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ORIGINAL ARTICLE

On the Exchange Rates Volatility and Economic Policy Uncertainty Nexus: A Panel VAR Approach for Emerging Markets

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Abstract

We examine the Economic Policy Uncertainty (EPU) transmission over the Exchange Rate Volatility (ERV) for 8 Emerging Market Economies (EME) using the recent panel VAR methodology of Abrigo and Love (Stata Journal 16:778–804, 2016). The econometric investigation reveals that: (a) both domestic and US-EPU shocks exert positive effects on the ERV, (b) the contribution of the US-EPU to the ERV fluctuations overcomes the own EPU's share, (c) the ERV acts as a possible transmission channel of the US-EPU to the domestic economic activity, (d) the domestic EPU increases in response to a higher US-EPU and vice versa and (e) the latter is surprisingly and markedly sensitive to EME macroeconomic conditions. Our findings are robust to different sensitivity analyses, provide novel insights into EPU international spillovers, and have interesting policy implications for EME decisions makers and investors.

Keywords Emerging market economies · Economic policy uncertainty · Exchange rates volatility · Panel VAR

JEL Classification G15 · E44 · C22

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Introduction

The predictive power of fundamentals on the exchange rate fluctuations remains one of the most discussed puzzles in international economics. While their long-run effects on currency movements are confirmed (Beckmann and Czudaj 2017), understanding their short-run impacts have much less empirical success (Chen and Chou 2015).[1] Nonetheless, the short-run exchange rate dynamics are particularly affected by transitory shocks including the economic policy uncertainty (EPU hereafter) (Bartsch 2019). At a general level, the applied literature provides evidence in support of EPU's harmful effects on economic activity (Baker et al. 2016; Bloom 2009) and asset prices (Pástor and Veronesi 2012; Brogaard and Detzel 2015; Arouri et al. 2016).[2] Within this growing literature, the foreign exchange market (FOREX) exposure to EPU shocks is, to date, explored only by a handful of studies. Firstly, they predict that a surge in the EPU coincides with a national currency depreciation (Abid 2020; Nilavongse et al. 2020) as well as a rise of the exchange rate volatility (ERV hereafter) (Chen et al. 2020; Bartsch 2019; Christou et al. 2018; Balcilar et al. 2016). Secondly, exchange rate movements are found to be more sensitive to the domestic rather than the foreign EPU (Nilavongse et al. 2020). From a technical point of view, it is clear that this branch of the literature has sustainable interest to time series econometric modelling mainly applied to advanced economies (Cf. Bartsch 2019; Nilavongse et al. 2020) or some major emerging markets such as China (Chen et al. 2020). Notable few exceptions are Balcilar et al. (2016) and Christou et al. (2018) who consider a mixture of developed and developing countries.

To complement this literature, our study primarily builds on the body of the research pioneered by Bloom (2009) in investigating the macroeconomic effects of uncertainty. Our main purpose is to examine how the ERV responds to both domestic and foreign EPU in Emerging Market Economies (EME). We contribute to the current debate in several ways. The first novelty belongs to the exclusive focus on EME as a case study.[3] These countries (i) display a higher ERV especially those having adopted floating exchange regimes (ii) face higher levels of uncertainty comparing to advanced economies (Bloom 2009) and (iii) are extremely vulnerable to shocks spillovers stemming from developed countries (Bhattarai et al. 2020).

In addition, this paper aims at revealing the extent to which considering cross sectional dependence between countries can affect the sensitivity of the ERV to the EPU. Using the recent Panel VAR (PVAR hereafter) methodology of Abrigo and Love (2016), our paper is not only the first to use a panel framework (to the best of our knowledge) but also one of the rare studies relying on VAR models to deal with

[1] The literature highlights a weak empirical performance of fundamentals in predicting exchange rates especially in the short run. See for instance the pioneer study of Meese and Rogoff (1983).

[2] Note that a wide array of papers primarily concentrates on how stock prices behave in response to the EPU.

[3] Abid (2020) finds evidence of depressive effects of the domestic EPU on exchange rates movements in EME. Therefore, a special focus on the ERV behavior in EME to both domestic and foreign EPU is worth noting.

ERV-EPU nexus.[4] Numerous reasons make this methodology a well suited tool for that purpose. First, it allows to account for the variables' interactions and to capture market interdependences. So, why such issues could be of interest? On the one hand, in a globalized economy, a shock from one country can easily spill to other countries/markets. As it is also the case of the EPU international transmission (Jiang et al. 2019 among others), a PVAR set might help better understand such spillovers given its ability to account for international transmission of shocks (Canova and Ciccarelli 2012). On the other hand, beyond the impacts running from the EPU to the ERV, the literature provides significant evidence on the ability of the EPU in a given country to predict the path of EPUs abroad (Gupta and Sun 2020; Jiang et al. 2019).[5] Furthermore, we assume that higher currency fluctuations lead governments to undertake macroeconomic policy actions. This policy decision-making process is expected to be a source of policy uncertainty. Accordingly, we conjuncture that a VAR setting might potentially (i) provide a novel insight regarding the endogenous linkage among these variables and (ii) be more relevant than single-equation models which could suffer from serious endogeneity biases resulting in possible misleading results.[6] Second, our procedure interestingly allows simulating the Impulse Response Functions (IRFs) conventionally used to analyze the size and the sign of shocks propagation. Third, this methodology offers the possibility of appreciating the contribution of each shock to the variance of the ERV using the Forecast Error Variance Decomposition (FEVD).

In what follows, "Data and Econometric Framework" section describes the data and the econometric framework. "Findings and Discussion" section reports the main findings. "Robustness Checks" deals with robustness issues. Finally, "Conclusion" offers some concluding remarks.

Data and Econometric Framework

Our study is conducted on a monthly basis for 8 EME: Singapore, China, Chile, India, Korea, Russia, Brazil and Mexico and includes 4 variables: the ERV, the domestic and foreign EPU, and the domestic output. While the sample covers the period from January 2003 through December 2018, the starting date is dictated by the data availability in order to ensure a balanced panel structure. Our sample period interestingly englobes turmoil phases that are likely to increase the EPU: the collapse of Lehman Brothers in 2008, the global financial crisis (2008–2009), the US

[4] Notable exceptions are Nilavongse et al. (2020) and Beckmann and Czudaj (2017) relying on time series VAR models to investigate the effects of the EPU on exchange rates returns and forecast errors respectively.

[5] For instance, Gupta and Sun (2020) find significant evidence of a predictive ability of wide array of EPUs in emerging and developed countries on BRIC's EPU.

[6] Panel data models are likely to exhibit high cross-sectional dependence in the errors. This arises when countries in the panel respond not only to their own specific shocks but also to common shocks across the other panel members.

loss of the AAA sovereign rating for the first time of its history (summer 2011), the mid-2014 oil price decline and the Sino-American trade conflict (2018).

