연세대학교 상경대학

경제연구소

Economic Research Institute

Yonsei Universit

서울시 서대문구 연세로 50

50 Yonsei-ro, Seodaemun-gu, Seoul, Korea

TEL: (+82-2) 2123-4065 FAX: (+82-2) 364-9149

E-mail: yeri4065@yonsei.ac.kr

http://yeri.yonsei.ac.kr/new

Financial vs. Policy Uncertainty in Emerging Market Economies

Sangyup Choi

Yonsei University

Myungkyu Shim

Sogang University

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Yonsei University

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Sangyup Choi† Myungkyu Shim‡

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Abstract

While the negative effect of uncertainty shocks on the economy is well-known, little is known about the extent to which these effects differ across the measures of uncertainty, especially in emerging market economies. Using the newly available economic policy uncertainty index from six emerging market economies (Brazil, Chile, China, India, Korea, and Russia), we compare the impact of financial uncertainty shocks—measured by stock market volatility—and that of policy uncertainty shocks on the economy. We find that financial uncertainty shocks have much larger and more significant impact on output than policy uncertainty shocks, except for China where the government has direct controls over financial markets. While our finding differs from the previous finding that policy uncertainty has no smaller effects on economic activity than financial uncertainty in advanced economies, it is consistent with the recent emphasis on financial frictions as a propagation mechanism of uncertainty shocks.

JEL classification: E20, E32

Keywords: Financial uncertainty, Policy uncertainty, Emerging market economies, Financial frictions, Vector Autoregressions, Local projections

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†School of Economics, Yonsei University. Email: sangyupchoi@yonsei.ac.kr

‡School of Economics, Sogang University. Email: mkshim@sogang.ac.kr

1 Introduction

The Great Recession and the Global Financial Crisis have renewed a long-lasting interest in the link between uncertainty and economic activity.[1] While uncertainty, in principle, can affect the economy differently depending on its origins, the empirical literature has focused mostly on common rather than heterogenous effects of different kinds of uncertainty shocks on economic activity. It is because of the high correlation among empirical measures of uncertainty. However, the recent observation that popular measures of uncertainty (stock market volatility and economic policy uncertainty) diverge from each other casts some doubt on this empirical practice (Pastor and Veronesi (2017)).[2]

We contribute to the literature by studying whether uncertainty regarding financial markets and economic policy have different impact on economic activity. While most existing studies analyzing the impact of economic policy uncertainty shocks have focused on the U.S. and other advanced economies, we focus on emerging market economies (henceforth EMEs). As of April 2017, there are only six emerging countries (Brazil, Chile, China, India, Korea, and Russia) where the standardized economic policy uncertainty (EPU) index constructed by Baker, Bloom, and Davis (2016) is available. This data constraint partly explains why no attempt has been made to compare the impact of different types of uncertainty shocks in EMEs.

In order to draw comparable results from Baker, Bloom, and Davis (2016), we closely follow their data construction and identification strategy: We additionally take account of the small open economy nature of EMEs into the Vector Autoregression (VAR) model. Two particular measures of uncertainty are used in our paper; (i) stock market volatility to gauge financial uncertainty and (ii) Baker, Bloom, and Davis (2016)'s EPU index to capture policy uncertainty. For EMEs, we construct a measure of financial uncertainty by estimating realized volatility of the local stock market, which corresponds to the widely used measure of financial uncertainty in Bloom (2009).

By estimating the VAR model similar to Baker, Bloom, and Davis (2016), we find that policy uncertainty shocks do not have much impact on real activity—such as output—in most of EMEs in our sample. This finding seems contradictory to the earlier findings that policy uncertainty shocks have

[1] We do not intend to summarize the literature about uncertainty and economic activity. See Bloom (2014) for a comprehensive review of the literature.

[2] For example, during the recent episodes of the U.K.'s referendum to leave the European Union and the U.S. presidential election, uncertainty regarding economic policy increased dramatically to the unprecedented level, whereas financial uncertainty about financial markets remained at the low level.

significant effects on output in the U.S. economy (Baker, Bloom, and Davis (2016)), the Euro area (Colombo (2013)), and other high-income small open economies (Stockhammar and Österholm (2016)). On the other hand, financial uncertainty shocks, measured by stock market volatility, have significant impact on output in EMEs.

Such relative importance between the two types of uncertainty shocks in EMEs is in sharp contrast to Stockhammar and Österholm (2016) who find that policy uncertainty shocks have larger effects on output than financial uncertainty shocks in a group of high-income small open economies. Our findings are robust to, for example, controlling for the spillover from U.S. uncertainty; changing the specifications of the baseline VAR model, such as Cholesky ordering or lag lengths; and using a different estimation technique such as the local projection method by Jordà (2005). One needs a caution when interpreting our findings: we do not claim that economic policy uncertainty is not important for EMEs. We rather suggest that the propergation mechanism of uncertainty shocks in EMEs might be different from advanced economies.

The recent literature highlights the role of financial frictions in amplifying the effect of uncertainty shocks on the real economy (Alfaro, Bloom, and Lin (2016); Caldara, Fuentes-Albero, Gilchrist, and Zakrajsek (2016); Popp and Zhang (2016); Choi, Furceri, Huang, and Loungani (Forthcoming)). The recent literature suggests that uncertainty shocks could have larger real effects in the presence of financial frictions via an increase in external borrowing costs (Choi (2016); Bhattarai, Chatterjee, and Park (2017)) or sudden stops in capital flows (Gourio, Siemer, and Verdelhan (2016); Choi and Furceri (2017)). To the extent that EMEs are subject to more financial frictions than advanced economies, our finding supports the relevance of the financial friction channel as a propagation mechanism of uncertainty shocks. Our finding that the impact of financial uncertainty shocks on Chinese output is insignificant does not necessarily undermine our conclusion. Because the Chinese government has direct controls over capital flows and interest rates, these potential propagation mechanisms of uncertainty shocks are effectively shut down.

Our finding is in line with the recent studies highlighting the relative importance among different kinds of uncertainty in explaining business cycles. For example, Caldara, Fuentes-Albero, Gilchrist, and Zakrajsek (2016) show that uncertainty shocks have an especially negative economic impact when financial conditions tighten. Born and Pfeifer (2014) find that uncertainty about fiscal and monetary policy does not explain much of the U.S. business cycles by estimating a New Keynesian model. Ludvigson, Ma, and Ng (2015) claim that uncertainty in financial markets is an "exogenous" driver of the economy while other types of uncertainty are "endogenous" responses to aggregate fluctuations. Taken together, these studies help understand why financial uncertainty shocks matter more in EMEs.

Our finding has clear implications on policymakers in EMEs. The recent development in the measurement of uncertainty (for example, Jurado, Ludvigson, and Ng (2015) and Ozturk and Sheng (Forthcoming)) allows for policymakers to consider the fluctuations in various uncertainty measures as an important input in the forecasts of future economic outcomes. While it is useful to understand that different types of uncertainty shocks could have different impact on economic activity, uncertainty regarding financial markets should be a priority of the policymakers in EMEs. In a related study, Choi (2016) finds that various empirical proxies for the degree of credit market imperfections in EMEs are particularly relevant for explaining the impact of financial uncertainty shocks: the negative impact tends to be more pronounced in a country with a weak financial institution, a shallow financial market, or financial dollarization.

