use their structural uncertainty shock series as an instrumental variable in my model. In this paper, the authors combine disaster events with inequality restrictions to identify both financial and uncertainty shocks. Thus, their methodology is particularly appealing since it accounts for both first and second-moment shocks, as well as for the endogeneity between uncertainty and economic growth through the use of disaster events. In addition, I estimate the model proposed by JLN which consists of a monthly VAR model in eight variables identified with timing restrictions, with uncertainty ordered after a financial index but before all the other variables, as in JLN. Aiming to control for potential confounding factors between first and second moment shocks, I also identify the JLN model with the penalty function approach proposed by Caldara et al. (2016) to disentangle uncertainty shocks that are orthogonal to financial shocks. The structural shocks series form these models are used as an IV in the baseline specification. Other proxies include the residuals from an AR(2) and an AR(1) regressions of VIX and respectively EPU indexes.[14] Figure C2 in Appendix C reports the posterior median of the impulse responses across these alternative specifications and shows that results are robust to the identification approach.

Additional controls. To preclude that the identification strategy is compromised by omitted confounding factors, I re-estimate the benchmark model with the following additional controls: linear and quadratic trend; the world demand proxied by Kilian's index of global real economic activity instead of the OECD industrial production index; the inclusion in the benchmark model of

[14]The length of the AR process is chosen via AIC test and suggests an AR(2) model for VIX and an AR(1) model for EPU.

four lags of the instrument as controls, the inclusion of lags and squared contemporaneous values of the global exogenous variables. Additionally, I follow Jarociński (2010) and Bhattarai et al. (2019) and include time dummies for the GFC (September-December 2008) and the European debt crisis (May 2010, and February and August 2011). Finally, I control for year-fixed effects and I also remove the four quarters of 2008 corresponding to the peak of the GFC. The results are robust to these checks (see Figure C3 in Appendix C). In line with findings in Caldara et al. (2016) and Bhattarai et al. (2019), removing the peak of the GFC leads to a smaller effect of uncertainty shocks on GDP (green + signed line in Figure C3 in Appendix C). This effect is expected to be even more pronounced in my application since the removal of the GFC episode affects the relevance of the instrument as well.

Violations of the exclusion restriction. The sensitivity checks performed may not dispel all the concerns regarding the validity of the exclusion restriction. To address this issue, in this exercise I follow Conley et al. (2012) and I assume that the exclusion restriction fails. If I found that the main results remain informative in the presence of strong violations of the exclusion restrictions, this would further raise confidence in the validity of my findings.

I implement the above approach by constructing four counterfactual scenarios in which the impact effect of uncertainty shocks on several variables in the model is compromised by failures of the exclusion restriction that can take a different degree of intensity (i.e. from smaller to larger violations). Thus, I recompute the GDP impulse responses to the uncertainty shocks under these counterfactual scenarios. Results reported in Figure C8 show that even implausibly large violations of the exclusion restriction would leave the inference informative about the GDP response to uncertainty shocks in EMEs (see Appendix B for a detailed description of the construction of the counterfactual scenario).

6 Conclusion

The aim of this paper is to examine the effects of uncertainty shocks in emerging economies. To this end, I develop a Bayesian algorithm to estimate a panel VAR model that accommodates IV identification. This model deals in an efficient way with the lack of data availability for emerging markets. The analysis focuses on fifteen small EMEs. I construct global and country-specific uncertainty measures using the approach proposed by JLN. To identify uncertainty shocks I use innovations in global uncertainty as an instrument for country-level uncertainty building on the premise that shocks in small EMEs are unlikely to affect global uncertainty.

My results have important implications. They suggest that uncertainty shocks generate a large and persistent drop in real GDP that is far larger compared to the GDP fall recorded in AEs. The shock triggers a negative co-movement between real GDP and CPI which poses serious challenges to the monetary authorities.

Finally, a counterfactual exercise reveals that uncertainty shocks were a crucial driver of the GDP growth fluctuations in EMEs.

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