The exchange rates examined are the daily spot rates of the domestic currencies against the US dollar and are retrieved from DataStream.[7] To account for the ERV for each country, the monthly standard deviation of the corresponding exchange rate is computed. The domestic and foreign EPU's are the Baker et al. (2016)'s News-based indexes obtained from www.policyuncertainty.com. This index is a monthly coverage of Newspapers text search of articles including at least one term related to three categories (i) economy/economic, (ii) uncertainty/uncertain and (iii) policy (e.g. legislation, deficit, regulation etc.). As a proxy for the foreign EPU, we use the US-EPU since it is a benchmark of the international policy uncertainty (Das and Kumar 2018).[8] Furthermore, as a measure of output, we use the Industrial Production Index (IPI) drawn either from DataStream or from the OCDE database. This choice is mainly due to the unavailability of the Gross Domestic Product (GDP) on a monthly basis. At a general level, the use of the IPI is not a challenging issue as it remains "a very good proxy" of real GDP (Fontaine et al. 2018). Finally, all our series are transformed in logarithm form.

In Eq. 1, we describe the estimated PVAR that associates the panel data approach allowing unobservable individual heterogeneity to VAR models assuming the endogeneity of all the variables (Love and Zicchino 2006).

$$Z_{it} = U_i + \sum_{j=1}^{p} A_j Z_{it-j} + \mu_{it} \tag{1}$$

where Z_{it} is a 4*1 vector of endogenous variables discussed above and A is a 4*4 coefficient matrix. The optimal lag p is chosen to minimize information criteria. U_i are vectors of country fixed effects that account for individual heterogeneity in the levels of the variables, and μ_{it} are independently and identically distributed disturbance terms. i and t denote temporal (month) and individual (country) dimensions, respectively.

One of the advantages of using the PVAR methodology is to explicitly introduce fixed effects which means that (i) each country in the sample can have a specific level of each variable used and (ii) the fixed effect can potentially capture other invariant factors (e.g. exchange rate regimes, country size, financial regulation etc.). However, estimation biases may occur since the fixed effects are likely to be correlated with regressors that contain lagged dependent variables (Love and Zicchino 2006). In such a circumstance, it is necessary to eliminate the fixed effects based on

[7] We select SGD/USD; CNY/USD; KRW/USD; BRL/USD; MXN/USD; CLP/USD; INR/USD and RUB/USD exchange rates respectively for Singapore, China, Korea, Brazil, Mexico, Chile, India and Russia.

[8] Note that a measure of the global Economic Policy Uncertainty (GEPU hereafter) is available from Baker et al. (2016). This index is a GDP-weighted average of national EPU for 21 emerging and developed countries. It is possible that the GEPU provides information beyond the US-EPU; however the main drawback of the GEPU index is that it includes each country's own EPU. Therefore, we make the choice to use the GEPU as an alternative measure of the foreign EPU in our robustness task.

the “Helmert” method, a commonly used tool for that purpose.[9] In doing so, we preserve the orthogonality between the transformed variables and the lagged regressors that are used to instrument the VAR dynamics. Finally, the estimation is conducted using the Generalized Method of Moments (GMM). Then, we check the stability condition via modules of each eigenvalues of the estimated models. The results reported in Fig. 3 in the Appendices confirm that all eigenvalues are inside the unit circle. Consequently, the estimated PVAR specification fully satisfies the stability condition.

Moreover, an important advantage of the PVAR models is to allow producing the orthogonalized IRFs. These functions capture the effects of one variable to another endogenous variable when keeping the other variables constant (this is what is known as an orthogonal shock). Once all the coefficients of the PVAR model have been estimated, the confidence bands of the orthogonalized IRFs are computed via Monte Carlo simulations as initially developed by Love and Zicchino (2006) and extended in Abrigo and Love (2016). To this end, we use the variance–covariance matrix and the estimated coefficients from the PVAR to randomly build a draw of the VAR coefficients. Hence, the 5th and 95th percentiles are generated by replicating this procedure 1000 times in such a way the confidence intervals of the IRFs are obtained.

Nevertheless, the variance–covariance matrix is unlikely to be diagonal (Love and Zicchino 2006). Accordingly, preserving the orthogonality of the residuals is essential in order to isolate shocks to one of the variables in the VAR system. In this case, a usual convention is to adopt a Cholesky decomposition of the variance–covariance matrix of the residuals i.e. transforming the VAR in a recursive form for an identification purpose. The Cholesky identification assumes that the variables enter the VAR system according to an ascending degree of endogeneity. Specifically, when a variable x appears earlier in the system and a variable y appears later, this means that x is exogenous with respect to y in the short run (Love and Zicchino 2006).

Our identification assumption of structural shocks is based on a Cholesky decomposition that closely follows the bulk of the literature.[10] We assume that the bloc of domestic variables can be affected by the US-EPU both contemporaneously and with a one-period delay. However, the US-EPU is able to react to domestic variables only with a lag. Within the bloc of domestic variables, the output is on the one hand assumed to exert an instantaneous effect on the ERV and the EPU as well as with a lag. On the other hand, it reacts to both variables only with a one-period delay. In order to constraint the exposure of the domestic EPU to the macroeconomic innovations, it is ordered last in the VAR (Colombo 2013). To briefly sum up,

[9] The “Helmert” procedure removes the mean of the future observation available in each country-year.

[10] The Cholesky decomposition means that the variables listed earlier in the VAR affect the following variables instantaneously and with a one-period delay. By contrast, the variables that come later exert an impact on previous variables only with a lag (Love and Zicchino 2006). Overall, the ordering of the variables follows a decreasing order of exogeneity. Broadly, our Cholseky decomposition is closely related to recent papers dealing with uncertainty transmission. Examples include Fontaine et al. (2018) and Colombo (2013) among others.

the following ordering of the variables is retained (US-EPU, domestic output, ERV, and domestic EPU).

Findings and Discussion

Prior to the estimation we have undertaken a preliminary analysis. The corresponding results are reported in the Table 1. Firstly, we conduct the Levin et al. (2002) 1st generation unit root test. As can be seen in Table 1, the results indicate the stationarity of all the variables used here. Second, we implement the Pesaran (2004) CD test in order to check for the cross-sectional dependence. The latter means that the countries forming the panel are expected to respond not only to their idiosyncratic shocks but also to common shocks across other panel members. We particularly account for this property given that panel data specifications are likely to present such a dependence that arises when error terms contain unobservable components. Our results clearly support the rejection of the null hypothesis of no cross-sectional dependence. This finding interestingly implies that panel members exhibit a strong exposition to common shocks. Hence, they might probably display similar macroeconomic policies features. Finally, our conclusion supports the adequacy of using a panel data framework in our study.