The rest of the paper is organized as follows. Section 2 describes the data and introduces the empirical models. Section 3 presents our main findings. Section 4 tests the robustness of these findings. Section 5 concludes.

2 Data and Empirical Models

We first describe the underlying macroeconomic data with a focus on two key measures of uncertainty, then introduce the empirical models used in the analysis.

2.1 Data Description To obtain empirical results that are comparable to the existing works, we use a similar set of the variables from Bloom (2009) and Baker, Bloom, and Davis (2016) as far as the data availability allows. The main macroeconomic variables include the domestic stock market index, the nominal effective exchange rate (NEER), the short-term policy rate, and industrial production. The main difference from Bloom (2009) and Baker, Bloom, and Davis (2016) is the inclusion of the exchange rate to take account of the small open economy nature of our sample.[3]

[3] See, for example, the recent studies on the effect of uncertainty shocks on the exchange rates in small open economies (Choi (2016); Bhattarai, Chatterjee, and Park (2017); Choi (2017)). However, we did not include the exchange rate in the VAR model in the earlier version of the paper and reached the same conclusion. To conserve space, these results are available upon request.

While most existing studies on the effect of uncertainty shocks on EMEs use quarterly variables, we use monthly variables in our analysis instead. Using monthly variables in estimating VAR models has the following advantages. First, it helps discover relevant "short-run" dynamics of uncertainty shocks highlighted in Bloom (2009) because aggregation into a lower frequency necessarily smoothes out much of the variation in the uncertainty index. Second, using monthly variables mitigates the identification issue when zero contemporaneous restrictions are used for structural interpretation. Zero contemporaneous restrictions on financial variables in quarterly data are harder to justify. Finally, the quarterly GDP data in EMEs might not correctly capture private sector behaviors due to their procyclical government expenditure.

To construct the financial uncertainty index we take the following daily domestic stock market indices from Bloomberg: the Bovespa index (Brazil), the Santiago Stock Exchange IPSA Index (Chile), the Shanghai Stock Exchange Composite Index (China), the NIFTY 50 Index (India), the KOSPI index (Korea), and the MICEX Index (Russia). To gauge the monetary policy response to uncertainty shocks in EMEs, we use the overnight rate for Brazil, Chile, India, and Korea and the discount rate for China and Russia where the overnight rate is not a good indicator of the monetary policy stance. The rest of the macroeconomic data are taken from the IMF International Financial Statistics. While our dataset ends in December 2015, the individual country coverage of data differs: it starts from January 2002 (Brazil), January 1994 (Chile), January 1997 (China), January 2003 (India), January 1991 (Korea), and October 1997 (Russia). The sample coverage is solely determined by the availability of the main variables.

2.2 Measures of Uncertainty in EMEs

Throughout the analysis, we use the two uncertainty indices (stock market volatility and economic policy uncertainty) that are widely used in the literature to capture different dimensions of uncertainty in the economy.

Financial uncertainty index: stock market volatility. The VIX—the implied volatility of the S&P500 index—is often used as a proxy for uncertainty about both U.S. and global financial markets given the dominant role of the U.S. in the global economy. For each of EMEs, we construct the realized volatility of daily returns from domestic stock markets as a measure of financial uncertainty. To the extent that the VIX captures one-month-ahead forward-looking information, the best counterpart for the VIX in EMEs is implied stock market volatility, such as the VKOSPI for the case of the Korean economy. However, implied volatility in EMEs is often available for a much shorter period, which prevents a meaningful time-series analysis. Thus we use realized volatility based on the high correlation between the two indices.[4] Annualized realized volatility (RV_t) at a monthly frequency is calculated by using daily stock prices (p_t) as follows:

$$RV_t = 100 \times \sqrt{12 \times \sum_{t=1}^{n} r_t^2}, \tag{1}$$

where $r_t = \ln \frac{p_t}{p_{t-1}}$.

Economic policy uncertainty index. According to Baker, Bloom, and Davis (2016), their EPU index concerns uncertainty about "who will make economic policy decisions, what economic policy actions will be undertaken and when they will be enacted, the economic effects of past, present and future policy actions, and uncertainty induced by policy inaction." Applying this criterion to capture uncertainty about economic policies, they construct the EPU index of various countries, including both advanced and emerging economies.[5] The EPU indices are downloaded from www.policyuncertainty.com.

Figure 1 shows the evolution of two uncertainty indices from each of the six EMEs. The correlation between the two indices is minor, ranging from -0.14 (Russia) to 0.25 (India). The overall weak correlations and the recent episodes of the divergence between the two indices highlighted by Pastor and Veronesi (2017) imply that effects of the two types of uncertainty shocks on the economy might be different.

2.3 Empirical Models with Shock Identification

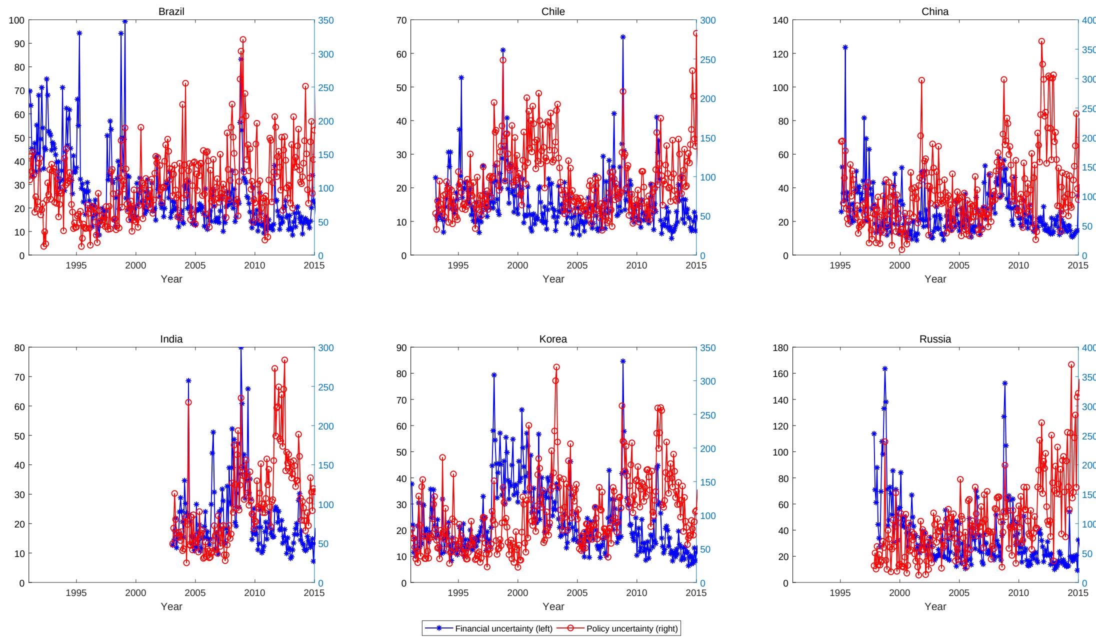
Consider the following structural VAR model:

$$Ay_t = \sum_{k=1}^{p} B_k y_{t-k} + e_t, \tag{2}$$

[4] For example, Choi (2017) shows that the effect of uncertainty shocks measured by implied volatility on output is near identical to that measured by realized volatility for the U.S. economy. We also find quantitatively similar results from the common subsample of the EMEs.

