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

Mirela S. Miescu†

November 28, 2018

This paper investigates the effects of domestic uncertainty shocks in emerging economies (EMEs). Aiming to deal with data limitations for EMEs we develop a new Bayesian algorithm to estimate proxy panel structural vector autoregressive (SVAR) models with hierarchical structure. We then construct a global uncertainty indicator as well as country uncertainty measures for fifteen relatively small emerging economies. To identify exogenous uncertainty shocks in the fifteen EMEs we propose the use of innovations in global uncertainty as an instrument for domestic uncertainty shocks. We find that uncertainty shocks cause severe falls in GDP and stock price indexes, depreciate the currency and are not followed by a subsequent overshoot in activity. Moreover our results are consistent with a "supply side" type uncertainty shock generating an increase in consumer prices and an ambiguous reaction of the monetary policy. Finally, we show that there is heterogeneity across economies in the response to uncertainty shocks which can be (in part) explained by country characteristics.

JEL Classification*:* C3, C11, E3

Keywords*:* Uncertainty shocks, proxy SVAR, Emerging economies, Panel data.

1 Introduction

Following the 2008 global financial crisis an extensive literature focused on the concept of uncertainty and its role in driving the business cycle. Although there is no single theory

*I am greatly indebted to Haroon Mumtaz for his valuable advice and supervision. I also thank Dario Caldara, Danilo Cascaldi-Garcia and the participants of the Research Department Divisional seminar at the IMF and for insightful comments.

†Queen Mary University of London, m.s.miescu@qmul.ac.uk

describing the effects of uncertainty, substantial evidence associates higher uncertainty with recessions and several explanations have been put forward. If some studies consider uncertainty as a cause of the business cycle, postulating that higher uncertainty induces precautionary saving of households or "wait and see" behavior of firms (Bloom, 2009; Basu and Bundick, 2017; Leduc and Liu, 2017; Bloom et al., 2018), some others propose uncertainty as a consequence of the lower economic growth assuming that recessions encourage risky behavior or reduce the information (Bachmann and Moscarini, 2011; Ilut and Saijo, 2016).

The lack of theoretical consensus regarding the direction of causality between uncertainty and business cycle poses important challenges to the empirical studies aimed at analyzing the role of uncertainty for business cycle. Many of the previous econometric analyses identify uncertainty shocks using structural VARs with recursive identification (see, among others, Bloom, 2009; Bachman et al., 2013; Carriere-Swallow and Cespedes 2013; Caggiano et al., 2014; Caggiano et al. 2017; Meinen and Roehe, 2017). However, this approach has been shown to be inadequate (see Ludvigson et al. 2017) for two reasons. First, it is not clear whether uncertainty should be placed before or after the real activity variables. Second, there is no conclusive theoretical reason for ruling out the contemporaneous co-movement between uncertainty and real activity, which is an implicit assumption in the recursive structure.

A recent strand of the literature addresses the "potential endogeneity" of uncertainty by means of novel identification procedures. Specifically, Mumtaz (2018), Piffer and Podstawski (2017) and Redl (2018) rely on external exogenous instruments to identify uncertainty shocks showing that such shocks can be a source of economic fluctuations. Caldara et al. (2016) find similar results adoptiong a penalty function approach within a VAR framework. Carriero et al. (2018) and Angelini et al. (2018) 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. (2017) 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 are a source of output fluctuations. Cesa-Bianchi et al. (2014) 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. In the light of these contrasting results the endogeneity of uncertainty remains an open debate.

Another challenge faced by the empirical studies aiming at validating the adverse effects of uncertainty shocks, is the lack of an objective measure of uncertainty; in fact several proxies have been employed in the literature. For example, Bloom (2009) proposes the stock market volatility as a measure for uncertainty, Baker et al. (2016) and Scotti (2016) focus on news based indicators, Bachmann et al. (2013) rely on business survey data to obtain uncertainty measures, Villaverde et al. (2011), Mumtaz and Zanetti (2013), Mumtaz and Theodoridis (2015), Alessandri and Mumtaz (2018) and Carriero et al. (2017) construct proxies of uncertainty based on the time-varying volatility of errors. Jurado et al. (2015) (hereafter, JLN) measure uncertainty as the unforcastable component of large sets of macro and financial variables, while Rossi and Sekhposyan (2015) infer uncertainty by means of forecast errors.

Although extensive research has been carried out on uncertainty shocks, little is known about the effects of such shocks in emerging economies. This lack of evidence can be largely attributed to the limited availability and accuracy of data for these countries.[1] However, the very few attempts made in this direction (Fernandez-Villaverde et al. 2011; Carriere-Swallow and Cespedes, 2013; Bhattarai et al., 2018), show that uncertainty shocks have large and detrimental macroeconomic effects in emerging countries raising the need for a deeper understanding of the topic.

This paper explores the impact of uncertainty shocks in EMEs while addressing the endogeneity concern regarding the relationship between uncertainty and the real activity. To this purpose, we develop a novel Bayesian framework that combines the panel VAR with hierarchical structure à la Jarocinski (2010), with the methodology proposed by Caldara and Herbst (2018) and Rogers et al. (2016) for the estimation of Bayesian proxy SVAR models. The model we obtain can be interpreted as a panel proxy VAR with random coefficients and it offers three key advantages. First, exploiting the cross section dimension of the data effectively deals with the limitations associated with the short samples. Second, the proxy extension accommodates the use of an instrumental variable approach for the shock identification; as such we do not rule out the potential co-movement between uncertainty and real activity. Finally, the hierarchical structure of the model allows for cross section heterogeneity which we examine in a regression analysis, to show that part of the differences across countries in response to uncertainty shocks can be linked to country characteristics.

The empirical exercise focuses on a group of fifteen relatively small EMEs. Following the methodology proposed by JLN we construct a global uncertainty indicator, as well as domestic uncertainty measures for each country in the sample. One advantage of using JLN approach is that this method captures the predictability of the economy, rather than the volatility, providing a proxy for uncertainty which is closer (than volatility) to the theoretical notion of economic uncertainty. Another advantage is that using a rich data environment as advocated by JLN method, reduces the possibility of biases caused by omitting relevant predictive information.

To identify the domestic uncertainty shock we propose a global to local approach for identification, in the spirit of Nakamura and Steinsson (2014) and Mumtaz (2018). To be more specific, we use innovations in global uncertainty as a proxy for domestic uncertainty shocks. Our identifying assumption is that global uncertainty fluctuations are uncorrelated with any domestic shock in the model other than the domestic uncertainty shock. In other words, innovations in the global uncertainty index are not contempora-

[1] Not only the macroeconomic variables in EMEs are available for short samples and they often involve episodes of high instability, but the uncertainty indicators proposed in the literature are mainly available for US and few other developed economies.

neously affected by domestic shocks occurring in the *individual* country in the sample[2]; to reinforce the instrument exogeneity assumption we deliberately exclude from the sample big emerging economies and major oil exporters. One concern might arise regarding the exclusion restriction condition which requires that the only channel through which global uncertainty innovations affect domestic economies is via their impact on the country uncertainty index. However, in a VAR setting the exclusion restriction condition is implicitly validated by the fairly standard assumption that the VAR is well specified[3]. In order to support the assumption that the VAR is well specified, we define a model that includes six endogenous variables with their lags and three global exogenous variables to control for world developments. Finally, even if the condition that the VAR is well specified is not fully believed, the regression coefficients of the GDP residuals on the instrument are close to zero and non statistically significant for all the countries in the sample which provides evidence in favor of the exclusion restriction[4].