The previous conclusion conducted us to check for the presence of unit roots relying on the 2nd generation panel unit root test of Pesaran (2007). Assuming cross-sectional dependence, this test highlights again the stationarity of all the considered variables.[11]

Moving now to the PVAR framework, two lags are selected as they were found to be optimal according to the selected information criteria. We report the corresponding results in Table 2.[12]

Once the estimated coefficients of the PVAR model obtained, the orthogonalized IRFs are generated. The Fig. 1 displays the IRFs that particularly plot the US-EPU spillover to EME. Our findings highlight that a positive US-EPU shock foreshadows domestic EPU increase.

It is argued that higher EPU induces more revision in expectations of the macroeconomic fundamentals which leads exchange rates to be subject to strong volatility (Krol 2014). In the particular context of EMEs, Bhattarai et al. (2020) explain that the US uncertainty is particularly perceived by EME policy makers as a major source of economic forecasts revisions and the volatility increase of the international

[11] Note that the Pesaran (2007) test is not able to provide results with respect the US-EPU and GEPU (robustness check) since the same variable is used for all the countries in the sample. We assume that these two variables are stationary in level based on the Levin et al. (2002)'s test.

[12] To perform this methodology, the optimal lag selection is a crucial step. We make the choice of initially considering 3 lags since having a higher number of lags generates a loss of degree of freedom that can result in over-parametrization. Our finding reported in this Table unanimously suggests 2 lags for the endogenous variables since it broadly minimizes the 3 information criteria. Besides, additional tests (not reported here, but available upon request) confirm that all usual assumptions on the residuals are also verified.

capital flows. Consequently, exchange rate volatility in EMEs may naturally increase.[13]

Furthermore, we find that an unanticipated increase of the US-EPU has no significant effect on the domestic output. Nevertheless, our evidence interestingly supports significant indirect effects. Firstly, we find that an ERV's increase significantly translates into an output contraction.[14] Secondly, combining this result with the observed positive US-EPU effects on the ERV, we emphasize the ERV role as a transmission mechanism of the negative US-EPU spillovers to the EME economic outlook. Accordingly, we conjecture that countercyclical current accounts and exports of EME (Bhattarai et al. 2020) could be more complicated with higher ERV induced by the foreign EPU. Such an effect leads to an aggregate supply decrease i.e. an output contraction. Overall, we support the role of (i) the US economy as a net transmitter of policy changes (Jiang et al. 2019) and (ii) the US-EPU as negative foreign aggregate demand disturbances. Finally, the results we obtained show that the domestic EPU is positively associated to the US-EPU positive shock. Hence, our evidence gives supports to the empirical literature on the international EPUs interdependence.

Let us now discuss the domestic EPU shock effects on all variables (Cf. Fig. 2). Our findings show a significant rise of the ERV following an unanticipated positive change of the domestic EPU, which is consistent with previous works (Chen et al. 2020; Bartsch 2019; Zhou et al. 2020). As explained above, it is recognized that currencies movements are altered through expectations about fundamentals (Beckmann and Czudaj 2017) and economic policies changes (Alesina et al. 1997). If the latter are significantly exposed to the EPU, currencies are expected to be highly volatile. While the effects running from EPU to ERV are confirmed in the empirical literature, the extent to which ERV can predict the path of the EPU is not clear enough. In this regard, we interestingly provide novelty by showing that an unanticipated increase of the ERV generates a positive change in domestic EPU (Cf. Fig. 4 in Appendices).[15] A candidate explanation is that higher exchange rate volatility is one of the sources of the macroeconomic instability especially in small open economies. Then, a better monetary and fiscal policies' coordination can help attain policy goals of macroeconomic stability. This is known as the monetary and fiscal policy mix which means that central banks and fiscal policy makers are expected to synergize in the conception, the implementation, and the monitoring of the macroeconomic policies. Such collaboration is also expected to revise the macroeconomic policies and to continuously share in public the policy orientations. Nevertheless, higher economic

[13] For example, the uncertainty induced by the implementation of non-conventional monetary policy and the announcement of the Fed regarding the quantitative easing in May 2013, has been associated to flight to safety. The latter means that investors reduce their participation in emerging markets and rebalance portfolios in less risky assets like the US treasury bills despite the higher domestic uncertainty. Therefore, EMEs have experienced increased currencies volatility as a response to the rise in capital movements (Gauvin et al. 2016).

[14] Results are available in Fig. 4 in Appendix.

[15] The observed bidirectional positive relationship between ERV and domestic EPU strengthens our intuition regarding their endogenous linkage (Cf. introduction).

Table 1 Preliminary analysis

Variables	1st generation panel unit root test of Levin et al. (2002)	Pesaran CD test	2nd generation panel unit root test of Pesaran (2007)
ERV	– 13.98***	25.84***	– 5.25***
US-EPU	– 10.51***	73.32***	–
EPU	– 7.57***	20.72**	– 5.08***
Output	– 5.20***	30.94***	– 2.70***
GEPU	– 5.64***	73.32***	–

This table summarizes the obtained results of the 1st and 2nd generation panel unit root tests, and the cross-sectional dependence test. GEPU indicates the global EPU index used for the robustness check purpose

** and *** denote statistical significance at 5 and 1% levels respectively

Table 2 Optimal lag selection

Lags	HQ	SIC	AIC
1	– 143.15	111.75	16.77
2	– 174.01	– 4.07	– 67.39
3	– 85.01	– 0.03	– 31.69

This table illustrates the results of the information criteria considered in order to properly choose the lags to include in the VAR system. HQ, SIC and AIC refer respectively to Hannan-Quinn, Schwarz and Akaike information criteria

uncertainty prevents authorities from making suitable decisions. In such unpredictable environment, the macroeconomic policy decision making process slowed down until uncertainty is dispelled.[16] This misalignment of the macroeconomic policies can, in turn, translate into a high EPU as it is a natural product of such government policy making process (Pástor and Veronesi 2012). To sum up, we suggest here that domestic EPU and ERV relationship is bidirectional in EME.

Moreover, we find no evidence of a significant output response to the domestic EPU shock. First, we conjecture that such puzzling result may be due to the selected lag structure.[17] Second, the sample size might play a role in this observation since the period of the study is constrained by the availability of the EPU index. Finally, another possible explanation relates to the composition of the industrial production. Given that we rely on monthly data, we use the industrial production index as a proxy of the output instead of GDP, not available at this frequency. Nevertheless,

[16] For instance, if central banks are expected to set monetary policy under economic uncertainty, they naturally react by reducing their policy responses or by modifying them gradually (Dupraz et al. 2020). Consequently, this behavior is likely to alter the monetary and fiscal policy mix and translates into higher EPU.

[17] Following almost of the previous empirical studies, we make the choice to set our lags on consideration to the information criteria.

