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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). We construct a global uncertainty indicator as well as country uncertainty measures for fifteen relatively small emerging economies. We adopt an instrumental variable approach to identify exogenous uncertainty shocks in the EMEs. To deal with the data limitations specific to emerging countries, we develop a new Bayesian algorithm to estimate a proxy panel structural vector autoregressive (SVAR) model. We find that uncertainty shocks in EMEs cause severe falls in GDP and stock price indexes, generate inflation, depreciate the currency and are not followed by a subsequent overshoot in activity. Estimation implies considerable 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.

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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 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 [2016]; 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 et al. [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 analyses aimed at investigating the role of uncertainty for business cycle. Most of the previous studies identify uncertainty shocks using structural VARs with recursive identification (see, among others, Bloom [2009]; Bachmann et al. [2013];Carrière-Swallow and Céspedes [2013];Caggiano et al. [2014]; Caggiano et al. [2017]; Meinen and Röhe [2017]). However, this approach has been deemed inadequate (see Ludvigson et al. [2015]) for two main reasons. First, when timing restrictions are imposed, 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 reverse causality 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 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. [2015] 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, Fernández-Villaverde et al. [2011], Carriero et al. [2018a], Clark et al. [2018] and Alessandri and Mumtaz [2019] 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] Nevertheless, the very few attempts made in this direction, such as Bhattarai et al. [2019] and Carrière-Swallow and Céspedes [2013], show that uncertainty shocks have large and detrimental macroeconomic effects in emerging countries.

This paper examines the impact of uncertainty shocks in EMEs while accounting for the

[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.

(potential) contemporaneous co-movement between uncertainty and the real activity through an instrumental variable approach. We develop a novel Bayesian framework that combines the panel VAR with hierarchical structure à la Jarociński [2010], with the methodology proposed by Caldara and Herbst [2019] and Rogers et al. [2018] for the Bayesian estimation of SVAR models identified with external instruments[2]. The model can be labeled as a panel proxy VAR with random coefficients and offers three key advantages[3]. First, the model exploits the cross section dimension of the data making a more efficient use of the limited data specific to emerging markets. Second, the proxy extension accommodates the use of an instrumental variable approach for the shock identification, which departs from the controversial timing restrictions embedded in the recursive identification. Finally, the hierarchical structure of the model allows for country specific results. The cross section heterogeneity is further examined in a regression analysis in which we show that part of the differences (across countries) in the responses to uncertainty shocks can be linked to country specific 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 the 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. In addition, 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 use a global to local approach for identification, in the spirit of Nakamura and Steinsson [2014] who exploit variation in military buildups at US *country* level as an instrument for computing *regional* spending multipliers. We extend their approach to a global framework, using innovations in *global* uncertainty as a proxy for uncertainty shocks at

[2]We have recently become aware of Bahaj [2019] who proposes an alternative algorithm to estimate a proxy VAR with a cross section dimension. The two algorithms have been developed independently and are different.

[3]The "proxy VAR", introduced by Stock and Watson [2012] and Mertens and Ravn [2013], is a VAR model that uses external instruments to proxy for specific structural shocks. 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 [2019], Rogers et al. [2018], Mumtaz [2018].

country level. The shock we identify can be interpreted as a movement in the domestic uncertainty index that is exogenous to domestic economic conditions[4]. It might be surprising that global uncertainty could act as an instrument given the possibility that changes in global uncertainty might spillover into domestic economic conditions through channels other than the domestic uncertainty. However, we control for other global shocks, and we find that the instrument has virtually no contemporaneous correlation with domestic GDP and inflation, while it is correlated with domestic uncertainty. Thus, it appears to satisfy the relevance and exclusion restrictions necessary for a valid instrument. Specifically, the validity of the instrument requires that fluctuations in global uncertainty are correlated with the domestic uncertainty shock (the relevance condition) and are uncorrelated with any other shock in the model (the exogeneity). While the relevance condition is testable, the exogeneity condition is based on two identifying assumptions. The first assumption builds on a small open economy argument and it states that macroeconomic developments in the EMEs considered are likely not to cause global uncertainty[5]. To preclude that the direction of causality could run from EMEs to the instrument, big emerging economies and major oil exporters are deliberately excluded from the sample. The second assumption necessary to ensure the exogeneity of the instrument is the exclusion restriction. Such condition requires that, *conditional on the observables*, the only channel through which global uncertainty innovations affect domestic economies is via their impact on the country uncertainty index. The exclusion restriction fails if, for example, the instrument correlates with other contemporaneous shocks which also affect the EMEs, say global demand and global supply, and such shocks are not controlled for. We control for these potential global channels by including in the country VAR three global variables that enter the model contemporaneously. We then compute the regression coefficients of the GDP residuals on the instrument, and we show that they are close to zero and non statistically significant for all the countries in the sample; this means that the uncertainty shock has zero effect on impact on the GDP, while bringing evidence in favor of

[4]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.

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

the exclusion restriction condition[6]. Moreover, we show that our results hold if we include lags of the innovations in global uncertainty as control variables. Thus, we rule out the concern that global uncertainty might be an omitted variable in the model[7].

Our identification approach is appealing for two main reasons. First, the proxy SVAR approach accounts for the potential measurement error in the instrument[8]; 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 exogenous 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 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

[6] See section 4.1 for a detailed explanation of the identification strategy. Table S2 in the Appendix reports the regression coefficients of GDP residuals on the instrument.

[7] If the identification strategy in a VAR model refers to the contemporaneous relationship between the variables, the omission of lags of relevant variables might lead to an informational deficiency bias as per Forni and Gambetti [2014]

[8] 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 [2019] for a detailed comparison between hybrid and proxy SVAR approaches.