Our identification approach is appealing for two main reasons. First, the proxy SVAR approach accounts for the potential measurement error in the instrument[5]; moreover the shocks we identify can be labeled as *domestic* uncertainty shocks. The second reason is related to the quality of our instrument. We rely on fairly standard assumptions to support the exogeneity of the instrument; furthermore, we show that our instrument is far more relevant than two other instruments obtained from alternative measures of global uncertainty used in the literature, namely the VIX index of equity volatility and the economic policy index of Baker et al. (2016).

The main findings of the paper can be summarized thus. We show that unanticipated changes in domestic uncertainty have significant macroeconomic and financial effects on the EMEs. A one standard deviation uncertainty shock leads, on average, to a persistent and substantial decline in the level of real GDP of about 1%, sharply decreases the stock prices with a peak effect of more than 7%, and depreciates the real currency by 0.6%. The shock generates negative co-movement between GDP and CPI, with an estimated increase in the price level of around 0.3%; the central bank reaction is ambiguous which is not surprising, considering the challenges posed by the negative trade-off between inflation and output. The model detects a certain degree of heterogeneity across countries in the response to uncertainty shocks which we examine in more detail in a regression analysis. From this exercise we learn that countries that are wealthier, more integrated in the

[2]This is similar to ordering the global uncertainty index before the country specific variables in a recursive framework. Ordering global variables before domestic variables is a fairly standard assumption for applications related to small open economies.

[3]A well-specified VAR implies that the VAR residuals are a linear combination of only structural shocks; as such global uncertainty innovations should affect the reduced form residuals only through their impact on the local uncertainty structural shock. If this condition does not hold we face an omitted variables issue and the assumption that the VAR is well specified fails.

[4]See table S2 in the Appendix

[5]Proxy SVAR models treat the instrument as a partial measure of the structural shock of interest accounting for potential measurement error in the proxy. A more straightforward alternative is to use the proxy as a variable in the model in a so-called hybrid VAR; this approach, however, does not account for the measurement error in the instrument. See Caldara and Herbst, 2018 for a detailed comparison between hybrid and proxy SVAR approaches.

global chains, and with more efficient labor and financial markets are less sensitive to uncertainty shocks; in contrast, countries with more efficient good markets and a higher trade share are more affected by uncertainty shocks. Finally, a counterfactual analysis shows that in the absence of uncertainty shocks, the recessionary effects experienced by EMEs during the global financial crisis and the European debt crisis would have been substantially lower.

This article makes three important contributions. To begin with, to the best of our knowledge, this is the first paper that investigates the effects of domestic macro uncertainty shocks in emerging economies, while accounting for the potential co-movement between uncertainty and the real activity. Second, from a methodological point of view we develop a novel Bayesian algorithm to estimate an extended version of a panel VAR with random coefficients, which accommodates for the use of proxies for the shock identification. Finally, from an economic perspective, we propose the use of a global to local approach for the identification of domestic uncertainty shocks. Compared to the country-to-state level used in Nakamura ad Steinsson (2014) and Mumtaz (2018), the global-to-country level approach adopted in this paper implies a potentially less restrictive instrument exogeneity assumption.

Our paper is related to the large literature that studies the relationship between business cycle and uncertainty (see Bloom, 2014 and Ludvigson et al., 2017 for an excellent review of the literature). In particular, this paper builds on Mumtaz (2018), who uses variation in country uncertainty to identify state-level uncertainty shocks in US, with two main departures: first, the methodology we employ is different since we use a proxy SVAR framework, instead of a single equation IV regression model; second, we are interested in the effects of uncertainty shocks in a group of EMEs, rather than in the US state level response to such shocks. World variables have also been used to instrument for local uncertainty by Bonfiglioli and Gancia (2015); however they examine the effect of uncertainty on structural reforms in a panel framework. We also differ from previous studies analyzing the effects of uncertainty in EMEs, such as Carriere-Swallow and Cespedes (2013) and Bhattarai et al. (2018), in that we account for the potential measurement error in the proxy for the uncertainty shock; moreover our shock can be labeled as domestic uncertainty shock rather that global or US uncertainty shock. We share the concerns regarding the appropriateness of the recursive framework for uncertainty shock identification with Cesa-Bianchi et al. (2014) as well; however we differ in the methodology and scope, since they develop a common factor model rather than a Panel VAR, and they aim at quantifying the relative importance of country-specific vs global volatility shocks. From a methodological point of view, we build on the method of external instruments for SVAR identification introduced by Stock and Watson (2012) and Mertens and Ravn (2013)[6], and on the literature exploiting the cross section dimension in VAR models (see Canova and Ciccarelli, 2013 for a survey).

The remainder of the paper is structured as follows. Section 2 describes the model

[6] A non-exhaustive list of studies using external instruments in SVAR includes Gertler and Karadi (2015), Carriero et al. (2015), Piffer and Podstawski (2017), Redl (2018), Caldara and Herbst (2018), Rogers et al. (2016), Mumtaz et al. (2018)

specification and estimation. Section 3 presents the data and the uncertainty measures. In section 4 we discuss the results obtained from both the VAR model and the regression analysis. In section 5 we run additional robustness checks while section 6 concludes. We relegate to the Appendix the detailed description of the data and the algorithm and some supplementary results.

2 Empirical model

In this section we describe the empirical model and we highlight the key points of the prior distributions and MCMC algorithm; we confine the details to the technical appendix.

2.1 The Panel Proxy SVAR with hierarchical structure

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

Consider a set of countries c= 1,....,C. For each country we define the following proxy SVAR:

$$Y_c = X_c\beta_c + Z_t\theta_t + u_c \tag{1}$$

$$u_c = R_c\varepsilon_c \tag{2}$$

$$u_{ic} = \gamma_{ic}M + \eta_{ic} \tag{3}$$

u_c ~ N(0,Σ) are the reduced form residuals for country c, X_c is the matrix of endogenous variables for country c while Z_t is a vector of exogenous variables common to all countries which enter the VAR equation at time t. For simplicity define $\Phi_c = \{\beta_c, \theta_t\}$ and $G_c = \{X_c, Z_t\}$.

The reduced form shocks can be related to the underlying structural shocks as per (2); for convenience we call ε_1 the structural shock of interest and ε_2 the remaining shocks. The goal is to identify the first column of matrix R for country c.

In a proxy SVAR framework the standard VAR model described by (1)-(2) is augmented by a measurement equation which links the reduced form residuals to the instrument for the targeted structural shock. Following Rogers et al. (2016) we define the measurement equation as in (3).