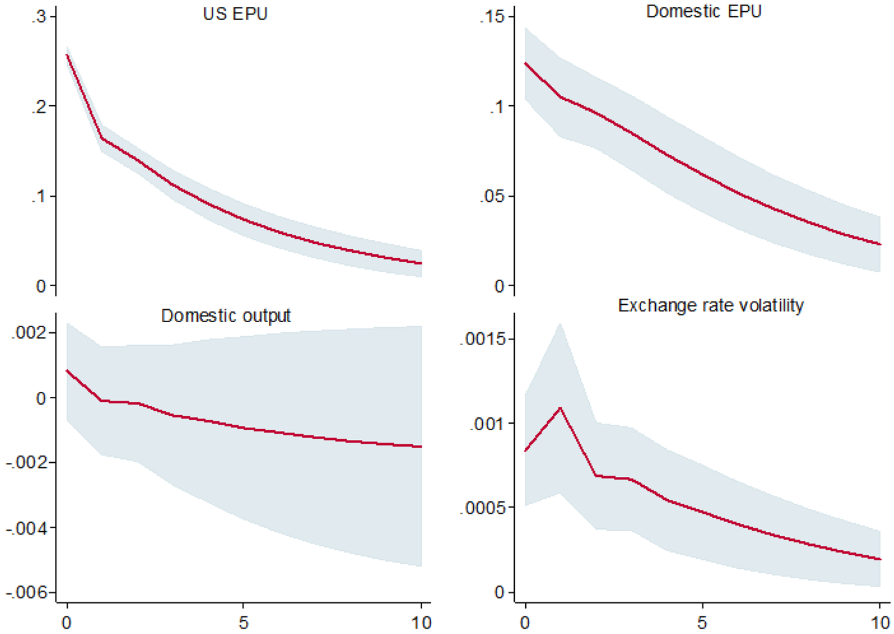

Fig. 1 US-EPU shock spillover to EME. This figure plots the orthogonalized impulse response of all the endogenous variables to a one standard deviation shock of the US-EPU. The red line presents the response of each variable. The bluish-gray boxes are the 95% confidence intervals constructed via Monte-Carlo simulations with 1000 replications. Periods are months (Color figure online)

our countries might feature different economic compositions where industrial production does not have the same proportion of the economy in each country.

Our evidence is consistent with the recent literature.[18] For instance, Baker et al. (2016) suggest that the short-run impact of the EPU on output is expected to be smaller. On the one hand, they show a negative but not statistically significant impact of the domestic EPU on output. On the other hand, they highlight that firms in policy exposed sectors experience drops in investment and employment growth rates in response to higher EPU. However, the authors conclude that the association of the EPU to the growth rate of these firms is muted in the short run.

Interestingly and perhaps surprisingly, we show that the US-EPU is positively responsive to the EME-EPU. Thus, we provide novel insights into EPU international spillovers and take a step further from studies supporting the prominent influence of the US on EME (Bhattarai et al. 2020).

Hence, we suggest that the US economy is not immune to a negative international policy shock. Even if the US is generally perceived as a net exporter of EPU (Klößner and Sekkel 2014), we show that it also appears as an importer of such an uncertainty. Therefore, we suggest an important role of the EME as an international policy uncertainty exporter. This can particularly make sense given

[18] See also Nilavongse et al. (2020) for a similar finding.

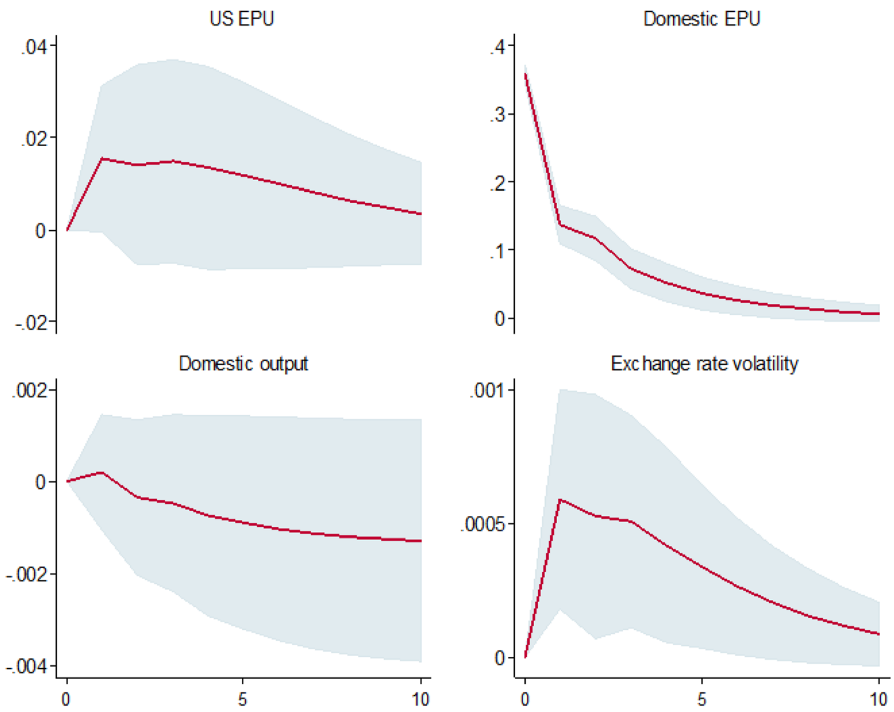

Fig. 2 Effects of the local EPU shock in EME. This figure plots the orthogonalized impulse response of all the endogenous variables to one standard deviation shock of the domestic EPU**.** The red line presents the response of each variable. The bluish-gray boxes are the 95% confidence intervals constructed via Monte-Carlo simulations with 1000 replications. Periods are months (Color figure online)

the Sino-American trade tensions, for instance. Finally, we find that a favorable economic outlook in EME (an increase in output) results in a higher US-EPU.

On one side, it is observed, during the recent years, that the emerging markets' influence on global economic growth, global trade and advanced economies is continuously growing. For example, China and India weight heavily on the world trade and they became increasingly an important player in the global economy. Furthermore, given the economic weight of the BRICS, these countries are gaining greater power to influence the World economic policy.

On another side, it is widely believed that the economic growth is positively correlated to stock returns. If economic growth in emerging markets is good for stockholders, investors can gain through holding assets in countries where economic activity is stable, and the growth prospects are strong. In these circumstances, emerging markets might be a privileged destination of foreign investments. Such an economic success is likely to influence the global competitiveness of developed countries and particularly the US. Hence, US decision makers may regard favorable EME conjuncture as valuable information that may alter their economic decisions. Consequently, the US-EPU would naturally increase.[19]

From the FEVD analysis in Table 3, we clearly observe that domestic and US-EPUs shocks explain nearly 10% of the ERV variance and their shares remain unchanged along all forecast horizons.