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 contributions to the literature. First, we compute novel measures of domestic uncertainty for the fifteen EMEs in the sample and we investigate the effects of domestic uncertainty shocks in emerging economies. Hence we differ from Carrière-Swallow and Céspedes [2013] and Bhattarai et al. [2019] who focus on the effects of global and respectively US uncertainty shocks in EMEs in a recursive framework. Second, we propose an instrumental variable approach for the identification of domestic uncertainty shocks and we show that the validity of our instrument relies on fairly standard assumptions. Third, we develop a novel Bayesian algorithm to estimate an extended version of a panel VAR with random coefficients, that accommodates the use of proxies for the shock identification.

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 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, 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 we define the following proxy SVAR:

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

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

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

Y_{tc} is a vector of N endogenous variables for country c, X_{tc} is a $N \times (N \times L + 1)$ vector of regressors specific to country c, while Z_t is a vector 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) 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 $N \times (N \times L + 1 + W)$ and $G_{tc} = \{X_{tc}, Z_t\}$ as the vector of regressors with dimension $N \times (N \times L + 1 + W)$.

The reduced form shocks can be related to the underlying structural shocks as per equation 2; for convenience we call ε_{t1} the vector structural shock of interest and ε_{t2} the vector of the remaining shocks. The goal is to identify one column of $N \times N$ matrix R for country c, corresponding to a the structural shock[9].

In a proxy SVAR framework the standard VAR model described by equations 1 and 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. [2018] we define the measurement equation as in equation 3.

$\eta_{ict} \sim$ N (0,ω^2) are the residuals of the measurement equation, u_{tic} is the i^{th} residual and M is

[9]The order of the column is arbitrary in a proxy SVAR framework, but for simplicity we normalize it as the first.

the instrument for the structural shock ε_{t1}.[10]

From the instrument validity assumptions which require that :

$$E(\varepsilon_{t1}M_t) = \alpha \text{ (Relevance condition)}$$

$$E(\varepsilon_{t2}M_t) = 0 \text{ (Exogeneity condition)}$$

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

$$R_{1c} = E(u_{2tc}M_t)/E(u_{t1c}M_t) \tag{4}$$

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 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 Φ_c and γ_{ic} coefficients as follows:

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

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

where 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 updated during the sampling procedure. The crucial parameters in

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

this setting are τ and λ who control the degree of heterogeneity in the model. As τ and $\lambda \rightarrow \infty$ 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 $\bar{\Phi}$, $\bar{\gamma}$, 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 Φ_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 $\bar{\Phi}$ and $\bar{\gamma}$ to obtain the estimates. Moreover, $\bar{\Phi}$ 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

2.2.1 Priors

Following Jarociński [2010] and Dieppe et al. [2016] 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 et al. [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.

2.2.2 Algorithm

We build on Caldara and Herbst [2019] and Rogers et al. [2018] 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):

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

and combining the priors with 7 we re-write the posterior as in Rogers et al. (2016):

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

where D contains both G and M.

We have non closed form conditional posteriors for 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 $P(\Phi_c^{new} \setminus \Theta)$ and $P(\Sigma_c^{new} \setminus \Theta, \Phi_c^{new})$ 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 a‘ la Jarociński [2010], while 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.

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. [2015] we define $y^C_{jt} \in Y^C_t = (y^C_{1t}, ... y^C_{NCt})$ be a variable in category C. Then its h-period ahead uncertainty, $U^C_{jt}(h)$ 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 the country specific series.[11]

A detailed list of the series used and data sources is available in the Appendix.

[11]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].

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.

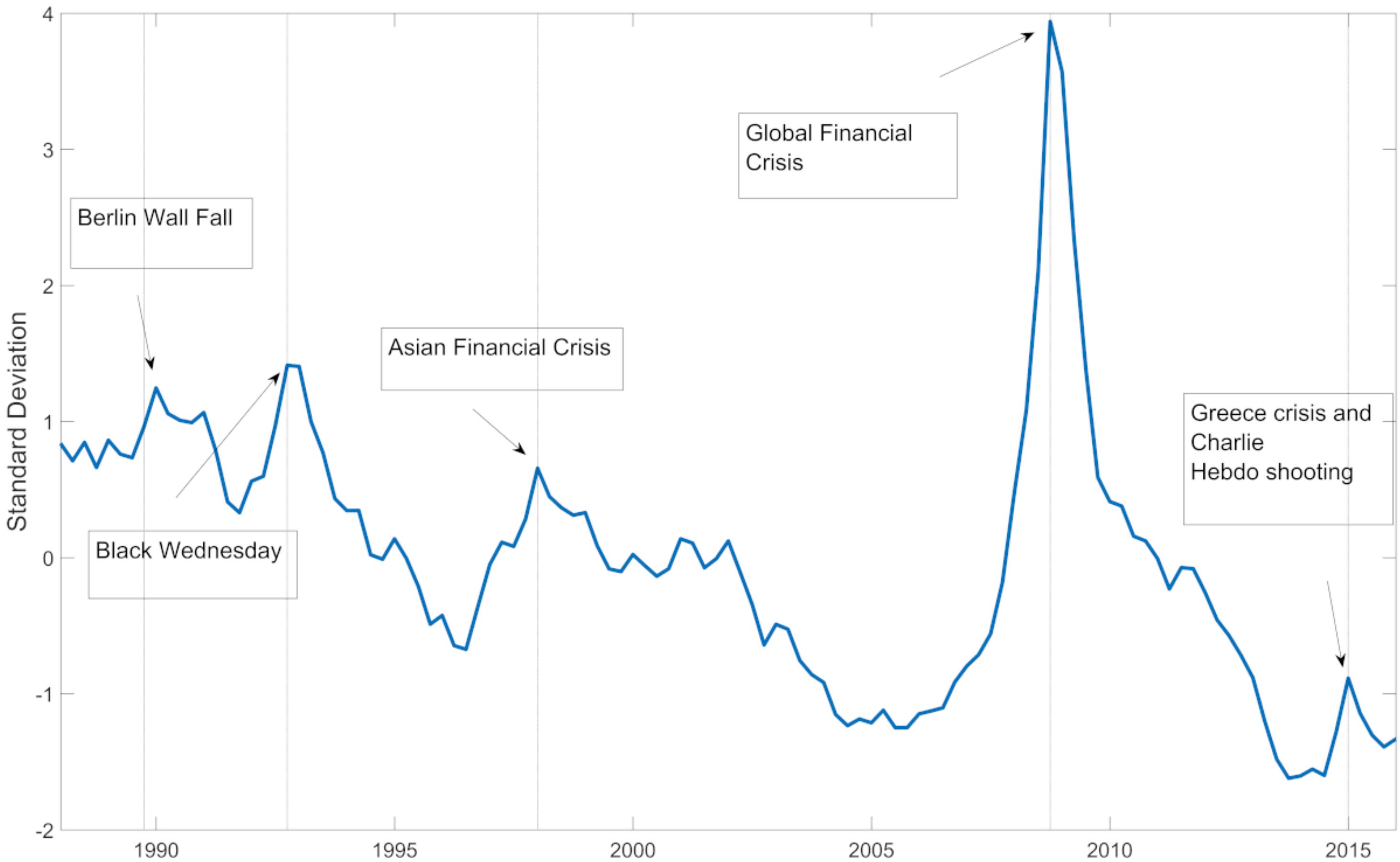
In Figure 2 we compare our global uncertainty index with alternative measures of global uncertainty such as the VIX, the measure proposed by Mumtaz and Theodoridis [2017] (hereafter M&T) which consists in the common standard deviation of the shocks to the world factors obtained from a dynamic factor 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[12].