[5] For example, in the case of Korea, they use six newspapers to construct the EPU index: *Donga Ilbo, Kyunghyang Shinmun, Maeil Business Newspaper* (from 1990), *Hankyoresh Shinmun, Hankook Ilbo,* and *the Korea Economic Daily* (from 1995). They calculate the number of news articles that considers the following terms relative to the entire news articles: uncertain or uncertainty; economic, economy or commerce; and one or more of the following policy-relevant terms: government, "Blue House", congress, authorities, legislation, tax, regulation, "the Bank of Korea", "central bank", deficit, WTO, law/bill or "ministry of finance." After the standardization of each paper's EPU to unit standard deviation during the sample period, they average across the papers by month and then rescale the resulting series to a mean of 100. For further details about the construction of the EPU index from other countries, see Baker, Bloom, and Davis (2016) and www.policyuncertainty.com.

Figure 1: Financial uncertainty vs. policy uncertainty



Note: The blue line displays the financial uncertainty index (left axis) and the red line displays the policy uncertainty index (right axis).

where y_t is an $n \times 1$ vector of observed economic variables described earlier; B_k are $n \times n$ matrices of coefficients; and e_t are an $n \times 1$ vector of structural shocks. We specify the simultaneous relations of the structural shocks by assuming that A is a lower triangular matrix,

$$A = \begin{pmatrix} 1 & 0 & \dots & 0 \\ a_{21} & 1 & \dots & 0 \\ \dots & \dots & \dots & 0 \\ a_{n1} & \dots & a_{nn-1} & 1 \end{pmatrix}.$$

A reduced form model can be obtained from (2):

$$y_t = \sum_{k=1}^{p} F_k y_{t-k} + A^{-1}\Sigma\epsilon_t, \qquad \epsilon_t \sim N(0, I_n), \tag{3}$$

where $F_k = A^{-1}B_k$ for $k = 1, 2, ..., p$, and

$$\Sigma = \begin{pmatrix} \sigma_1 & 0 & ... & 0 \\ 0 & \sigma_2 & ... & 0 \\ ... & ... & ... & 0 \\ 0 & ... & 0 & \sigma_n \end{pmatrix},$$

where σ_i is the standard deviation of each of the structural shocks.

For a comparable analysis to Baker, Bloom, and Davis (2016), we use a level specification instead of taking difference or HP-filtering. With the presence of unit roots in macroeconomic variables, the level specification is preferred in a large body of the VAR literature (see, Sims, Stock, and Watson (1990) and Lin and Tsay (1996)). We use the same identifying assumption (except for the exchange rate) from Baker, Bloom, and Davis (2016) with the following Cholesky ordering to identify uncertainty shocks: the level of the policy uncertainty index, the level of the financial uncertainty index, the log level of the stock market index, the log level of the NEER, the level of the policy rate, and the log level of industrial production.[6]

This Cholesky ordering implies that both types of uncertainty shocks affect financial and macroeconomic variables instantly, while these variables can feedback into uncertainty variables with a one period lag. Thus this baseline identifying assumption highlights the role of uncertainty shocks as an exogenous driver of business cycles (Bloom (2009)). To the extent that we use relatively high-frequency (monthly) variables, this identifying assumption seems innocuous. Moreover, in a small open economy, heightened uncertainty is often driven by the world-wide events so that the measures of uncertainty seem quite exogenous to domestic economic conditions. Nevertheless, this identifying assumption effectively rules out the possibility that uncertainty could increase as an "endogenous" response to aggregate fluctuations (Ludvigson, Ma, and Ng (2015); Plante, Richter, and Throckmorton (2016); Fajgelbaum, Schaal, and Taschereau-Dumouchel (2017)). We test the robustness of our finding by reversing the Cholesky ordering, which implies that both types of uncertainty can respond to the innovations to other variables contemporaneously. Following Baker, Bloom, and Davis (2016), our baseline VAR specification includes three lags of the variables, but we still test the robustness of the results using alternative lag lengths.[7]

[6] Using the log level of the uncertainty indices do not affect the results.

[7] Akaike Information Criterion (AIC) suggests four lags (Russia), three lags (Brazil and Korea), and two lags (Chile, China, India) while the Schwarz' Bayesian Information Criterion (SBIC) suggests only one lag for the six EMEs.

2.3.1 Local Projections

Impulse-response functions (IRFs) from standard VARs might have substantial errors, especially at longer horizons (Phillips (1998)). This is because the IRFs in a standard VAR model are derived iteratively, relying on the same set of original VAR parameter estimates, moving forward period-by-period. This iterative process magnifies any model misspecification. A local projection method proposed by Jordà (2005) is known to be robust to the misspecification problem. We illustrate briefly the computation of IRFs and refer to Jordà (2005) for details on the local projection method. This approach has been advocated by, among others, Auerbach and Gorodnichenko (2013) and Nakamura and Steinsson (2017) as a flexible alternative that does not impose the dynamic restrictions embedded in vector autoregressive specifications. As in Jordà (2005), we define the impulse response at time $t+s$ arising from the experimental shocks in $d_{i,t}$ at time t as:

$$IR(t,s,d_{i,t}) = \frac{\partial y_{t+s}}{\partial \delta_t} = E[y_{t+s}|\delta_t = d_{i,t}; X_t] - E[y_{t+s}|\delta_t = 0; X_t] \tag{4}$$

for $i = 0,1,2,...,n$; $s = 0,1,2,...,$; $X_t = (y_{t-1}, y_{t-2}, ...,)'$, where operator $E[.|.]$ is the best mean squared error predictor, y_t is an n-dimensional vector of the variables of interest, and d_t is a vector additively conformable to y_t. The expectations are formed by linearly projecting y_{t+s} onto the space of X_t:

$$y_{t+s} = \alpha^s + B_1^{s+1} y_{t-1} + B_2^{s+1} y_{t-2} + ... + B_p^{s+1} y_{t-p} + U_{t+s}^s, \tag{5}$$

where α^s is a vector of constants and B_j^{s+1} are coefficient matrices at lag j and horizon $s+1$. For every horizon $s = 0,1,2,...,h$, a projection is performed to estimate the coefficients in B_j^{s+1}. The estimated IRFs are denoted by $\hat{IR}(t,s,d_i) = \hat{B}_1^s d_{i,t}$, with the normalization $B_1^0 = I$. Thus an innovation to the i-th variable in the vector y_t produces an impulse response of $\hat{B}_1^s$. The identifying assumption uses the same Cholesky ordering in Section 2.3.