Our result highlights the relevance of the US-EPU over the bloc of domestic variables in explaining the ERV. The US-EPU contribution is twice higher than the share of the domestic EPU across all horizons. Moreover, the share of US-EPU innovations is greater than the contribution of the domestic output (6.9% against 0.4%) in the short run. Such a result strengthens our evidence that alongside domestic variables, the US-EPU is an important influential factor of EME currencies.[20]

Contrary to previous papers but in line with our IRFs, we show that the US-EPU contribution to the output fluctuation is surprisingly weak. Furthermore, our FEVD highlights that the short-run domestic EPU fluctuation is driven to a great extent (nearly 25%) by US-EPU (18.9%) and output shocks (5.9%). The contribution of US-EPU (output) shocks slightly (considerably) decreases (increases) with the forecast horizon.[21] Specifically, the role of the US-EPU (output) shocks is more pronounced in the short (long) run.

What can explain the prominent role of the US-EPU especially in the short run? As previously discussed, the US uncertainty plays an important role in revising economic expectations by EME policy makers. Because of the ubiquity of television and social media, natural cycles of the EPU are short. Reasonably economic expectations are quickly influenced since EPU information is extracted from daily newspapers (Bartsch 2019). Second, even though policy uncertainty can also have a long run effect on economic activity, political events-driven uncertainty (elections, for example) affects fundamentals' expectations particularly in the short-run (Beckmann and Czudaj 2017). Naturally, it is expected that the US-EPU' impacts on EME are greater in the short-run.

Interestingly, we also observe that the fraction of the EME output in explaining the US-EPU fluctuations rises along forecast horizons to achieve one third in the

[19] Given that we rely on a PVAR model, we have chosen to be parsimonious in the baseline specification since a high number of variables reduce degrees of freedom. Nonetheless, we have also estimated our specification augmented with the US output (to control for US macroeconomic conditions), and domestic short-term interest rates (to control for monetary effects). The variables are introduced in the following order: US output, US-EPU, domestic output, short term interest rate, ERV, domestic EPU (see for example, Fontaine et al. (2018); Colombo (2013)). Interestingly, our evidence highlighted above remains unchanged. The results we obtained are not reported here to save space but are available from the corresponding author upon request.

[20] Note that the literature supports the sensitivity of EME currencies to domestic factors. For instance, Abid (2020) finds that short and long runs currency movements in emerging markets (India, Korea, Brazil, Mexico, and Chile) are significantly explained by fundamentals. The latter include monetary variables such as policy rates, money supply, foreign exchange reserves and inflation, and non-monetary variables such as industrial production index and terms of trade. Furthermore, Hviding et al. (2004) and Krol (2014) find that exchange rate volatility is EME is significantly affected by foreign exchange reserves and inflation, respectively.

[21] Our finding is closely related to Gupta and Sun (2020) which show for the BRIC that models including foreign EPU provide better forecasts than those with domestic EPU alone.

Table 3 Forecast error variance decomposition results

h	(A) ERV				(B) EPU				(C) Output				(D) US-EPU			
	ERV	USEPU	EPU	Output	ERV	USEPU	EPU	Output	ERV	USEPU	EPU	Output	ERV	USEPU	EPU	Output
12	89.9	6.9	2.6	0.4	3.2	18.9	74.6	5.9	5.1	0.2	0.1	94.5	0.1	86.6	3.1	10.0
24	89.0	6.9	2.6	1.3	3.4	17.4	65.6	13.4	6.3	0.4	0.2	92.9	1.0	74.0	2.7	22.2
36	88.3	6.9	2.6	2.0	3.6	16.3	61.5	18.4	6.7	0.5	0.2	92.3	1.7	66.3	2.4	29.4

This table reports the FEVD results highlighting the fraction of the forecast variance of row variables (A, B, C and D boxes) attributable to innovations in columns variables. The first column "h" refers to the forecast horizon i.e. 12 months, 24 months and 36 months long-run. This not only echoes again our IRFs simulations but also gives support to our conclusion regarding the EME economic outlook as a source of US economic changes.

There is a possible explanation of the increasing effect of the output on the US-EPU along the forecast horizon. When the economic environment is unpredictable, governments undertake policy actions to reduce uncertainty. However, the complexity of the policy decision-making process raises concerns regarding the efficiency of policy actions as to achieve the expected outcomes. Because the latter, in the best-case, scenario, take time to be attained, this effect further amplifies the EPU.

Robustness Checks

To investigate the robustness of our findings, we have undertaken several sensitivity analyses. Specifically, we check if our results are altered if we (i) re-estimate IRFs based on an alternative lag structure, (ii) use the Global EPU (GEPU) index as an alternative proxy of the foreign EPU[22] and (iii) cut Singapore and China out of our sample since they have adopted different exchange regimes compared to the other countries.[23] Our sensitivity findings confirm that the overall dynamics of our PVAR are immune to all modifications.[24] Therefore, we interestingly provide strong and robust evidence.

Conclusion

In this paper we use the recent panel VAR methodology of Abrigo and Love (2016) that accounts in particular for variables' interaction, and cross-country lagged interdependencies to investigate the Exchange Rate Volatility (ERV) response to Economic Policy Uncertainty (EPU) shocks, which is, to our best knowledge the first attempt in this context. Our results suggest that the ERV in EME is sensitive to both domestic and foreign EPU. Such findings support the negative US uncertainty spillovers to macroeconomic activities abroad (e.g. Colombo 2013) and complement this by showing that the ERV acts as a possible channel of such transmission. By showing that the US-EPU accounts more than the domestic EPU in explaining the ERV fluctuation, we provide novel insights into FOREX-EPU nexus which generally conclude that domestic activity (exchange rates) is more reactive to the global (domestic) EPU (Nilavongse et al. 2020). Assuming that such a difference is probably due to our procedure and specific context, we support the key role of markets cross-sectional dependence when dealing with EPU implications. Then, it seems not

[22] This variable enters the PVAR system in logarithmic form and it is stationary in level. See Table 1 for more details on the panel unit root test results.

[23] According to the Annual Report on Exchange Arrangements and Exchange Restrictions of the IMF in 2018, the former (latter) adopt a soft pegged regime (managed floating) regime. The remaining countries adopt floating regimes.

[24] The sensitivity analysis results are detailed in Appendix B.

suitable to generalize time series results and advanced economies or some major EME (e.g. China) findings to the whole emerging economies context.

Beyond the transmission of the policy uncertainty over the ERV, two important results emerge from our investigation. First, we provide evidence of a positive effect of the ERV increase on the domestic EPU. Second, another important finding is the responsiveness of the US-EPU to EME outlook. Hence, even though the US is perceived as a net exporter of EPU, it also imports such an uncertainty from EME.