η_{ic} ~ N(0,ω^2) are the residuals of the measurement equation, u_{ic} is the i^{th} residual where i= 1,.....N, represents the number of endogenous variables per country, M is the instrument for the structural shock ε_1.[7]

From the instrument validity assumptions which require that :

$$E(\varepsilon_1 M) = \alpha \text{ (Relevance condition)}$$

[7]Since we do not adopt a recursive identification the order of the variables has no implication for our object of interest (Impulse response functions).

$$E(\varepsilon_2 M) = 0 \text{ (Exogeneity condition)}$$

it can be shown that the instrument identifies R up to a scale and sign. In particular, the first column of R, assumig a unit shock, can be estimated as follows:

$$R_{1c} = E(u_{2c}M)/E(u_{1c}M) \tag{4}$$

Alternative ways of specifying a proxy SVAR model from a Bayesian perspective have been proposed by Caldara and Herbst (2018), 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 main departure of the model described by (1)-(3) from the standard proxy SVAR approach is that we exploit the cross section dimension of the data and we assume a hierarchical prior for $\mathit{\Phi}_c$ and γ_{ic} coefficients as follows:

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

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

where O_c and $\mathit{\Xi}_c$ are standard Minnesota priors and reflect the scale of the data, $\bar{\mathit{\Phi}}$ and $\bar{\gamma}$ are cross sectional average coefficients updated during the sampling procedure. The crucial parameters in this setting are τ and λ who 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 $\lambda = 0$ the model is equivalent to the pooled estimator. Ideally, τ and λ should reflect a good balance between individual and pooled estimates. In a standard Bayesian framework $\bar{\mathit{\Phi}}$, $\bar{\gamma}$, τ and λ are parameters to be calibrated while in the current context they are treated as random variables and have their own distribution.

In brief, equations (5) and (6) reveal that country coefficients are assumed to be drawn from a common distribution centered around the cross sectional mean 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 $\mathit{\Phi}_c$ and γ_{ic} are weighted averages of the country specific OLS estimates and the prior mean defined in (5) and (6).

The hierarchical structure of the model offers several advantages which are relevant to our study. First the average impulse response function can be computed using the mean model coefficients $\bar{\mathit{\Phi}}$ and $\bar{\gamma}$ to obtain the estimates. Moreover, $\bar{\mathit{\Phi}}$ and $\bar{\gamma}$ contain information from the whole panel which is likely to improve the estimation precision. In addition, the hierarchical prior shrinks the country specific coefficients towards the common mean leading to a more efficient use of the data and more precise estimates of the unit specific coefficients. Finally, since we model each country as an individual VAR our empirical framework easily accommodates for (time) unbalanced data.

2.2 Prior specification and posterior sampler

Priors

Following Jarocinski (2010) and Dieppe et al. (2017) we assume diffuse priors for $\bar{\Phi}$, $\bar{\gamma}$, Σ and ω^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 (2006) shows that results can be sensitive to the choice of the values for s_0 and v_0 and suggest the use of a uniform prior with 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.

Algorithm

We build on Caldara and Herbst (2018) and Rogers et al. (2016) to draw from the posterior using a Metropolis Hastings (MH) within Gibbs algorithm.

For ease of exposition we split the parameters Θ in two groups, the VAR parameters and the IV parameters :

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

We define the joint likelihood of the VAR data (G) and the instrument data (M):

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

and combining the priors with (6) we re-write the posterior as in Rogers et al. (2016):

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

where D contains both G and M.

The non closed form conditional posteriors are the Φ and Σ while the rest of the parameters are standard with a known distribution to draw from.

The algorithm can be summarized thus:

1. Draw $P\left(\Phi_c^{new} \setminus \Theta\right)$ and $P\left(\Sigma_c^{new} \setminus \Theta, \Phi_c^{new}\right)$ using an Independence MH step in which the proposal density for Φ takes the form of the known posterior for the case of a Panel VAR with hierarchical prior (see Jarocinski, 2010) and the proposal density for Σ takes the form of the known inverse-Wishart distribution when classical diffuse prior is assumed. Accept the proposal with probability:

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

2. Draw γ_{ic}, ω_c^2 and R_{ic} from known posterior distributions using a Gibbs sampler.

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

3. Draw $\bar{\Phi}$, $\bar{\gamma}$, τ and λ from known posterior distributions using a Gibbs sampler using the information from all countries.

Please 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.

We use 35,000 replications and base our inference on the last 15,000 replications saving one every 5 draws.

A Monte-Carlo experiment which indicates that the proposed algorithm performs well and some evidence in favor of convergence are presented in the appendix.

3 Data

3.1 VAR analysis data

In the empirical exercise we limit our attention to 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), Turkey (TUR). We deliberately exclude from the sample big emerging economies such as China, India, Brazil and the oil exporter countries; we do so in order to insure the exogeneity of the instrument which requires that economies are small enough to avoid that domestic economic fluctuations affect the global uncertainty indicator. For each country we 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, 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, we follow previous studies and we add Z_t, a vector of exogenous variables common to all countries. Z_t contains a commodity price index, the OECD industrial production index as a proxy for world demand, the US Federal Fund Rate which captures the risk appetite, a constant and a linear trend. The variables are at quarterly frequency and run from 1997q2 to

2016q4 for nine countries while the sample span varies for the remaining six EMEs due to constraints arising from data availability and quality. We highlight that 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

We construct measures of uncertainty based on JLN method which captures the deterioration in the agents ability to predict economic outcomes.

In brief, the statistical measure of uncertainty is obtained aggregating over a large number of estimated uncertainties. Following Ludvigson et al. (2017) we define y_{jt}^{C} $\in Y_t^C = (y_{1t}^C, ... y_{NCt}^C)$ 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 information available. Specifically:

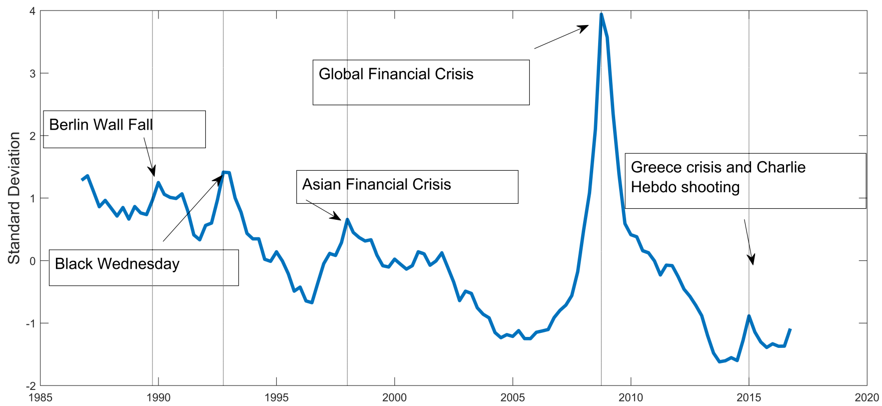
$$U_{jt}^{C}(h) = \sqrt{E\left[\left(y_{jt+h}^{C} - E\left[y_{jt+h}^{C} \mid I_t\right]\right)^2 \mid I\right]} \tag{9}$$

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 predicable 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 we employ the dataset from Mumtaz and Musso (2018) which contains quarterly financial and macroeconomic variables from first quarter of 1960 to the fourth quarter of 2016 for 22 OECD countries. For each country a number of 20 variables is considered with series ranging from real activity variables, consumer prices, labor market variables, asset prices, interest rates, credit market variables, money, trade variables and exchange rates. In addition, the data-set includes 20 more international variables referring to international prices of commodities and some emerging markets indicators. In total there are 460 time series; the global uncertainty indicator is obtained as the average across uncertainty measures for each of the 460 series constructed according to equation (8).