3 The Effects of Uncertainty Shocks in the EMEs

This section provides key empirical findings of the paper. Although a few studies examine the effects of uncertainty shocks on a group of EMEs (Akıncı (2013); Carrière-Swallow and Céspedes (2013); Choi (2016); Bhattarai, Chatterjee, and Park (2017); Biljanovska, Grigoli, and Hengge (2017)), none of them compares the effects of different types of uncertainty shocks on the economy. As a warm-up exercise, we first study whether heightened policy uncertainty affects EMEs differently from advanced economies by comparing Korea with the U.S. In order for obtaining comparable results from Baker, Bloom, and Davis (2016), we follow their empirical strategy as close as possible and estimate the five-variable VAR model.[8] We choose Korea for a warm-up exercise because of its longest coverage of the EPU index and other macroeconomic variables at a monthly frequency (January 1991-December 2015). We then extend our analysis to other EMEs by imbedding the small open economy nature of these economies to the identifying assumption in the VAR model.

3.1 The Impact of Policy Uncertainty Shocks in Korea and the U.S.

The left panel in Figure 2 shows the IRFs of the stock market, the short-term policy rate, employment, and output measured by industrial production to a one standard deviation shock to the Korean EPU index.[9] An increase in policy uncertainty is followed by an instant drop in the stock market index, implying that financial markets respond quickly to an increase in policy uncertainty. However, its effects on real variables such as employment and industrial production are not statistically significant.[10] This result is in sharp contrast to (i) the common perception that higher policy uncertainty curbs business investment and employment and (ii) the recent empirical findings that policy uncertainty shocks—measured by a shock to the EPU index in recursively-identified VAR models—have significantly negative impact on advanced economy output.

To confirm that the insignificant impact of policy uncertainty shocks on Korean output is not driven by the shorter sample period used here than Baker, Bloom, and Davis (2016), we run the same VAR model using the U.S. data covering the same sample period. The right panel in Figure 2 confirms that an increase in policy uncertainty is followed by statistically significant and persistent declines in every variable. While a decline in the Federal Funds rate and U.S. output after policy uncertainty shocks is consistent with the previous studies, it is not the case for the Korean economy where the short-term policy rate increases initially (insignificantly though) in response to policy uncertainty shocks.[11]

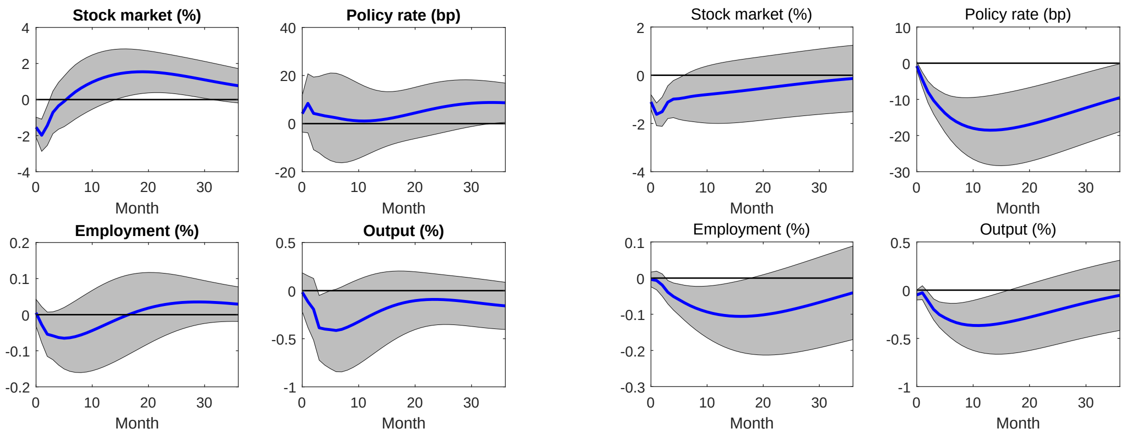
[8] In this analysis, we do not include the financial uncertainty index for comparison with Baker, Bloom, and Davis (2016). To recover orthogonal shocks, Baker, Bloom, and Davis (2016) use a Cholesky decomposition with the following ordering: the EPU index, the log of the S&P500 index, the federal funds rate, log employment, and log industrial production using three lags.

[9] 90% confidence intervals are plotted using 200 bootstraps.

[10] See Shin, Zhang, Zhong, and Lee (2018) for a similar finding about the muted response of Korean output to policy uncertainty shocks.

[11] See Choi (2016) for the theoretical mechanism through which uncertainty shocks raise the short-term interest rate in EMEs where credit market imperfections are prevalent.

Figure 2: Impact of policy uncertainty shocks: Korea (left) vs. the U.S. (right)



Note: The left panel shows the response of Korean economic variables to Korean policy uncertainty shocks, while the right panel shows the response of U.S. economic variables to U.S. policy uncertainty shocks. Each graph displays the IRFs with bootstrapped 90% confidence intervals to a one standard deviation shock to policy uncertainty.

We further compare the importance of policy uncertainty shocks in explaining the economic fluctuations in Korea and the U.S. by estimating the variances of the four domestic macroeconomic variables that are explained by the policy uncertainty shock. Table 1 shows that policy uncertainty shocks account for a much smaller share of the macroeconomic variables in Korea compared to the U.S.. For example, after one year, about 10% of the variances of employment and output are explained by policy uncertainty shocks in the U.S. economy, while only 3% of the variances are explained by policy uncertainty shocks in the Korean economy. Taken together, we question the popular claim that policy uncertainty is bad for the macroeconomy, at least for the Korean case.[12] In the following section, we extend our analysis to other EMEs and check whether this suggestive evidence can be generalized.

3.2 Policy Uncertainty vs. Financial Uncertainty in EMEs

How do we reconcile our finding that policy uncertainty shocks have no significant effect on output of the Korean economy with the vast empirical evidence on the importance of uncertainty shocks in the business cycles of many other countries? In particular, a few studies find that the impact of uncertainty shocks on economic activity is even greater in EMEs than advanced economies (Carrière-Swallow and Céspedes (2013); Choi (2016)). However, it is worth noting that these studies rely on stock market volatility, not the EPU index as

[12]By no means, we do not claim that policy uncertainty does not affect economic activity. Vast theoretical and empirical evidence found that policy uncertainty curbs economic activity (Aizenman and Marion (1993); Handley and Limao (2015). We simply find that the results from VARs using the Korean EPU index give little support to the claim that heightened policy uncertainty is critical for economic activity in Korea, unlike the U.S. case.

Table 1: Forecast error variance decomposition: Korea vs. the U.S.

	Korea				U.S.			
Horizon	Stock market	Policy rate	Employment	Output	Stock market	Policy rate	Employment	Output
1	6.97	0.27	0.01	0.02	11.44	0.45	0.06	1.02
6	3.77	0.34	2.43	2.72	9.43	15.90	4.58	7.52
12	3.05	0.28	2.34	3.08	5.83	22.43	9.85	10.76
24	6.53	0.46	1.60	3.92	3.76	27.81	11.63	9.56
36	7.77	1.45	1.74	3.87	2.90	29.83	9.65	7.35

Note: The share of forecast error of each variable explained by policy uncertainty shock in the five-variable model.

a measure of uncertainty. By construction, stock market volatility captures the different dimension of uncertainty from the EPU index.