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)

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

Figure 1: Global Uncertainty Measure



- 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)

Figure 2: Alternative measures of Global Uncertainty

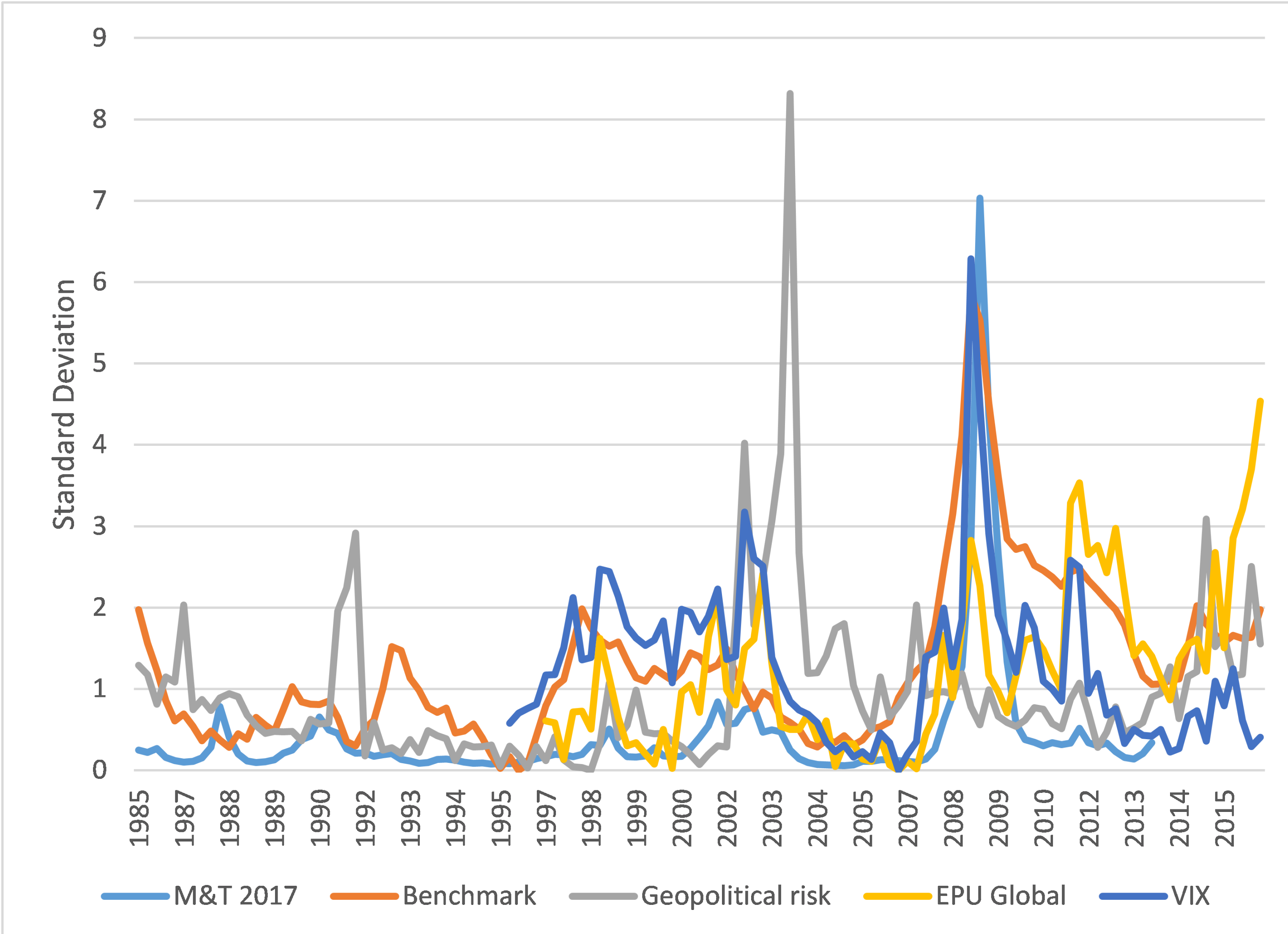
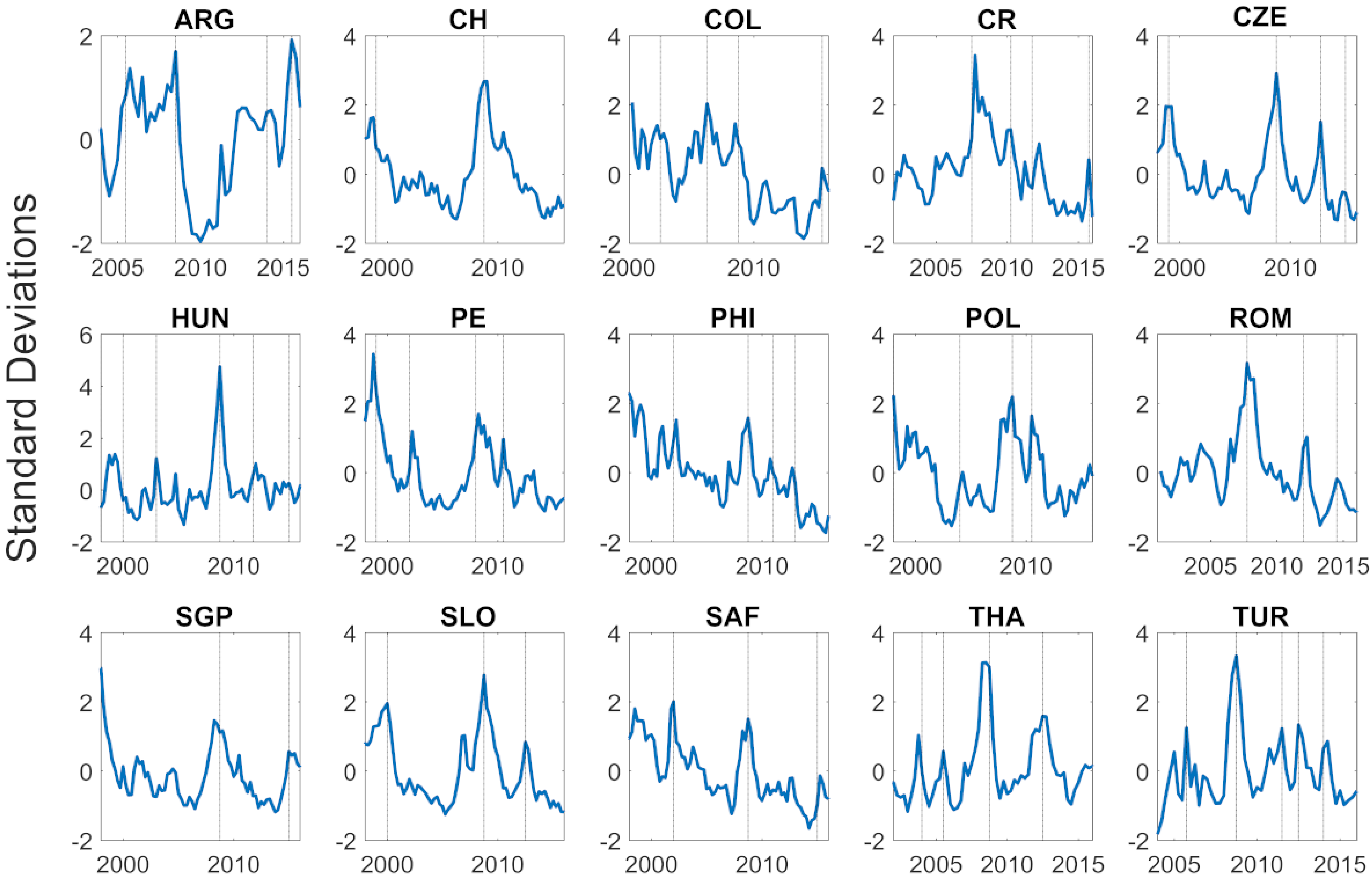