Regarding the data used to construct the domestic uncertainty measures the sample runs from 1996Q1 to 2016Q4; however the sample span and number of series included for each country varies according to data availability. We complete the data-set prepared for the VAR analysis with measures of trade (import, export), unemployment, international liquidity, international reserves and money variables. The domestic uncertainty for each country is calculated as the average across the 1 period ahead uncertainty measures for

Figure 1: Global Uncertainty Measure



the country specific series.[8]

Where necessary variables are log differences and seasonal adjusted. A detailed list of the series used and data sources is available in the Appendix.

3.3 Uncertainty estimates

Figure 1 reports our 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.

In Figure 2 we compare our proxy for global uncertainty with alternative measures of global uncertainty such as the VIX, 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). Our measure displays some independent variation compared to the other indices and unsurprisingly it exhibits the highest correlation of 0.72 with M&T measure (which is also the most similar conceptually to our measure), followed by VIX and EPU with recorded correlations of 0.64 and 0.45 respectively. There is no correlation (-0.07) between our 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. [9]

[8] The data-set used to extract the factors for the domestic uncertainties contains all EMEs data augmented by the OECD data from Mumtaz and Musso (2018).

[9] Notice that the geopolitical risk measure is the only one not spiking around the 2009 global financial

Figure 2: Alternative measures of Global Uncertainty

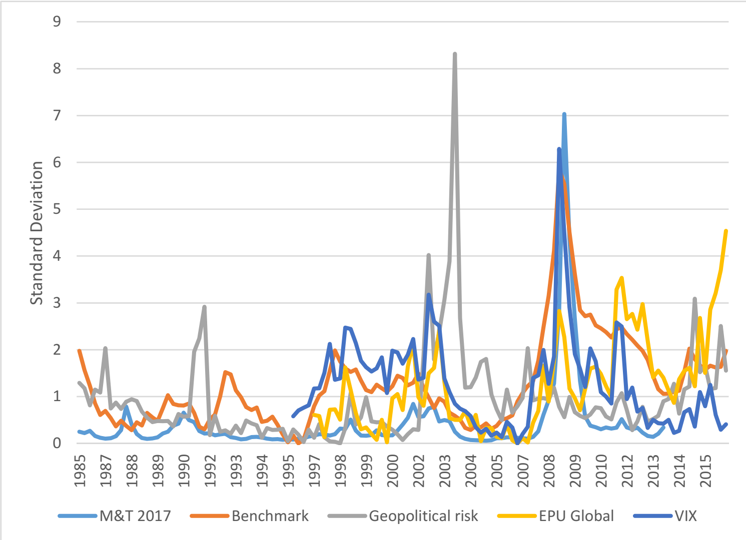
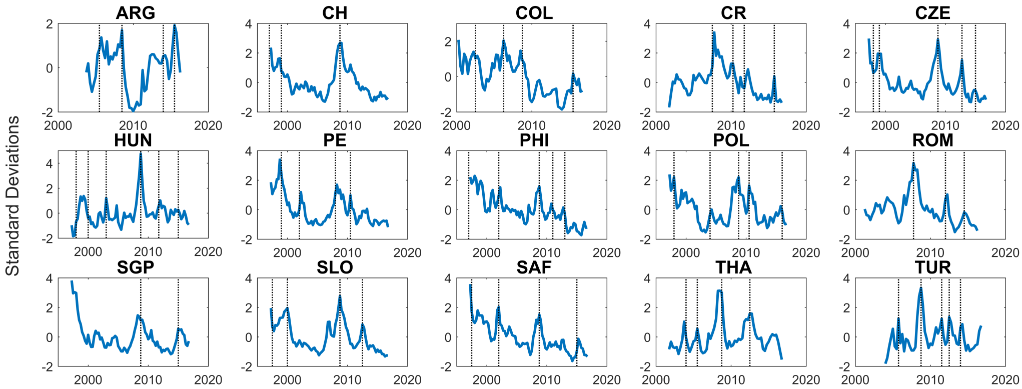


Figure 3 shows the estimated country-specific uncertainty measures for the fifteen EMEs in the sample. It is interesting to note that the domestic uncertainty measure spikes around the recent global crisis for all countries. Moreover we detect peaks in uncertainty during events such as:

- 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)

crisis.

Figure 3: Domestic Uncertainty



4 Results

4.1 Instrument validity

Following Stock and Watson (2012) we use the residuals of an AR(2) regression of the proposed instrument, namely the global uncertainty index, as a proxy for the domestic uncertainty shock.[10] We claim that domestic uncertainty shocks can have a local origin (such as an earthquake) or a foreign origin (a global crisis). As such, innovations in global uncertainty index can be seen as a partial measure of the domestic uncertainty shock.

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

$$E(\varepsilon_1 M) = \alpha \text{ (Relevance condition)}$$

$$E(\varepsilon_2 M) = 0 \text{ (Exogeneity condition)}$$

The exogeneity of the instrument in a proxy SVAR framework requires that the proxy M, is uncorrelated with any structural shock in the model other than the domestic uncertainty shock**.** Since this condition is not testable, it relies on our identifying assumption that business cycle fluctuations in small enough EMEs have no contemporaneous impact on the innovations in the global uncertainty index. In other words, fluctuations in the global uncertainty are exogenous to shocks occurring in small emerging countries. The exclusion restriction condition, which requires that global uncertainty innovations affect business cycle in EMEs only through their impact on domestic uncertainty, is not a concern in a well specified VAR setting in which the omitted variables are not a concern. Moreover, the regression coefficient of the GDP residuals on the instrument (reported in the Appendix) are close to zero and not significant, reinforcing the validity of the assumption that global uncertainty is not an omitted variable in the country VAR model.

[10]We choose the length of the AR process using the AIC test.

On the other side, the relevance of the instrument can be formally tested but it is a rather challenging task in proxy SVAR models 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 running F tests on the measurement equation (Gertler and Karadi, 2015; Piffer and Podstawski, 2017; Rogers et al., 2016), others report a squared correlation coefficient (Mertens and Ravn, 2013; Caldara and Herbst, 2018) while Drautzburg (2016) tests the validity of the instrument computing Bayes Factors under different scenarios.

Since performing a standard F test is problematic in the current application[11] we address the relevance of our instrument in two ways. We report the posterior median estimates of γ_{1c} and 95% HPDI (see Table 1) and the ratio between the median estimates of γ_{1c} and their correspondent standard errors. Results suggest that the hypothesis of γ_{1c} being equal to zero is rejected for each state; moreover the value of the ratio between the measurement equation coefficients and their standard errors (Column 4 in Table 1) favors the hypothesis of a strong instrument[12]. In addition, in Figure (7) we show that our 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, in the spirit of Drautzburg (2016), we use a goodness of fit statistic to check whether the instrument data brings useful information to the model. Specifically, we compute the Deviance Information Criteria (DIC)[13] for the 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 the light of these results we are comfortable to claim that our instrument performs well in terms of relevance.

4.2 Results for the average emerging economy

We first report the results for an 'average' emerging economy computed using the posterior estimates of the average parameters $\bar{\Phi}$ and $\bar{\gamma}$. Figure 4 presents the posterior median

[11] There are several reasons for which the standard F test is inappropriate for our empirical model. First, the two equations (1)-(2) defining the model are linked through the joint likelihood specification, hence the IV equation informs the VAR equation. It is therefore difficult to imagine a coherent F test in this context. Second, the model described by (1)-(4) has a hierarchical structure which adds to the complexity of performing an accurate F test. Third, the residuals u_{ic} in equation (3) depend on the VAR specification; therefore if the VAR is miss-specified the F test could erroneously suggest that the proxy is weak even if this is not the case. Finally, the F test it is not coherent with a Bayesian framework.