Our findings have interesting implications to decisions makers and investors in EME. Picking sound economic policies and reducing the exposure to the US economic policy fluctuations is relevant for their future monitoring of exchange rate fluctuations. In addition, EME investors should incorporate domestic and abroad policy information in order to properly manage their exchange exposure and optimize portfolios allocation. On the US side, policy decisions makers' should probably monitor the EME macroeconomic conditions in order to predict their own EPU changes.

Finally, a nonlinear assessment of the ERV-EPU nexus is worth mentioning as a potential avenue for future researches.

Appendix A: The PVAR Estimation

See Appendix Figs. 3 and 4.

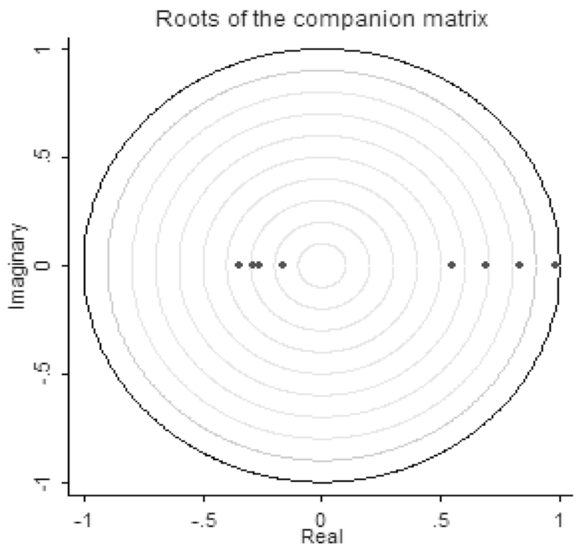

Fig. 3 Stability of the PVAR estimates

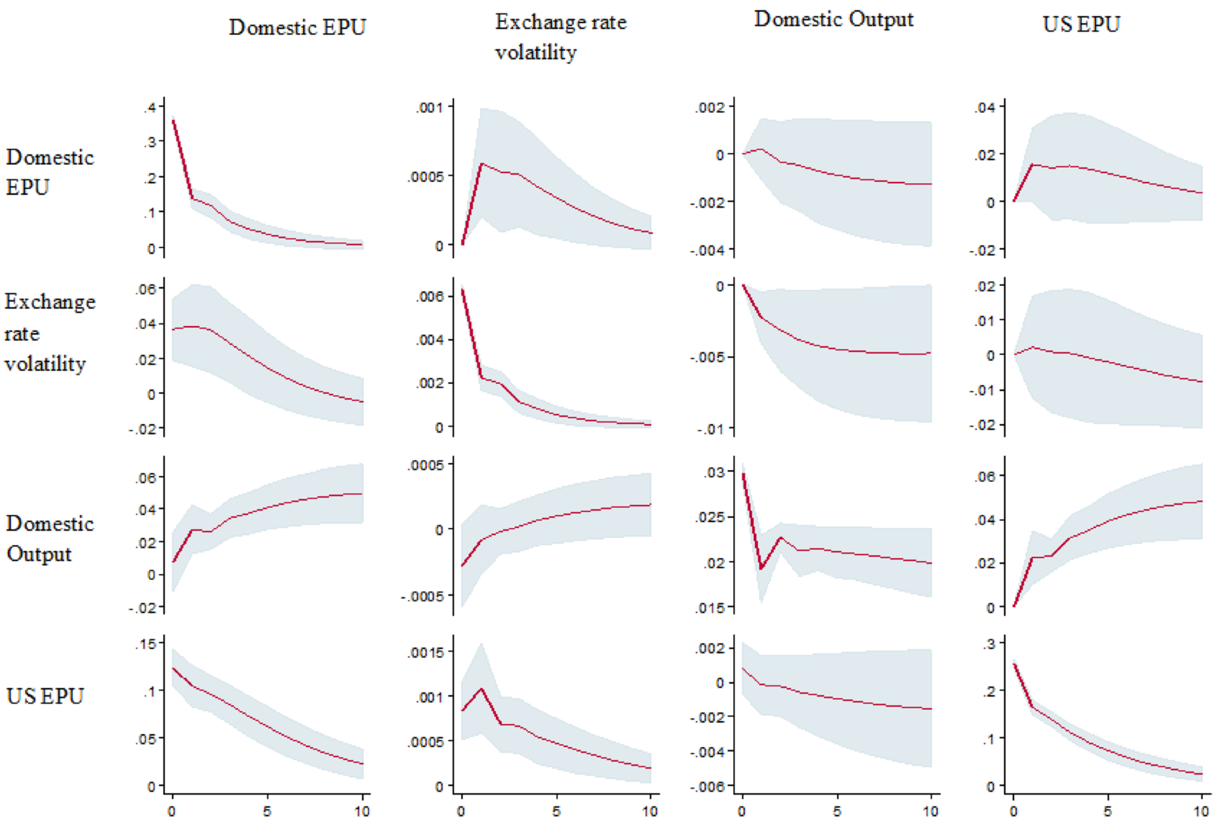

Fig. 4 IRFs for PVAR model. This figure plots the orthogonalized IRFs of all the variables to a positive one standard deviation shock of each variable in the PVAR system along with 95% error bands. These plots show the response of the column variable to an innovation on the row variable based on PVAR estimates with two lags. The bluish-gray boxes are confidence intervals constructed via Monte-Carlo simulations with 1000 replications. Periods are months. Non-zero effects i.e. significant shocks impacts are observed when the zero line is outside of the corridor (Color figure online)

Appendix B: Robustness Check

Estimating the PVAR Model with an Alternative Lag Structure

See Appendix Fig. 5.

The results illustrated in Fig. 5 indicate the stability of the PVAR model with three lags.

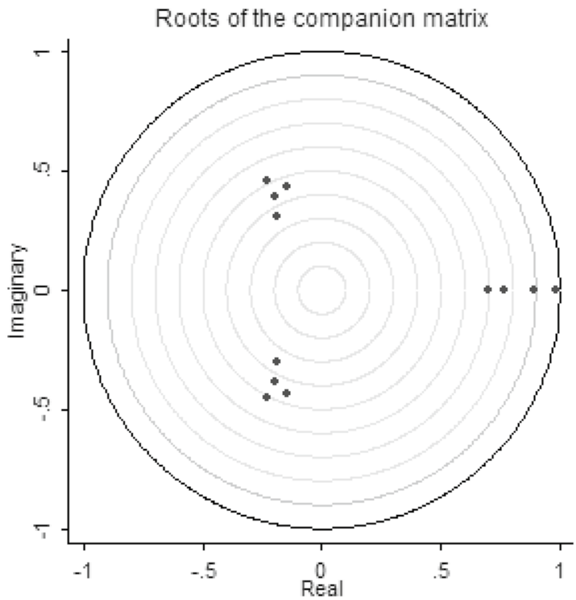

Fig. 5 Stability of the PVAR model augmented with a lag

See Appendix Fig. 6.