In EMEs where financial markets are less developed than advanced economies, the transmission mechanism of financial uncertainty shocks could be stronger via an increase in external borrowing costs (Choi (2016); Bhattarai, Chatterjee, and Park (2017)) or sudden stops in capital flows (Gourio, Siemer, and Verdelhan (2016); Choi and Furceri (2017)). Recent studies also highlight the role of financial frictions in amplifying the effect of uncertainty shocks on economic activity (Alfaro, Bloom, and Lin (2016); Caldara, Fuentes-Albero, Gilchrist, and Zakrajsek (2016); Popp and Zhang (2016); Choi, Furceri, Huang, and Loungani (Forthcoming)).

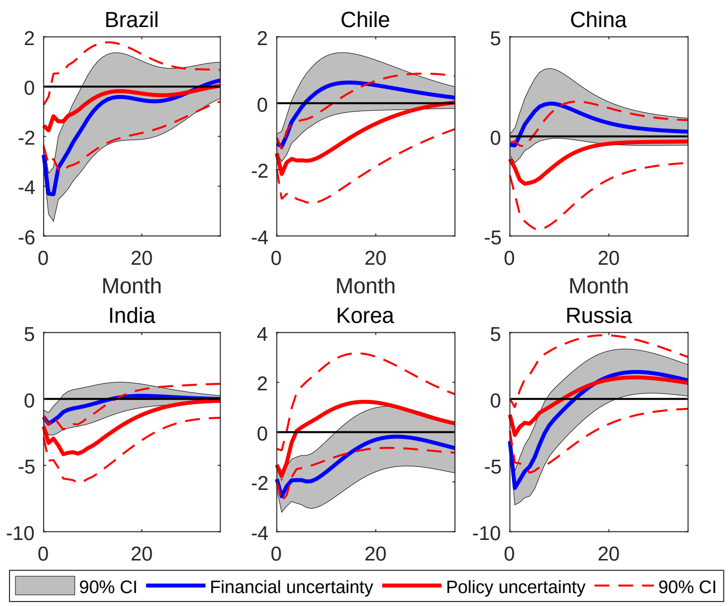
We test the hypothesis that financial uncertainty could have larger impact on economic activity than policy uncertainty in EMEs by estimating the augmented VAR model in which both measures of uncertainty are included. To obtain conservative results, we place the policy uncertainty index before the financial index throughout the analysis.[13] We present the estimation results by showing the responses of individual variables to both types of uncertainty shocks.

The individual estimation results for each variable are shown in Figure 3 to 6. Similar to the case of Korea in Figure 2, the stock markets respond to policy uncertainty shocks instantly in Figure 3. Thus the impact of policy uncertainty shocks on stock markets does not differ substantially between the U.S. and EMEs. Not surprisingly, financial uncertainty shocks have strong negative impact on the stock markets except for China. This result is well expected given the negative relationship between the level and the volatility of the stock market. Overall, we do not detect any meaningful difference between the

[13] Reversing the ordering between the two uncertainty indices only strengthens our conclusion that financial uncertainty shocks are a far more important business cycle driver than policy uncertainty shocks.

responses of of the stock market index to both types of uncertainty shocks.

Figure 3: Responses of the stock market in EMEs



Note: Each graph displays the IRFs with 90% bootstrapped confidence intervals to a one standard deviation shock to financial uncertainty (blue) and policy uncertainty (red).

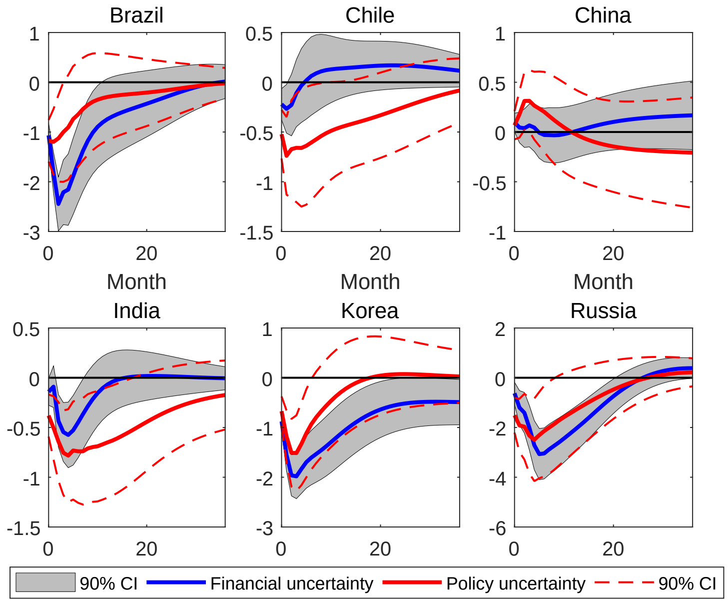
Figure 4 shows that both financial and policy uncertainty shocks in EMEs are followed by a sharp depreciation of local currencies, again except for China.[14] While this finding supports the "flight-to-safety" channel of uncertainty shocks in the global context (Rey (2015); Choi (2016); Gourio, Siemer, and Verdelhan (2016); Choi and Furceri (2017)), we do not find much difference between the responses of the nominal exchange rate to both types of uncertainty shocks.

Interestingly, the response of monetary policy in EMEs to higher uncertainty is qualitatively different from that in the U.S. While the Federal Reserve lowers the policy rate in response to an increase in policy uncertainty, the central banks in EMEs, except for China and India, increase the policy rates sharply. In an integrated international financial market system, an increase in uncertainty is likely to induce the flight-to-safety types of capital flows from EMEs to safe haven economies. Thus despite the heightened uncertainty dragging down economic activity, the ability of central banks to lower the short-term policy rate could be limited due to the fear of capital flow reversals in EMEs.

Lastly, Figure 6 summarizes the novel finding of the paper. While financial uncertainty shocks

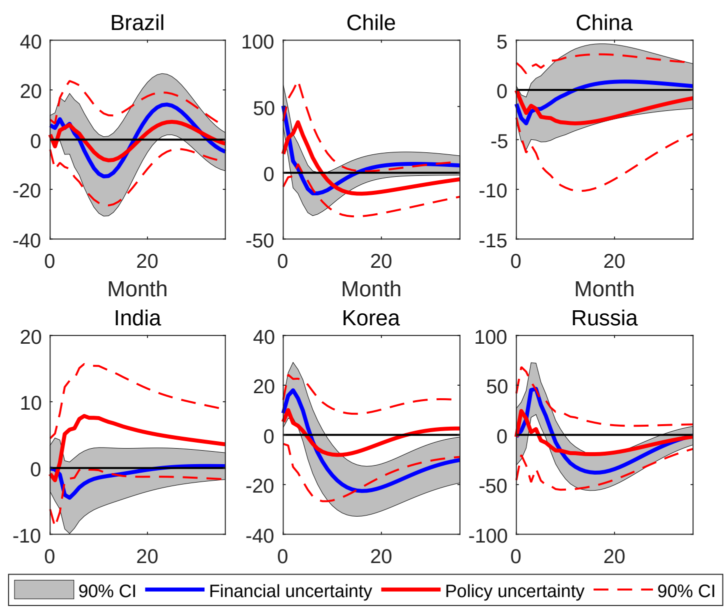
[14] The insignificant response of the Chinese exchange rate to both types of uncertainty shocks is expected because China maintained the fixed exchange rate regime for the most of the sample period. Even after China moved to the managed floating regime, its exchange rate is only allowed to float within a very narrow band.