[12] In a classical perspective a value of the squared ratio between the measurement equation coefficient and its standard error, above 10 would suggest a strong instrument. Our estimates indicate a squared ratio value of 28.84 for the benchmark model.

[13] We 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., 2003).

Table 1: Instrument relevance statistics. Benchmark case.

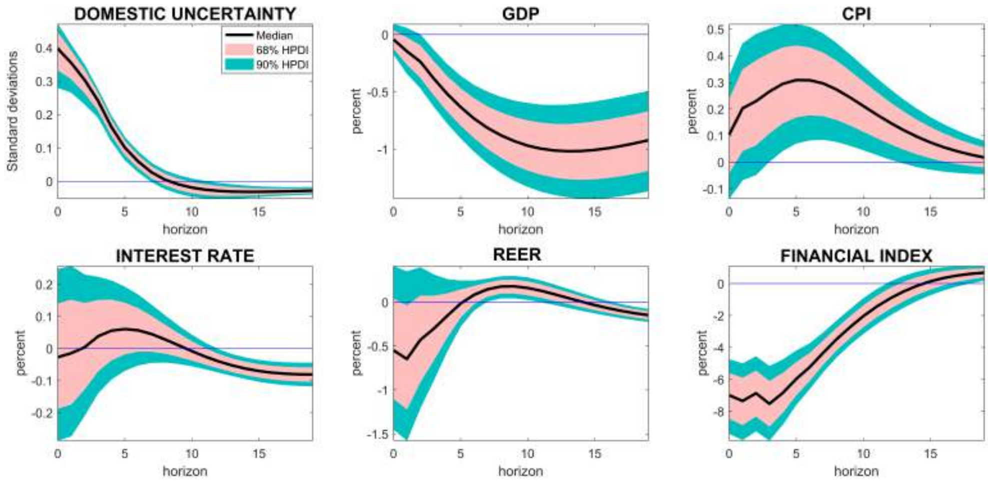
Country	Median γ_{1c}	95 HPDI	γ_{1c} /SE	DIC benchmark	DIC No Instrument
1	0.2328	(0.1496 ; 0.3445)	5.53	3615.36	3648.88
2	0.2404	(0.1591 ; 0.3329)	5.55	2600.70	2627.92
3	0.2449	(0.1646 ; 0.3424)	5.4	3468.10	3748.32
4	0.2258	(0.1334 ; 0.3122)	5.16	3864.41	3954.84
5	0.2300	(0.1408 ; 0.3138)	5.34	4026.92	4120.37
6	0.2321	(0.1439 ; 0.3196)	5.32	3242.27	3340.16
7	0.2373	(0.1391 ; 0.3115)	5.34	3561.53	3654.09
8	0.2365	(0.1551 ; 0.3225)	5.55	2177.46	2998.72
9	0.2352	(0.1542; 0.3238)	5.54	3742.28	3830.24
10	0.2343	(0.1470; 0.3241)	5.33	3501.69	3552.24
11	0.2363	(0.1364 ; 0.3126)	5.19	2581.06	3239.13
12	0.2263	(0.1377 ; 0.3158)	5.17	2757.92	2720.93
13	0.2275	(0.1527 ; 0.3261)	5.44	3299.37	3309.32
14	0.2315	(0.1455 ; 0.3202)	5.36	2913.23	3064.44
15	0.2345	(0.0673; 0.3262)	5.33	3064.63	3255.98
Average	0.2331		5.37	3227.79	3404.37

of the response to a one standard deviation domestic uncertainty shock which increases the country uncertainty measure by 0.4 standard deviations. 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 and the detrimental effects the shock has on the financial variables are completely absorbed only after 15 quarters. Moreover 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 Villaverde et al. (2011a), Mumtaz and Theodoridis (2015) and Batharai et al. (2018). If we now turn to the REER and the policy rate, we observe that following an uncertainty shock the currency depreciates while the response of the monetary policy is ambiguous. This last result highlights the fact that these shocks pose serious challenges to the central bankers 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. At short horizons the shock contribution is small for the macro variables while it explains a high share of around 25% of the financial index variability at all horizons. 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 small.

Overall our results regarding the impact of uncertainty shocks on GDP and CPI in emerging economies fall in the range of previous findings analyzing the effects of such shocks in US (Mumtaz and Theodoridis, 2015; Carriero et al. 2015; Caldara et al. 2016;

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



Carriero et al. 2018); in change we estimate more severe disruptions of financial markets in EMEs compared to values reported for developed economies. Interestingly, our results are also qualitatively similar to Batharai et al. (2018) who instead focus on spillover effects from US uncertainty shocks in emerging markets suggesting that whether the origin of the uncertainty shock is domestic or foreign does not have important implications for the transmission mechanism of the shock.[14]

In summary, these results show that uncertainty shocks have substantial consequences in emerging economies leading to disruptions in both real and financial sectors. Moreover we estimate a negative co-movement in GDP and CPI; this poses additional constraints to the monetary authorities which cannot easily mitigate this type of shock.

4.3 Heterogeneity across countries

Our empirical framework is well suited to compute country specific results as well. In particular, the 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. Given that the empirical literature is mainly concerned with the recessionary effects of uncertainty shocks, in this section we limit our attention to the response of GDP to such shocks. Country results regarding the remaining variables are provided in the Appendix. Figures (5) and (6) plot the GDP impulse responses (scaled across countries to increase the domestic uncertainty by 1 unit) and respectively the GDP variance decomposition estimates for each country in the sample. Results show that the model detects a certain degree of heterogeneity which translates into different scale

[14] An analogous result is reported in Mumtaz and Theodoridis, 2015 who show that uncertainty shocks originating in US have similar effects in both US and UK

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

Horizon	Uncertainty	GDP	CPI	R	REER	Financial index
4 Q	0.90	0.02	0.03	0.02	0 .03	0.24
	(0.87,0.92)	(0.01,0.05)	(0.01,0.08)	(0.01,0.06)	(0.01,0.1)	(0.17,0.31)
8 Q	0.81	0.08	0.03	0.02	0 .03	0.26
	(0.76,0.84)	(0.05,0.13)	(0.01,0.08)	(0.01,0.06)	(0.01,0.1)	(0.20,0.33)
12 Q	0.73	0.12	0.05	0.02	0 .03	0.26
	(0.68,0.78)	(0.07,0.18)	(0.02,0.11)	(0.01,0.06)	(0.01,0.1)	(0.20,0.33)
20 Q	0.68	0.15	0.05	0.03	0 .03	0.25
	(0.61,0.72)	(0.10,0.21)	(0.01,0.10)	(0.02,0.07)	(0.01,0.09)	(0.19,0.31)