Figure 3: Domestic Uncertainty



4 Results

4.1 The global to local approach for identification

Following Stock and Watson [2012] we use the residuals of an AR(2) regression of the global uncertainty index as a proxy for the domestic uncertainty shock.[13] The domestic uncertainty shock should be interpreted as a movement in the domestic uncertainty index that is exogenous to the other variables in the system. Such shock can have either a local origin (for example an earthquake) or a foreign origin (for example a global crisis).

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

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

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

4.1.1 Exogeneity of the instrument

The exogeneity of the instrument in a proxy SVAR framework requires that the proxy M_t, is uncorrelated with any structural shock in the model other than the shock of interest. Since this condition is not testable, it relies on the identifying assumptions. In our application, the first identifying assumption excludes the reverse causality between the domestic variables and the instrument. Specifically, the assumption states 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 validity of this assumption is reinforced by including in the sample only relatively small EMEs.

The second identifying assumption is the exclusion restriction condition. Such condition requires that, conditional on the observables, global uncertainty innovations affect business cycle in EMEs only through their impact on the domestic uncertainty. The exclusion restriction is violated if the

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

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 the global demand and supply shocks, which in turn affect EMEs and these shocks are not controlled for, then, the identification fails. To clean for such effects, we include in the system three exogenous variables that enter the model contemporaneously. In addition, we show that the regression coefficients of the GDP residuals on the instrument (reported in the Appendix) are close to zero and not significant for all the countries in the sample[14].