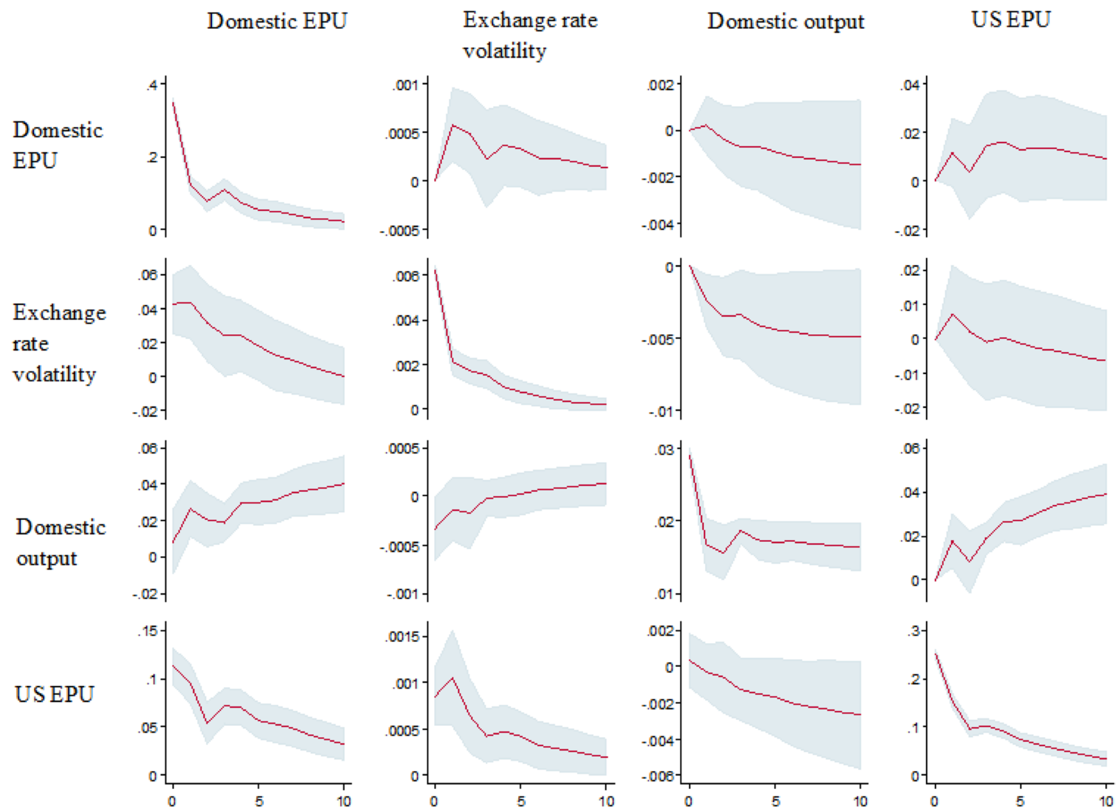

Fig. 6 Orthogonalized IRFs. Robustness Check (PVAR model augmented with a lag). This figure plots the orthogonalized IRFs of all the variables to a positive one standard deviation shock of each variable in the PVAR system along with 95% error bands. These plots show the response of the column variable to an innovation on the row variable based on PVAR estimates with three lags. The bluish-gray boxes are confidence intervals constructed via Monte-Carlo simulations with 1000 replications. Periods are months. Non-zero effects i.e. significant shocks impacts are observed when the zero line is outside of the corridor (Color figure online)

Estimating the PVAR Model with an Alternative Proxy of the Foreign EPU

See Appendix Fig. 7.

Our PVAR estimates using the GEPU are stable as highlighted in the Fig. 7

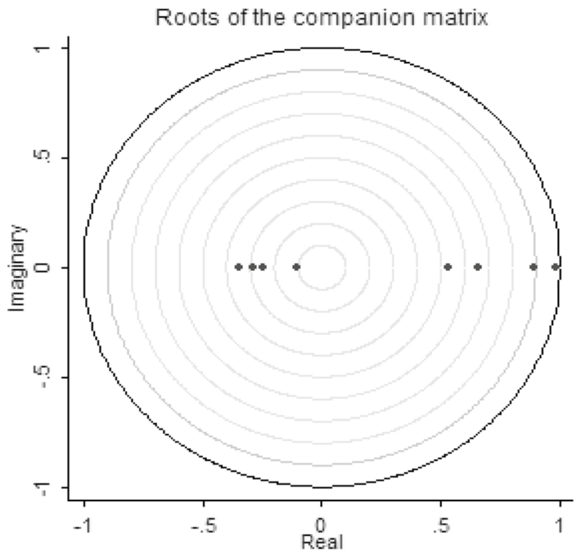

Fig. 7 Stability of the PVAR model with Global EPU (GEPU)

See Appendix Fig. 8.