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

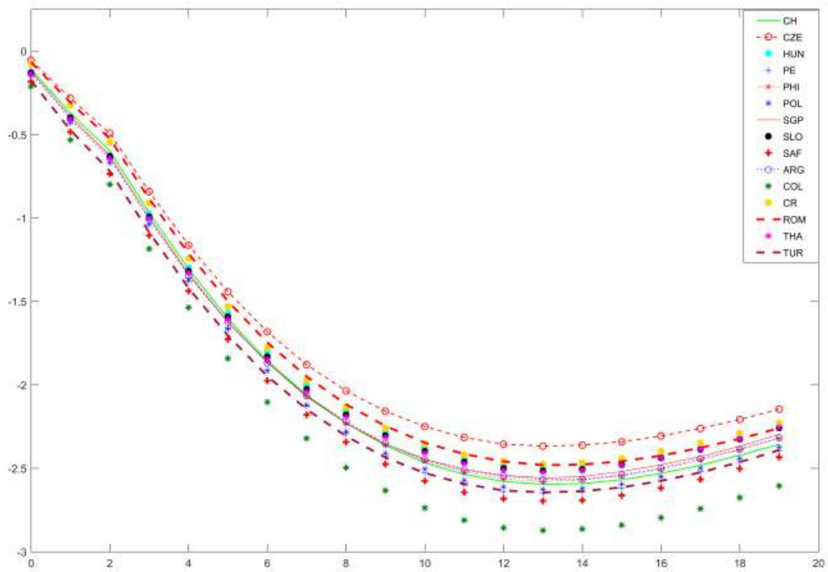
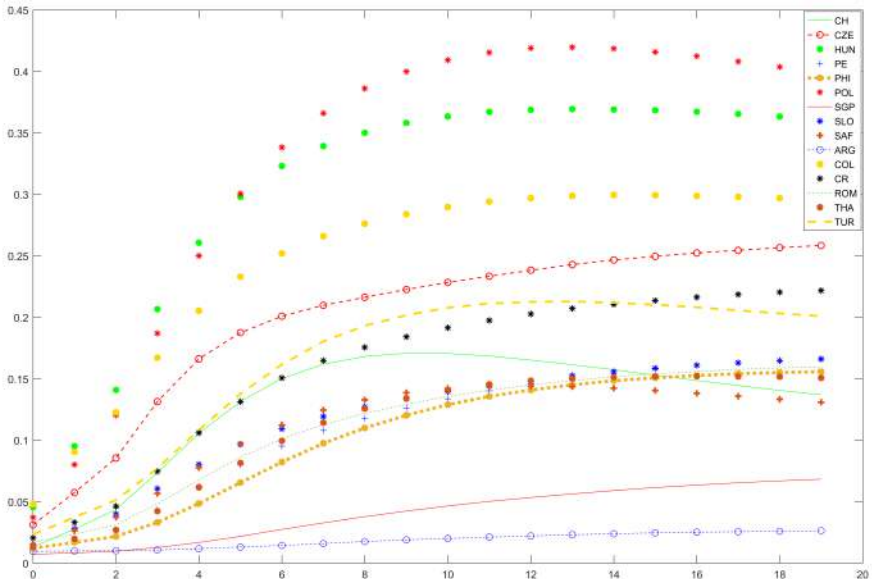


Figure 6: GDP variance decomposition. Posterior median estimate for each country.



of responses to shocks. Their shapes however are similar and close to those of the mean model responses, a finding in line with Jarocinski (2010). In terms of impulse responses, the most recessionary effects are experienced by Colombia, followed by South Africa, Poland and Turkey while the less affected economies appear to be Czech Republic, Romania and Croatia. If instead we turn our attention to the variance decomposition, our estimates suggest that uncertainty shocks explain a higher share of the GDP variability for countries such as Poland, Hungary and Colombia while in Argentina and Singapore uncertainty shocks explain a negligible share of GDP fluctuations.

We further explore the heterogeneity in the effects of uncertainty shocks on GDP in a regression analysis. Following Carriere-Swallow and Cespedes (2013) and Clayes and Vasicek (2017) we consider regressors such as: the degree of dollarization reported by Levy Yeyati (2006) to measure the importance of the currency denominated debt, domestic credit to private sector as a proxy for financial depth, GDP per capita, trade (% of GDP) as a proxy for country openness and the Herfindahl-Hirschman index of product concentration which is also related to the degree of product diversification. If the theory predicts that the degree of openness has ambiguous effects on the capacity of a country to absorb shocks, more diversified economies should be more resilient to adverse fluctuations. We also include manufacturing value added (% of GDP) as a proxy for integration in the global value chains and labor market and goods market efficiency indexes to account for economic flexibility. The sub-set of preferred regressors is chosen via the leaps-and-bounds algorithm of Furnival and Wilson (1974). The ranking of the relevant regressors is further confirmed by the spike and slab variable selection algorithm as per Koop (2016) (see Table S1 in the appendix).

IRFs are scaled across countries and represent the response of economy to a shock

Table 3: Country characteristics and uncertainty shocks. The dependent variables are GDP cumulative IRFs and Variance decomposition, 12 quarters ahead.

	(1)	(2)
VARIABLES	GDP IRF	GDP vardec
GDPpc (log)	1.571	-0.203
	(0.540)	(0.0451)
Dollarization	2.341	-0.281
	(1.335)	(0.0619)
Manufacturing	0.137	-0.0296
	(0.0550)	(0.00386)
Trade		0.00260
		(0.000397)
Credit to private sector		-0.00268
		(0.000550)
Goods mkt efficiency	-1.271	0.211
	(0.527)	(0.0341)
Product concentration		-0.0260
		(0.0171)
Product diversification		-0.0134
		(0.00744)
Labor mkt efficciency	1.877	
	(0.568)	
Constant	-38.94	2.004
	(6.047)	(0.482)
Observations	14	14
R-squared	0.751	0.953

Robust standard errors in parentheses

that increases the uncertainty measure by 1 unit; GDP cumulative impulse responses and variance decomposition, twelve quarters ahead, are regressed against the sub set of chosen regressors.

Table 3 reports the results from the preferred specification for the two dependent variables, the GDP IRFs (first column) and variance decomposition (second column) corresponding to the uncertainty shock. In line with previous studies our estimates of GDP impulse responses show 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 while the efficiency in the goods market seems to enhance the recessionary effects of such shocks. One way of explaining this less intuitive result is that countries with better quality of institutions and business regulations attract and rely more on investment (domestic and foreign) which according to some studies, is one of the most affected GDP component following an uncertainty shock.[15] A similar message is delivered also by the variance decomposition specification.[16] In addition, from the second regression we learn that countries with more developed financial sectors and with a higher degree of dollarisation are less sensitive to uncertainty shocks, while a greater trade share corresponds to a bigger vulnerability to such shocks.

However possible bias in the findings of the regression analysis might arise due to the small sample size; therefore these results should be interpreted with caution.