As a simple example of how the global to local approach for identification works, assume that the underlying model is a bi-variate VAR, while the contemporaneous link between forecast errors, shocks, exogenous foreign variables (shocks), and the instrument is defined as follows:

$$u_{1t} = r_{11}\varepsilon_{1t} + r_{12}\varepsilon_{2t} + r_{13}\varepsilon_{t\_other} \tag{10}$$

$$u_{2t} = r_{21}\varepsilon_{1t} + r_{22}\varepsilon_{2t} + r_{23}\varepsilon_{t\_other} \tag{11}$$

$$u_{1t} = \gamma_1 M_t + \eta_{1t} \tag{12}$$

$$u_{2t} = \gamma_2 M_t + \eta_{2t} \tag{13}$$

$$\varepsilon_{1t} = \delta_1 \varepsilon_{t\_local} + \delta_2 \varepsilon_{t\_global} \tag{14}$$

$$\varepsilon_{t\_global} = \lambda_1 \varepsilon_{2t} + \lambda_2 \varepsilon_{t-1\_global} + \lambda_3 \varepsilon_{t\_other} \tag{15}$$

where $u_t \sim \mathrm{N}(0,\Sigma)$ is the bi-variate vector of reduced form residuals. The reduced form shocks

[14]In the sensitivity analysis section we also check the robustness of our findings to the inclusion of lagged values of the instrument in the model. The results hold under this scenario too.

are related to the underlying structural shocks as per equations 10 and 11, while 12 - 13 are the measurement equations specific to the proxy SVAR framework. We call for convenience ε_{1t} the domestic uncertainty shock, ε_{2t} a business cycle shock while ε_{t_other} is an omitted variable from the system[15]. Equation 14 states that the domestic uncertainty shock can be caused by local or global events. We allow for the reverse causality between the instrument and the system through the term $\lambda_1\varepsilon_{2t}$ in 15 ; we also allow for potential failure of the exclusion restriction condition through the omitted variable ε_{t_other} which appears in equations 10, 11 and 15.

The identification strategy in a Proxy SVAR model is based on the assumptions that $E(M_t \mathrm{u}_{1t})= r_{11}\alpha$ and $E(M_t \mathrm{u}_{2t})= r_{21}\alpha$, where $\alpha = E(\varepsilon_{1t}M_t)$ captures the relevance of the instrument. Therefore, the identification fails in two cases: either if ε_{t_other} is an omitted variable correlated with the instrument (i.e. $r_{13} \neq 0$ and $r_{23} \neq 0$ and $\lambda_3 \neq 0$), or if $\lambda_1 \neq 0$ in which case we have reverse causality bias[16].

In our framework, the first identifying assumption, based on a small open economy argument, imposes that $\lambda_1 = 0 \implies E(M_t\varepsilon_{2t}) = 0$, and it excludes the reverse causality bias. On the other side, the exclusion restriction is verified if either $E(M_t\varepsilon_{t\_other})$=0 or if $r_{13} = r_{23} = 0$. This condition is ensured by the second identifying assumption which states that the instrument is not an omitted variable in the model [17].

If the estimate of γ_2 in 13 is equal to zero (as it is the case in our empirical application) and the first identifying assumption is valid (i.e $E(M_t\varepsilon_{2t}) = 0$) it follows that:

$$E(M_t u_{2t}) = r_{11}E(M_t\varepsilon_{1t}) + r_{23}E(M_t\varepsilon_{t\_other}) = 0 \tag{16}$$

Equation 16 is verified in two cases:

1. The two terms on the right hand side are both equal to zero, and therefore the instrument is

[15]Notice that if the model is well specified, $r_{13} = r_{23} = 0$

[16]Assuming that $\lambda_1 = 0$ there might still be a concern that the instrument causes both shocks ε_{1t} and ε_{2t} implying $E(M_t\varepsilon_{2t}) \neq 0$ but in that case the two shocks are correlated and cannot be interpreted as primitive shocks (see Ramey [2016]).

[17]This is a less stringent assumption than the informational sufficiency which requires that $r_{13} = r_{23} = 0$ and implies the validity of the exclusion restriction

valid. From a practical perspective, if the instrument is relevant, this coincides to assuming that the second variable does not react on impact to the uncertainty shock ($r_{11} = 0 \implies r_{23}E(M_t\varepsilon_{t\_other}) = 0$).

2. The two terms on the right hand side are perfect opposites in which case the instrument is not valid. This scenario is verified if the instrument affects the second variable through two different channels which perfectly offset each other. For example, if we assume that the global uncertainty increases the domestic uncertainty, which in turn decreases the local GDP, the second scenario requires first that there is an unobserved variable ε_{t_other} that is increasing/decreasing in the global uncertainty and it has expansionary/recessionary domestic effects; and second it requires also that such effects are of identical magnitude with the overall effect of the domestic uncertainty shock[18]. However, this scenario is hard to imagine in practice.

Summing up, given the validity of the small open economy argument, the identification strategy reduces to assuming that case 1 in equation 16 is more likely than case 2, which is a fairly reasonable assumption.

4.1.2 Relevance

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. [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.

Since performing a standard F test is not coherent with a Bayesian framework, we address the relevance of our instrument in two ways. We report the posterior median estimates of γ_{1c} and

[18] Expansionary/recessionary means positively/negatively correlated with the GDP

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[19]. 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, 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)[20] 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 can 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 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

[19]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.

[20]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. [2004]).

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 a 'supply type' uncertainty shock in line with the conclusions reached in Fernández-Villaverde et al. [2011], Mumtaz and Theodoridis [2015] and Bhattarai et al. [2019]. 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 (see for example Mumtaz and Theodoridis [2015]; Carriero et al. [2015]; Caldara et al. [2016]; Carriero et al.