Figure 4: Responses of the nominal exchange rate in EMEs



Note: Each graph displays the IRFs with 90% bootstrapped confidence intervals to a one standard deviation shock to financial uncertainty (blue) and policy uncertainty (red).

Figure 5: Responses of the short-term policy rate in EMEs

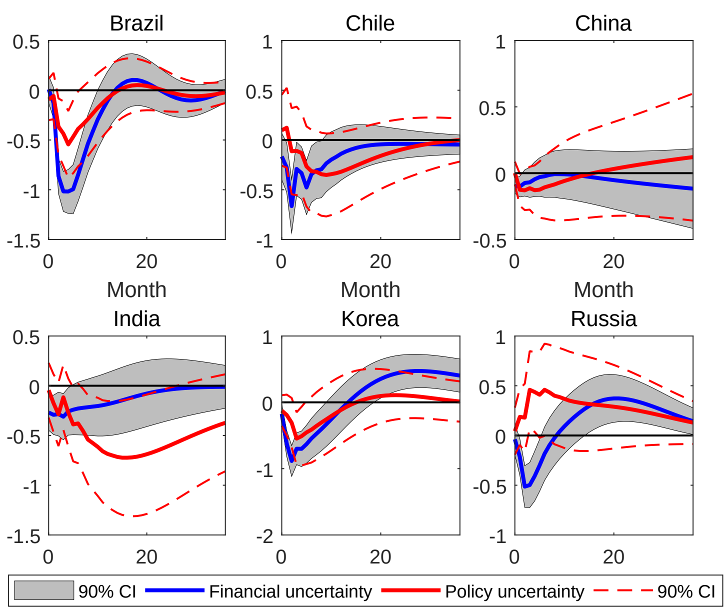


Note: Each graph displays the IRFs with 90% bootstrapped confidence intervals to a one standard deviation shock to financial uncertainty (blue) and policy uncertainty (red).

have significantly negative impact on output of the five EMEs (except for China), the impact of policy uncertainty shocks is much smaller and often statistically insignificant (except for India). Our finding is in sharp contrast to Stockhammar and Österholm (2016) who find that policy uncertainty matters more than financial uncertainty in the analysis of nine high-income small open economies. We also conduct a similar test using the U.S. data to highlight the difference between advanced economies and EMEs. As shown in Figure 7, policy and financial uncertainty shocks have similar quantitative effects on the economy, especially for real variables.

The difference in the responses of output to financial and policy uncertainty shocks in EMEs suggests that one cannot simply generalize the existing finding about advanced economies—and the associated policy implications—to the EME context. The insignificant impact of financial uncertainty shocks in China does not necessarily undermine our finding. While uncertainty about financial markets could affect economic activity via an increase in external borrowing costs or sudden stops in capital flows, the Chinese government has controls over capital flows and interest rates, effectively shutting down these potential channels. In this regard, the case of China supports, not contradicts the importance of financial uncertainty shocks in EMEs.[15]

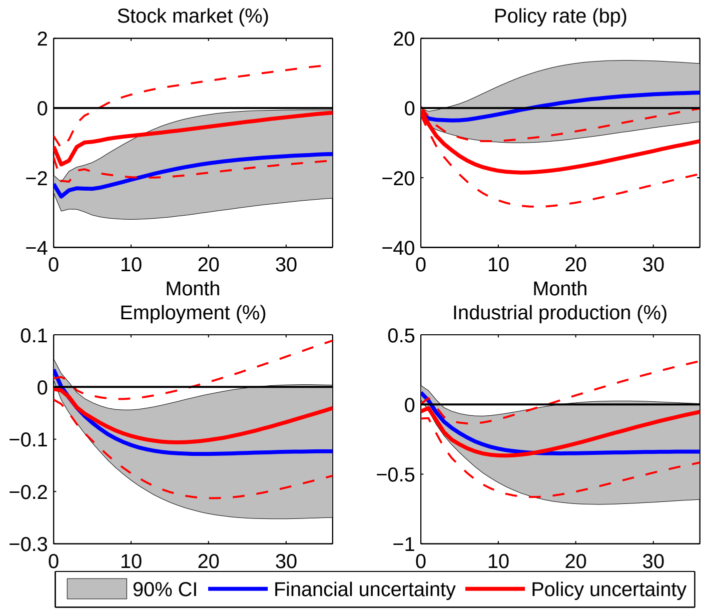
Figure 6: Responses of output in EMEs



Note: Each graph displays the IRFs with 90% bootstrapped confidence intervals to a one standard deviation shock to financial uncertainty (blue) and policy uncertainty (red).

[15]A seemingly strange response of Russian output to policy uncertainty shocks is likely due to the positive correlation (0.25) between oil prices and the Russian EPU index for the period 1994:01-2015:12 and the high reliance of the Russian economy on oil exports. See Antonakakis, Chatziantoniou, and Filis (2014) for the spillover between oil prices and economic policy uncertainty.

Figure 7: Impact of uncertainty shocks in the U.S. economy



Note: Each graph displays the IRFs with 90% bootstrapped confidence intervals to a one standard deviation shock to financial uncertainty (blue) and policy uncertainty (red).

We also provide the results from forecast error variance decomposition of the domestic variables by both types of uncertainty shocks. To capture both the short-run and long-run effects of uncertainty shocks, we gauge the variance decomposition after 6 and 36 months, respectively. Table 2 supports the relative importance of financial uncertainty shocks in explaining output fluctuations in EMEs with an exception of China and India.

4 Robustness Checks

In this section, we run a battery of sensitivity tests to confirm our findings in the last section. Because our novel finding is about the difference between the responses of output to both types of uncertainty shocks, we only report the response of output to save space.