4.4 Counterfactual analysis

Up to know 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. We conclude this section with a counterfactual exercise aiming to provide a model-based narrative on the historical role played by uncertainty shocks in shaping the GDP growth fluctuations. The question of interest is how different would have been the GDP growth in the absence of uncertainty shocks?[17]

The analysis involves three steps. First, we reconstruct the historical series of structural shocks. This step involves solving numerically for the entire matrix R, which links the reduced form residuals to the structural shocks; we impose a recursive structure for the remaining shocks[18]. We then replace the sequence of structural uncertainty shocks with zero and we recompute the reduced form residuals accordingly. Finally we simulate the

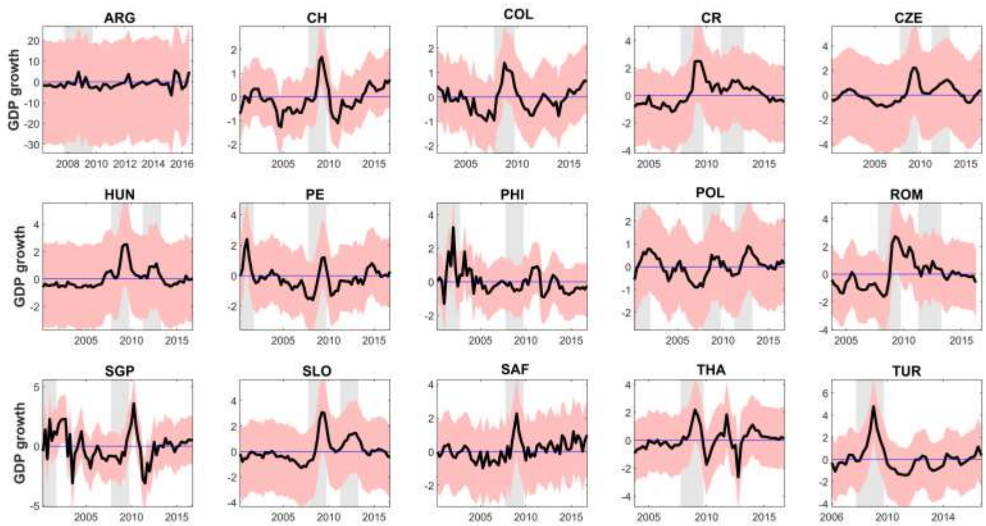
[15]Carriere-Swallow and Cespedes, 2013 show that following an uncertainty shock in EMEs the drop in investment is around -4% while the decrease in consumption is around -1.2%. Bloom et al. 2018 report a negative reaction in investment and consumption of - 30 and respectively -2% following an uncertainty shock combined with a first moment productivity shock .

[16]The same regressors are significant in both specifications with opposite sign.

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

[18]In order to identify the 6x6 R matrix we need to impose ten additional restrictions to the five restrictions obtained using the instrumental variable approach. We impose a recursive structure for the remaining shocks in a way that we do not restrict the contemporaneous response of uncertainty to the other shocks, as if uncertainty had been ordered last in the model.

Figure 7: 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 global financial crisis, the Euro debt crisis for European countries and some selected recessionary episodes. 68 HPDI bands are reported.



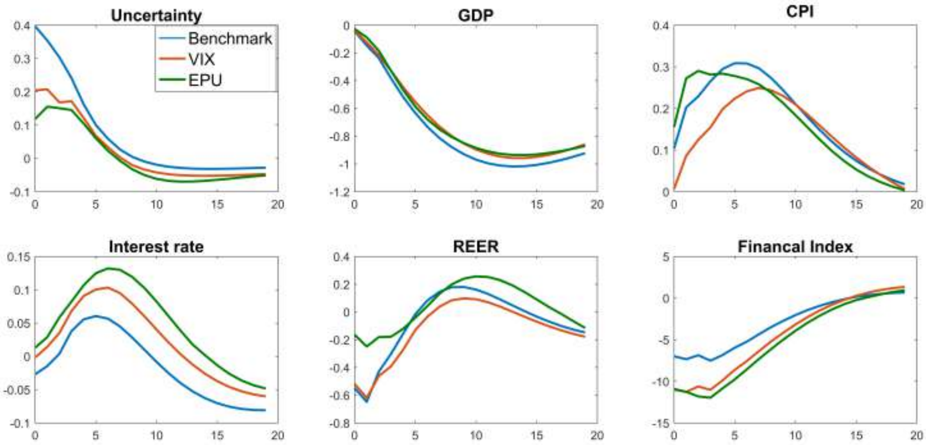
evolution of GDP growth under this new sequence of residuals.[19]

Figure 7 illustrates the results. For each country we report the difference in the GDP growth under the counterfactual assumption of no uncertainty shocks and the actual data. Our estimates suggest that without uncertainty shocks the GDP growth would have been more than 2% higher during the global financial crisis for almost all countries in the sample. Moreover, it is interesting to notice that according to our model, all European countries in the sample experienced recessionary effects during the European debt crisis which can be attributed to uncertainty shocks. Our results also reveal that in the early 2000s when internet bubble burst, uncertainty shocks had particularly detrimental effects in countries with pre-existing vulnerabilities, such as Singapore and Philippines (which were recovering from the Asian crisis) and Peru (which experienced a credit crunch in 1999). Finally, we 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; our results provide evidence on the relevance of the uncertainty shocks in emerging markets from an economic point of view, strengthening the usefulness of our findings.

[19]Since we do not change the values of the parameters, this exercise is not subject to the Lucas' critique as per Benati, 2010

Figure 8: Posterior median impulse responses across different instrument specifications. Average country results.



5 Sensitivity analysis

We perform an additional sensitivity analysis to check the robustness of the results. We provide a summary description in this section; detailed results are available in the appendix.

First we test the sensitivity of our findings to the proxy employed in the VAR exercise. To this end, we re-estimate the model using two alternative proxies, specifically the residuals from an AR(2) and an AR(1) regressions of VIX and respectively EPU.[20] Figure (7) shows the posterior median of the impulse responses across the three specifications of the instrument. We notice that results are fairly stable.

Additionally, we re-estimate the benchmark model with the following modifications: no linear trend; 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 results are robust to these checks as well.

6 Conclusion

The aim of this paper is to examine the effects of uncertainty shocks in emerging economies. To this end we develop a novel Bayesian algorithm to estimate a model that combines a panel VAR with random coefficients with a proxy SVAR approach. This model deals in an efficient way with the lack of data availability for emerging markets while preserving the advantages of a proxy SVAR approach.

In the empirical exercise we limit our attention to fifteen small EMEs. We construct

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

global and domestic uncertainty measures using the approach proposed by JLN. To identify the uncertainty shock we use innovations in global uncertainty as a proxy for the domestic uncertainty shock assuming that global uncertainty fluctuations are exogenous to business cycle developments occurring in a particular country in the sample.

We show that positive uncertainty shocks generate a persistent drop in real GDP and a severe decline in stock prices. The same shock causes a negative co-movement between real GDP and CPI while the monetary authority reaction is ambiguous.

We then turn to the country specific results and find evidence of cross country heterogeneity in responses to uncertainty shocks. We examine further this variability in a regression analysis. We notice the presence of statistically significant correlation between heterogeneity in the magnitude of GDP impulse responses to uncertainty shocks and selected cross country characteristics. In particular, countries that are wealthier, with higher share of manufacturing and with more efficient labor markets experience less recessionary effects following uncertainty shocks; countries with more efficient goods market and with a higher trade share are more affected by such shocks. Finally, a counterfactual exercise reveals that uncertainty shocks were an important driver of the GDP growth fluctuations in EMEs.

References

Alessandri, P. and Mumtaz, H., 2018. Financial regimes and uncertainty shocks. Journal of Monetary Economics.

Angelini, G., Bacchiocchi, E., Caggiano, G. and Fanelli, L., 2018. Uncertainty across volatility regimes.

Bachmann, R. and Moscarini, G., 2011, July. Business cycles and endogenous uncertainty. In 2011 Meeting Papers (Vol. 36). Society for Economic Dynamics.

Bachmann, R., Elstner, S. and Sims, E.R., 2013. Uncertainty and economic activity: Evidence from business survey data. American Economic Journal: Macroeconomics, 5(2), pp.217-49.