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

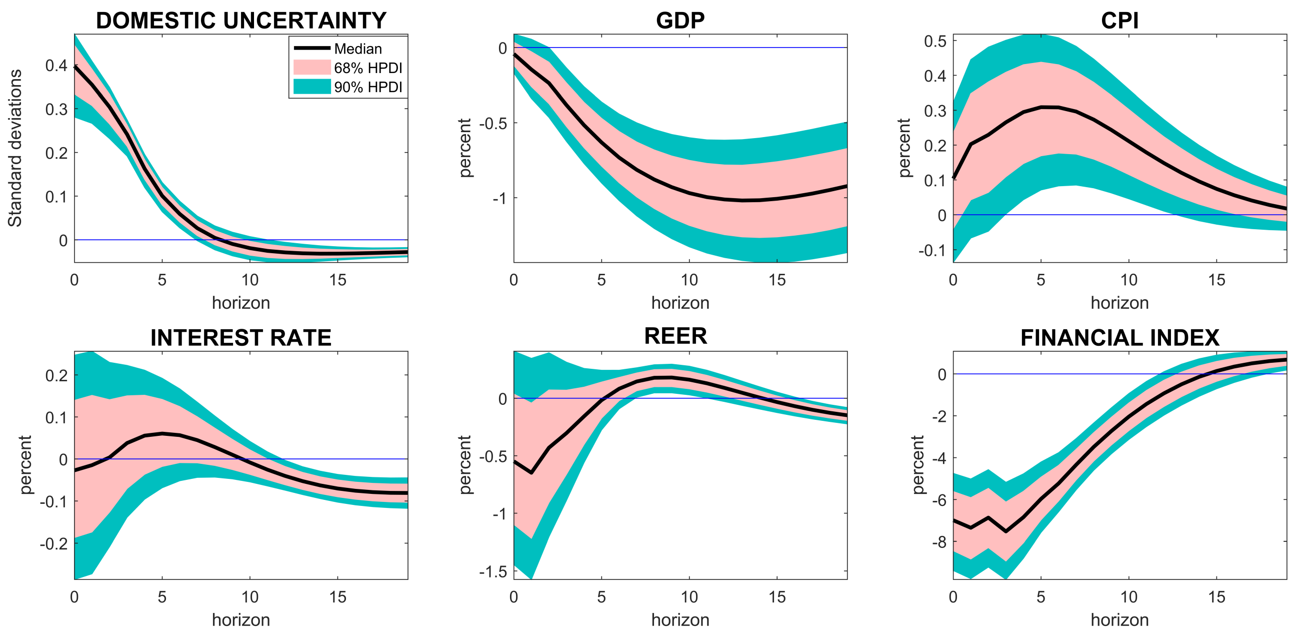


Table 2: Variance decomposition for the average country. Posterior median with 68 percent HPDI in parenthesis

Horizon	Uncertainty	GDP	CPI	R	REER	Financial index
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)

[2018b]); 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 Bhattarai et al. [2019] 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.[21]

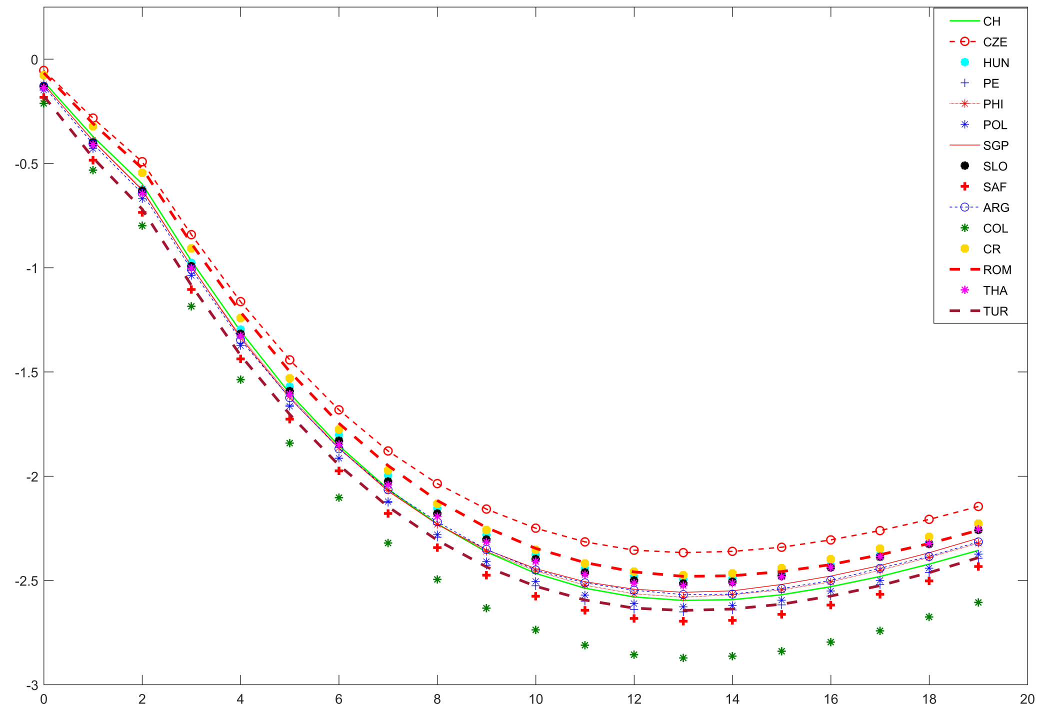
In summary, these results show that uncertainty shocks have substantial consequences in emerging economies leading to disruptions in both real and financial sectors. Moreover we estimate a negative co-movement in GDP and CPI; this poses additional constraints to the monetary authorities which cannot 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 of responses to shocks. Their shapes however are similar and close to those of the mean model responses, a finding in line with Jarociński [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