4.1 U.S. Uncertainty Spillover One might argue that our analysis is not fully compatible with the existing studies, such as Stockhammar and Österholm (2016). While they analyze the impact of U.S. uncertainty shocks on the domestic economy (i.e., measuring spillover effects), we analyze the impact of domestic uncertainty shocks. Thus it is still possible that uncertainty about U.S. economic policy has a significant impact on EME output, while uncertainty about their own domestic economic policy

Table 2: Forecast error variance decomposition in emerging economies

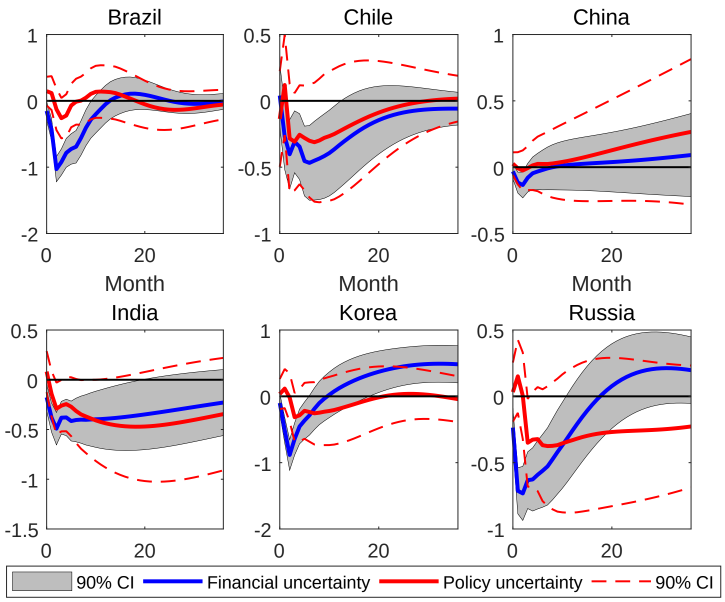
Horizon	Stock market		Nominal exchange rate		Policy rate		Output	
	Financial uncertainty	Policy uncertainty	Financial uncertainty	Policy uncertainty	Financial uncertainty	Policy uncertainty	Financial uncertainty	Policy uncertainty
Brazil								
6 month	28.81	4.97	35.87	9.85	1.03	0.53	47.96	10.68
36 month	12.46	2.37	23.39	5.59	5.05	1.53	29.30	6.89
Chile								
6 month	4.42	18.19	0.75	10.28	5.10	6.05	11.05	2.86
36 month	3.30	13.71	1.64	12.41	4.77	7.21	6.83	4.66
China								
6 month	0.81	6.28	0.19	3.56	1.85	1.13	2.05	2.50
36 month	3.67	5.52	0.77	2.17	0.79	3.39	3.57	0.79
India								
6 month	5.45	33.42	8.65	19.43	1.53	2.98	8.98	4.58
36 month	3.41	49.86	5.98	35.01	1.35	17.48	6.69	22.13
Korea								
6 month	11.36	2.86	25.74	14.13	2.49	0.43	12.81	4.54
36 month	7.28	4.31	26.64	8.19	13.54	1.17	14.50	3.34
Russia								
6 month	19.22	2.55	13.50	14.68	3.39	0.58	10.76	5.28
36 month	10.12	2.71	22.47	13.78	9.06	2.64	12.08	8.60

Note: The share of forecast error of each variable explained by financial and policy uncertainty shocks at the 6th and 36th month horizon.

does not. Considering the size of the U.S. economy accounting for the global economy, it is a valid criticism. To test this hypothesis, we replace our measures of domestic uncertainty (both policy and financial uncertainty) with the measure of U.S. uncertainty. Again, we place the U.S. EPU index before the U.S. stock market volatility index. Following Choi (2016), we impose further identifying restrictions by preventing feedback from domestic variables into the U.S. variables ($B_{k,1,j} = B_{k,2,j} = 0$ for all $j \neq 1, 2$ and $k = 1, 2, ..., p$). This block exogeneity restriction is consistent with a small open-economy assumption in the model.[16] Figure 8 shows that our conclusion hardly changes even when using the U.S. uncertainty indices. Consistent with the existing findings on the spillover of U.S. financial uncertainty shocks on EMEs (Carrière-Swallow and Céspedes (2013); Choi (2016); Bhattarai, Chatterjee, and Park (2017)), U.S. financial uncertainty shocks have significantly negative impact on output of most EMEs in the sample. However, U.S. policy uncertainty does not have much impact on EME output, despite its relevance in shaping the global policy context.

[16]Relaxing the small open-economy assumption and letting the data free to speak regarding this assumption do not change the main results.

Figure 8: Responses of output: U.S. uncertainty spillover



Note: Each graph displays the IRFs with 90% bootstrapped confidence intervals to a one standard deviation shock to financial uncertainty (blue) and policy uncertainty (red).

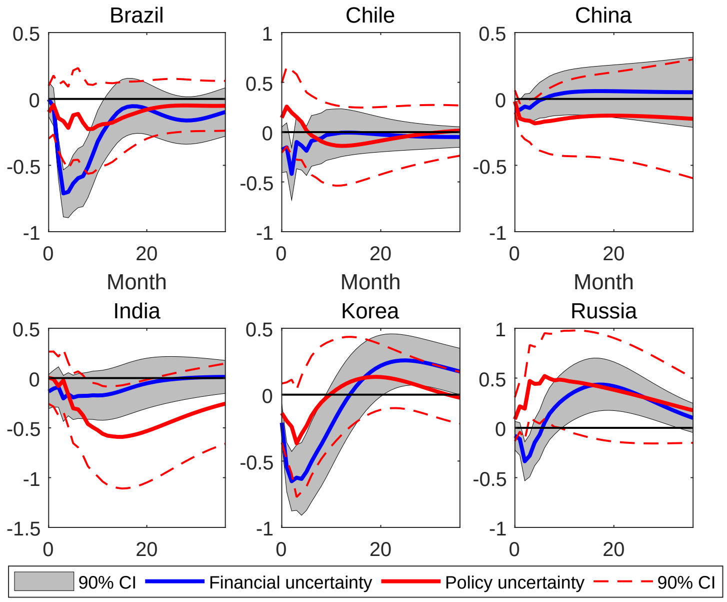
4.2 Controlling for U.S. Uncertainty

Complementing the above robustness check regarding U.S. uncertainty spillover, we also control for U.S. uncertainty when evaluating the impact of both types of domestic uncertainty shocks. As shown in Figure 8, U.S. financial uncertainty shocks have strong negative impact on EME output. To the extent that global financial markets are integrated, however, what we try to capture by—using domestic stock market volatility—might simply be U.S. financial uncertainty. To obtain more conservative estimates that are purged of U.S. uncertainty, we place both U.S. policy and financial uncertainty indices before the domestic variables and impose the similar block exogeneiry restriction above (i.e., we estimate the eight-variable VARs here). Figure 9 confirms that controlling for U.S. uncertainty does not change our main conclusion.