Baker, S.R., Bloom, N. and Davis, S.J., 2016. Measuring economic policy uncertainty. The Quarterly Journal of Economics, 131(4), pp.1593-1636.

Basu, S. and Bundick, B., 2017. Uncertainty shocks in a model of effective demand. Econometrica, 85(3), pp.937-958.

Bhattarai S., Chatterjee, A. and Park, Y.W, 2016. Global spillover effects of US uncertainty. Working paper.

Bloom, N., 2009. The impact of uncertainty shocks. econometrica, 77(3), pp.623-685.

Bloom, N., 2014. Fluctuations in uncertainty. Journal of Economic Perspectives, 28(2), pp.153-76.

Bloom, N., Floetotto, M., Jaimovich, N., Saporta-Eksten, I. and Terry, S.J., 2018. Really uncertain business cycles. Econometrica, 86(3), pp.1031-1065.

Bonfiglioli, A. and Gancia, G.A., 2015. Economic uncertainty and structural reforms.

Caggiano, G., Castelnuovo, E. and Groshenny, N., 2014. Uncertainty shocks and unemployment dynamics in US recessions. Journal of Monetary Economics, 67, pp.78-92.

Caggiano, G., Castelnuovo, E. and Pellegrino, G., 2017. Estimating the real effects of uncertainty shocks at the zero lower bound. European Economic Review, 100, pp.257-272.

Caldara, D., Fuentes-Albero, C., Gilchrist, S. and Zakrajšek, E., 2016. The macroeconomic impact of financial and uncertainty shocks. European Economic Review, 88, pp.185-207.

Caldara, D. and Herbst, E., 2016. Monetary policy, real activity, and credit spreads: Evidence from bayesian proxy svars. American Economic Journal: Macroeconomics (forthcoming).

Caldara, D. and Iacoviello, M., 2018. Measuring geopolitical risk.

Canova, F. and Ciccarelli, M., 2013. Panel Vector Autoregressive Models: A Survey☆ The views expressed in this article are those of the authors and do not necessarily reflect those of the ECB or the Eurosystem. In VAR Models in Macroeconomics–New Developments and Applications: Essays in Honor of Christopher A. Sims (pp. 205-246). Emerald Group Publishing Limited.

Carrière-Swallow, Y. and Céspedes, L.F., 2013. The impact of uncertainty shocks in emerging economies. Journal of International Economics, 90(2), pp.316-325.

Carriero, A., Mumtaz, H., Theodoridis, K. and Theophilopoulou, A., 2015. The impact of uncertainty shocks under measurement error: A proxy SVAR approach. Journal of Money, Credit and Banking, 47(6), pp.1223-1238.

Carriero, A., Clark, T.E. and Marcellino, M., 2017. Measuring uncertainty and its impact on the economy. Review of Economics and Statistics, (0).

Carreiro, A., Clark, T.E. and Marcellino, M.G., 2018. Endogenous Uncertainty.

Cesa-Bianchi, A., Pesaran, M.H. and Rebucci, A., 2014. Uncertainty and economic activity: A global perspective.

Dieppe, Alistair, Romain Legrand, and Björn Van Roye., 2017. "The BEAR toolbox."

Drautzburg, T., 2016. A narrative approach to a fiscal DSGE model.

Fernández-Villaverde, J., Guerrón-Quintana, P., Rubio-Ramírez, J.F. and Uribe, M., 2011. Risk matters: The real effects of volatility shocks. American Economic Review, 101(6), pp.2530-61.

Gelman, A., Carlin, J.B., Stern, H.S. and Rubin, D.B., 2003. Bayesian Data Analysis, 2nd edn., ed. C. Chatfield, M. Tanner, & J. Zidek, Texts in Statistical Science.

Gelman, A., 2006. Prior distributions for variance parameters in hierarchical models (comment on article by Browne and Draper). Bayesian analysis, 1(3), pp.515-534.

Gertler, M., & Karadi, P., 2015. Monetary policy surprises, credit costs, and economic activity. American Economic Journal: Macroeconomics, 7(1), 44-76.

Ilut, C.L. and Saijo, H., 2016. Learning, confidence, and business cycles (No. w22958). National Bureau of Economic Research.

Jarociński, M., 2010. Responses to monetary policy shocks in the east and the west of Europe: a comparison. Journal of Applied Econometrics, 25(5), pp.833-868.

Jurado, K., Ludvigson, S.C. and Ng, S., 2015. Measuring uncertainty. American Economic Review, 105(3), pp.1177-1216.

Koop, G., 2016. Bayesian Methods for Fat Data.

Leduc, S. and Liu, Z., 2016. Uncertainty shocks are aggregate demand shocks. Journal of Monetary Economics, 82, pp.20-35.

Ludvigson, S.C., Ma, S. and Ng, S., 2015. Uncertainty and business cycles: exogenous impulse or endogenous response? (No. w21803). National Bureau of Economic Research.

Meinen, P. and Roehe, O., 2017. On measuring uncertainty and its impact on investment: cross-country evidence from the euro area. European Economic Review, 92, pp.161-179.

Mertens, K., & Ravn, M. O. 2013. The dynamic effects of personal and corporate income tax changes in the United States. American Economic Review, 103, pp. 1212-47.

Mumtaz, H. and Zanetti, F., 2013. The impact of the volatility of monetary policy shocks. Journal of Money, Credit and Banking, 45(4), pp.535-558.

Mumtaz, H. and Theodoridis, K., 2015. The international transmission of volatility shocks: An empirical analysis. Journal of the European Economic Association, 13(3), pp.512-533.

Mumtaz, H. and Theodoridis, K., 2017. Common and country specific economic uncertainty. Journal of International Economics, 105, pp.205-216.

Mumtaz, H., Pinter, G. and Theodoridis, K., 2018. WHAT DO VARS TELL US ABOUT THE IMPACT OF A CREDIT SUPPLY SHOCK?. International Economic Review, 59(2), pp.625-646.

Mumtaz, H., 2018. Does uncertainty affect real activity? Evidence from state-level data. Economics Letters, 167, pp.127-130.

Mumtaz, H. and Musso, A., 2018. The evolving impact of global, region-specific and country-specific uncertainty.

Nakamura, E. and Steinsson, J., 2014. Fiscal stimulus in a monetary union: Evidence from US regions. American Economic Review, 104(3), pp.753-92.

Piffer, M. and Podstawski, M., 2016. Identifying uncertainty shocks using the price of gold. The Economic Journal.

Redl, C., 2018. Uncertainty matters: evidence from close elections.

Rogers, J.H., Scotti, C. and Wright, J.H., 2016. Unconventional monetary policy and international risk premia. Journal of Money, Credit and Banking.

Rossi, B. and Sekhposyan, T., 2015. Macroeconomic uncertainty indices based on nowcast and forecast error distributions. American Economic Review, 105(5), pp.650-55.

Scotti, C., 2016. Surprise and uncertainty indexes: Real-time aggregation of real-activity macro-surprises. Journal of Monetary Economics, 82, pp.1-19.

Spiegelhalter, D.J., Best, N.G., Carlin, B.P. and Van Der Linde, A., 2002. Bayesian measures of model complexity and fit. Journal of the Royal Statistical Society: Series B (Statistical Methodology), 64(4), pp.583-639.

Stock, J.H. and Watson, M.W., 2012. Disentangling the Channels of the 2007-2009 Recession (No. w18094). National Bureau of Economic Research.