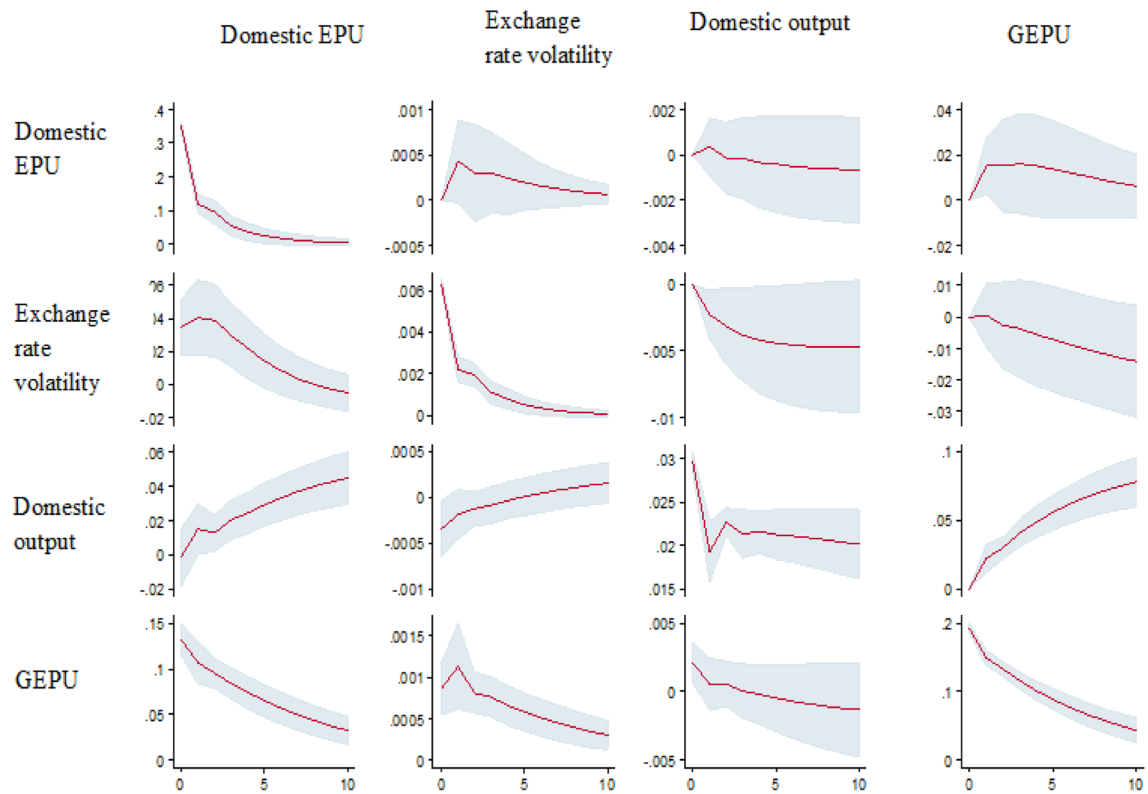

Fig. 8 Orthogonalized IRFs. Robustness Check (PVAR model with GEPU). This figure plots the orthogonalized IRFs of all the variables to a positive one standard deviation shock of each variable in the PVAR system along with 95% error bands. These plots show the response of the column variable to an innovation on the row variable based on PVAR estimates when replacing the US-EPU by the GEPU. The bluish-gray boxes are confidence intervals constructed via Monte-Carlo simulations with 1000 replications. Periods are months. Non-zero effects i.e. significant shocks impacts are observed when the zero line is outside of the corridor (Color figure online)

Estimating the PVAR Model with a Different Sample

See Appendix Fig. 9.

We drop both Singapore and China out of the sample and re-estimate our PVAR model. The optimal lag selection based on the three information criteria retained previously also provides indicative evidence of two optimal lags. Corresponding results are not reported here but are available on request. Regarding the stability condition, we can observe on Fig. 9 that eigenvalues are inside the unit circle indicating a strong stability of this alternative PVAR specification.

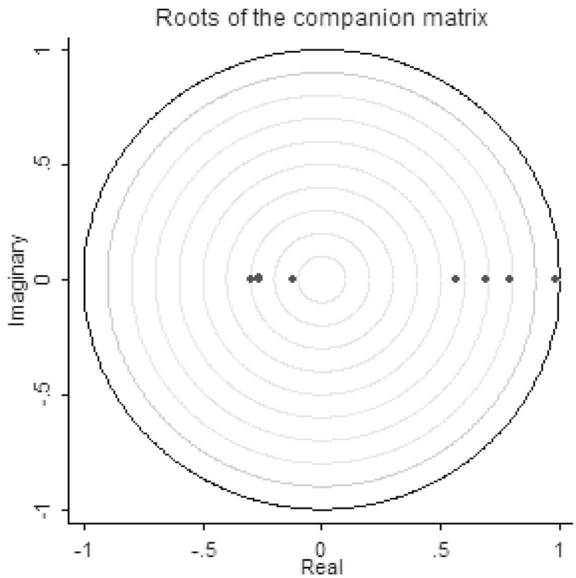

Fig. 9 Stability of the PVAR model excluding Singapore and China from the sample

See Appendix Fig. 10.

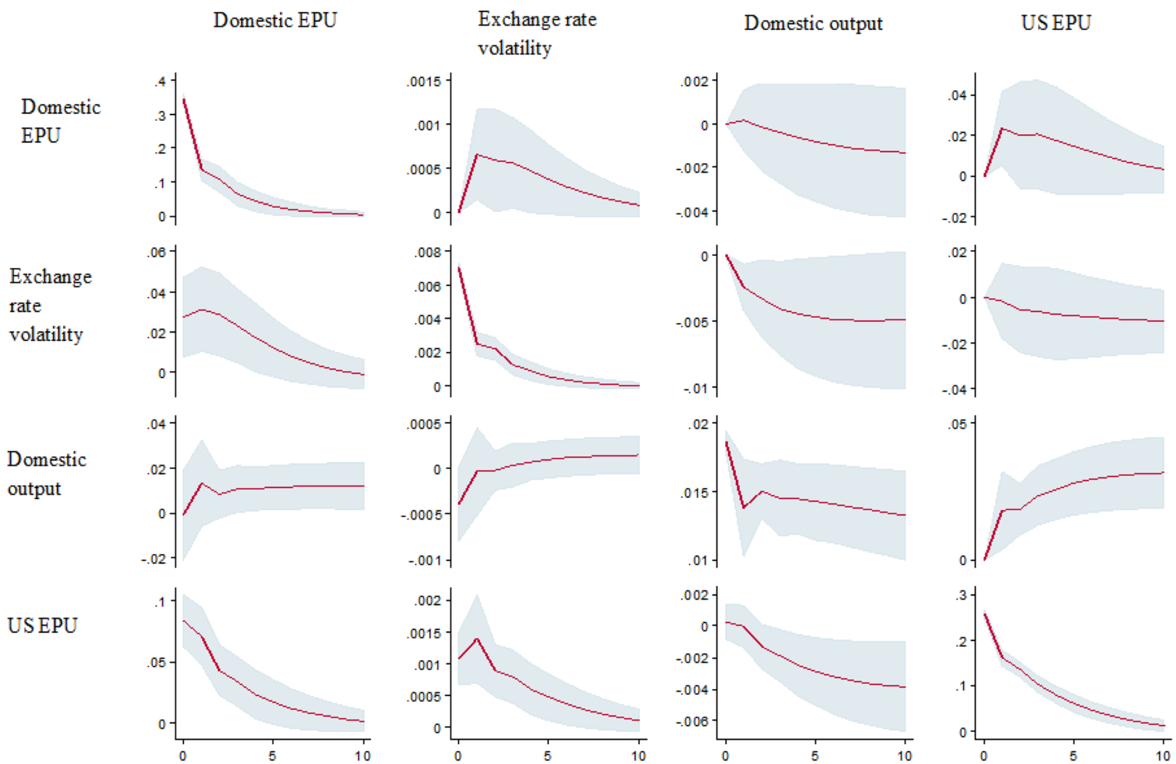

Fig. 10 Orthogonalized IRFs. Robustness Check (PVAR model excluding Singapore and China). This figure plots the orthogonalized IRFs of all the variables to a positive one standard deviation shock of each variable in the PVAR system along with 95% error bands. These plots show the response of the column variable to an innovation on the row variable based on PVAR estimates when excluding china and Singapore out of the sample. The bluish-gray boxes are confidence intervals constructed via Monte-Carlo simulations with 1000 replications. Periods are months. Non-zero effects i.e. significant shocks impacts are observed when the zero line is outside of the corridor (Color figure online)

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