4.3 Alternative Model Specifications

In this section, we explore whether the baseline results that financial uncertainty shocks have a larger and more significant impact on EME output than policy uncertainty shocks are robust to changes in the specification of the VAR model. First, the Cholesky ordering used in the baseline VAR model does not allow for uncertainty to respond to the innovations to macroeconomic and financial variables contemporaneously. While the use of monthly variables mitigates this issue, the baseline identifying assumption could be too restrictive. Following Bloom (2009)

Figure 9: Responses of output: Controlling for U.S. uncertainty



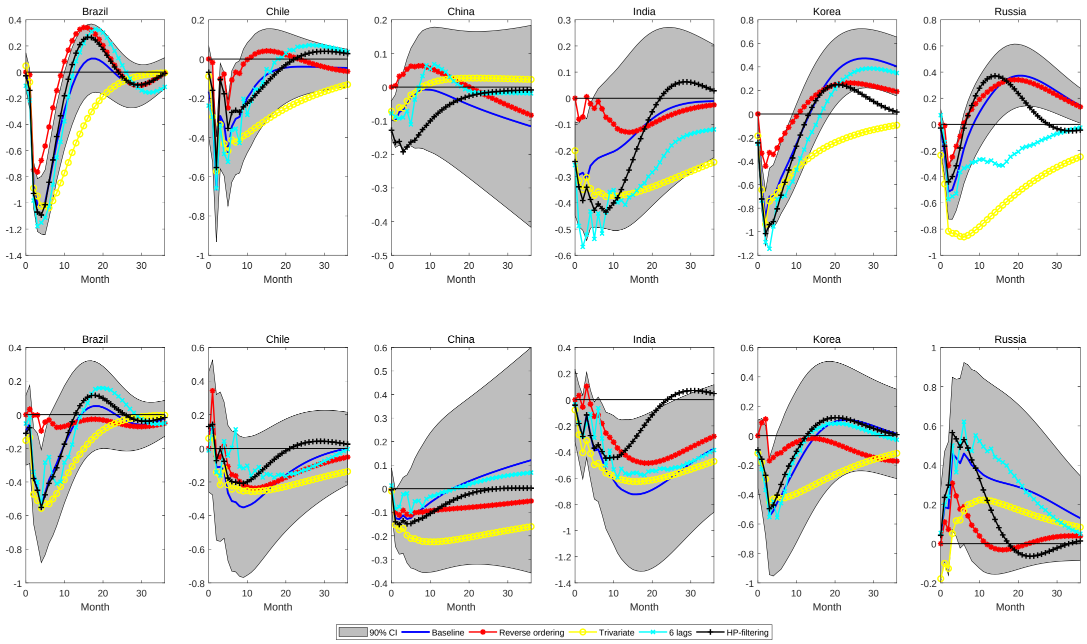
Note: Each graph displays the IRFs with 90% bootstrapped confidence intervals to a one standard deviation shock to financial uncertainty (blue) and policy uncertainty (red).

and Baker, Bloom, and Davis (2016), we test the robustness of our finding by reversing the ordering of the Cholesky decomposition—still placing the policy uncertainty index before the financial uncertainty index. Second, we also estimate the most parsimonious model with only three variables (policy uncertainty, financial uncertainty, and output). Third, although we have applied information criteria to select the proper lag lengths in the baseline VAR model, some residual serial correlation might still be present. Thus we re-estimate the VAR model using six lags, following the practice in Baker, Bloom, and Davis (2016). Last, we use the HP-filtered variables in the VAR model similar to Bloom (2009).[17] Overall, Figure 10 confirms that our conclusion does not depend on the modification of the VAR model.

4.4 Local Projections We re-estimate the impact of both types of uncertainty shocks on output by applying the local projection method. Despite the stark differences reported in the last section, the IRFs from a standard VAR model might reveal substantial errors on longer horizons. This is because the iterative derivation of impulse responses in a standard VAR model relies on the same set of original parameter estimates, thereby magnify any model misspecification (Phillips (1998)). A local projection method proposed by Jordà (2005) is known to be robust to the misspecification problem. Figure 11

[17] The HP-filtering parameter is 129,600 in this case.

Figure 10: Responses of output: Alternative specifications



Note: The top panel displays the response of output to financial uncertainty shocks while the bottom panel displays the response of output to policy uncertainty shocks.

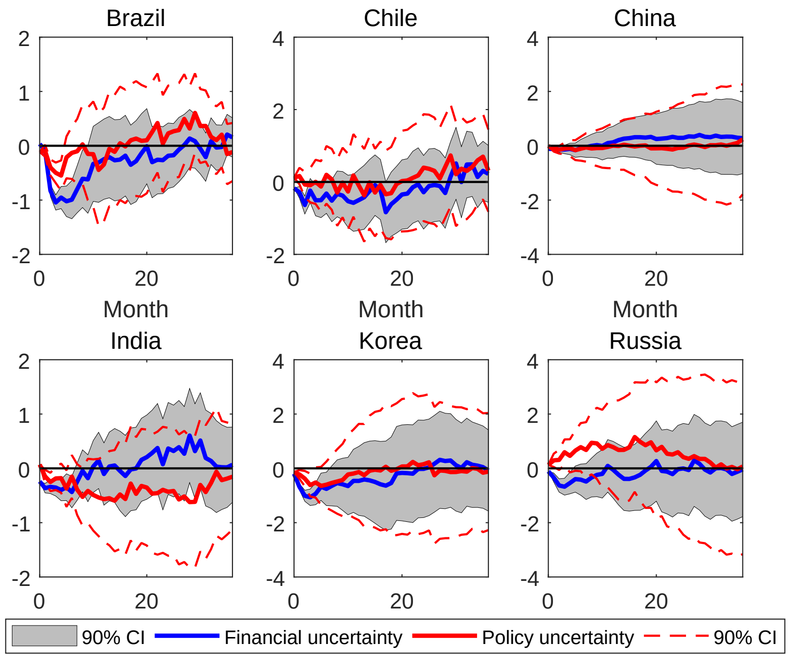
shows the responses of output to the two types of uncertainty shocks when local projections are applied. Our key findings do not depend on any particular estimation technique, as the alternative method still yields a larger and more significant impact of financial uncertainty shocks on output than policy uncertainty shocks (except for China and India).

5 Conclusion

Using two different measures of uncertainty (financial vs. policy) capturing the different aspects of the economy, we find that financial uncertainty shocks have much larger and more significant impact on output than policy uncertainty shocks in EMEs, despite their similar impact on financial variables. While our finding seemingly contrasts with Stockhammar and Österholm (2016) who find that policy uncertainty matters more than financial uncertainty in the analysis of nine high-income small open economies, we do not reject the uncertainty-based explanation of business cycles, rather emphasize the different propagation mechanisms of uncertainty shocks between the two groups of economies.

Consistent with the recent emphasis on financial frictions as a amplification mechanism of uncertainty

Figure 11: Responses of output: Local projections



Note: Each graph displays the IRFs from local projections with 90% confidence intervals to a one standard deviation shock to financial uncertainty (blue) and policy uncertainty (red).

shocks, we offer an alternative explanation of our finding. To the extent that EMEs are subject to more financial frictions than advanced economies, our finding supports the financial friction channel as an important propagation mechanism of uncertainty shocks. In a related study, Choi (2016) also finds that the negative impact of financial uncertainty shocks tends to be more pronounced in a country with a weak financial institution, a shallow financial market, or financial dollarization. Therefore, our finding has clear implications on policymakers in EMEs. While it is useful to understand that different types of uncertainty shocks could have different impact on economic activity, uncertainty regarding financial markets should be a priority of the policymakers in EMEs, especially for the economy subject to more financial frictions.

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