[21] 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

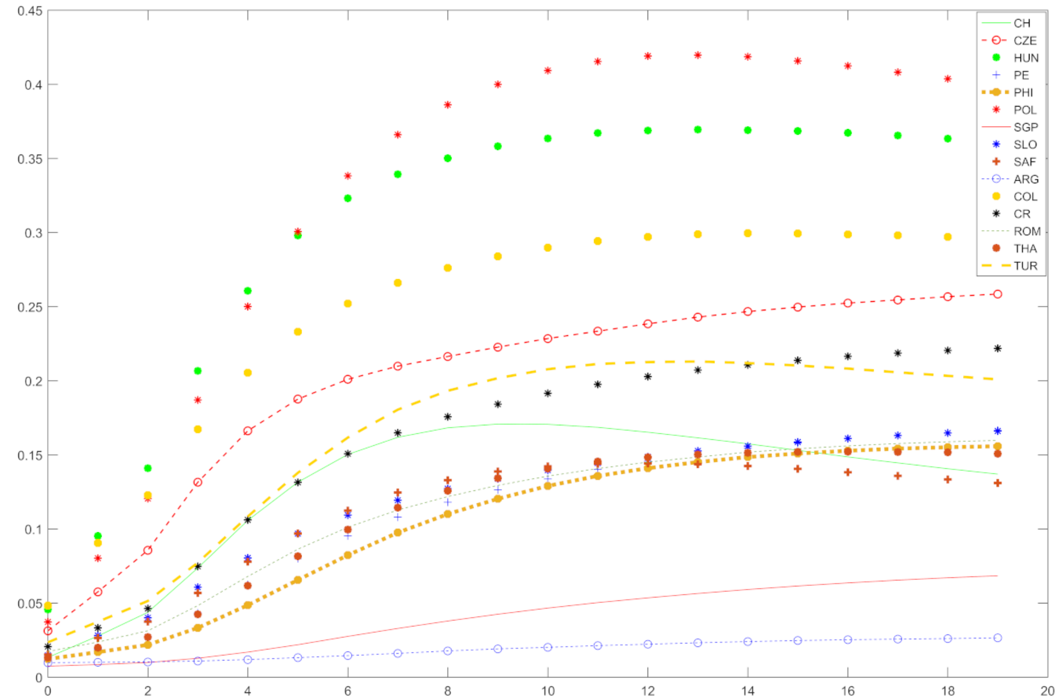
Figure 5: GDP impulse responses. Posterior median estimate for each country. The shock is scaled to increase the country uncertainty by 1 unit.



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 Carrière-Swallow and Céspedes [2013] and Claeys and Vašíček [2019] we consider regressors such as: the degree of dollarization reported by 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-

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



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 that increases the uncertainty measure by 1 unit. GDP cumulative impulse responses and variance decomposition, for each country, twelve quarters ahead, are regressed against the sub set of chosen regressors. The regressors enter the model as time averages over the period used in the VAR analysis.

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

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

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.[22] A similar message is delivered also by the variance decomposition specification. 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. 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?[23]

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[24]. We then replace the sequence of structural uncertainty shocks with zero and we recompute the reduced form residuals accordingly. Finally we simulate the evolution of GDP growth under this new sequence of residuals.[25]

[22]Carrière-Swallow and Céspedes [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 .

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

[24]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.

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

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.

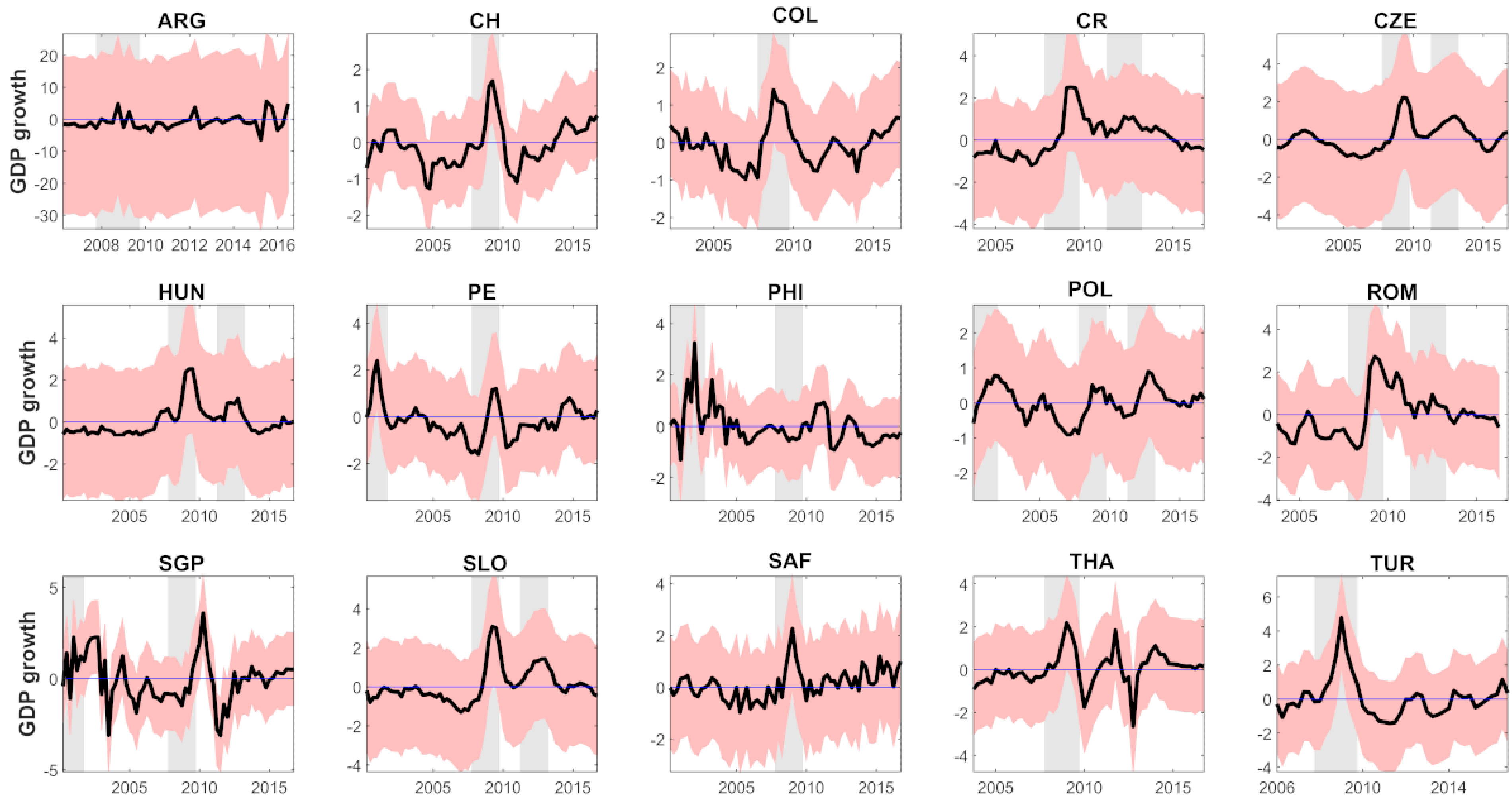


Figure 7 illustrates the results. For each country we report the difference in the GDP growth under the counterfactual assumption of no uncertainty shocks and the actual data. Our estimates suggest that without uncertainty shocks the GDP growth would have been more than 2% higher during the global financial 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.

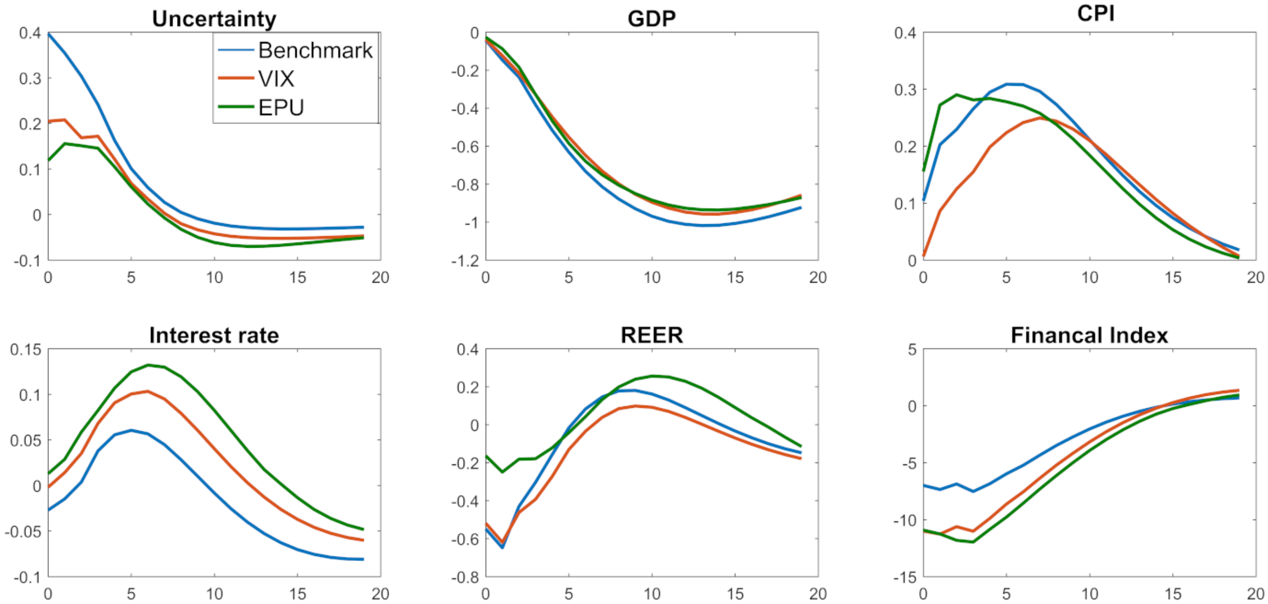
5 Sensitivity analysis

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.[26] Figure 8 shows the posterior median of the impulse responses across the three specifications of the instrument. We notice that results are fairly stable. That said, the benchmark instrument is still preferred since it is far more relevant than VIX and EPU.

[26]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.

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



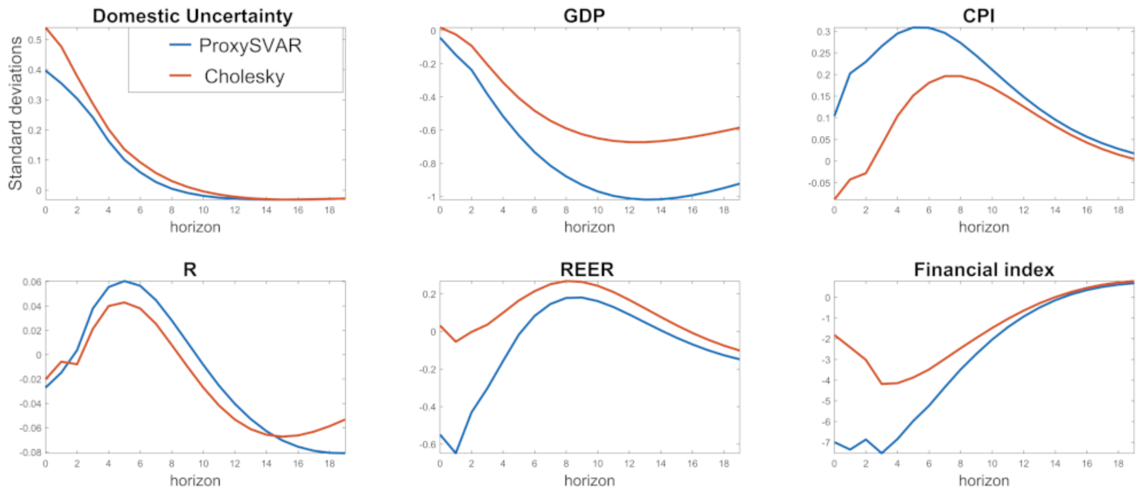
Next, we compare the benchmark IRFs for the average economy with the ones obtained using the recursive approach. The impulse responses reported in Figure 9 show that failing to control for the contemporaneous endogeneity between the uncertainty and the domestic conditions, leads to results of a substantial lower magnitude.

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 inclusion of lags of the instrument as control variables in the model. 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

Figure 9: Comparison between impulse responces computed with the proxy vs cholesky identification



approach.

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

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