Financial vs. Policy Uncertainty in Emerging Economies: Evidence from Korea and the BRICs*

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Abstract

This paper examines the effects of different types of uncertainty shocks on emerging economies, using Korea as a benchmark. We consider two types of uncertainty: (1) financial uncertainty (volatility from the stock market) and (2) policy uncertainty (constructed by Baker, Bloom, and Davis (2016)). Whereas policy uncertainty shocks have no significant real effects in Korea, Brazil, Russia, India, and Chile, financial uncertainty shocks have strong effects on output of these economies. China with heavily controlled financial markets is the only exception to this pattern. This result seems contradictory to findings from the existing studies on advanced economies that policy uncertainty has no smaller effects on the real economy than financial uncertainty. However, once different levels of financial market development are considered, our finding is consistent with the recent emphasis on financial frictions as a transmission mechanism of uncertainty shocks.

JEL classification: E20, E32

Keywords: Business cycles, Financial uncertainty, Policy uncertainty, Emerging economies, Financial frictions, Sign-restriction VARs, Local projections

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1 Introduction

The Great Recession and the Global Financial Crisis have renewed long-lasting interest in the link between uncertainty and economic activity (see Bloom (2014) for a comprehensive review of the literature). Whereas uncertainty, in principle, can affect the economy differently depending on its origins, the literature has focused mostly on common, rather than heterogenous effects of different kinds of uncertainty shocks based on the high correlations among empirical measures of uncertainty and their countercyclical nature. The recent observation that popular measures of uncertainty diverge from each other casts some doubt on the homogenous effects of uncertainty shocks from different origins.[1]

We contribute to the literature by studying whether uncertainty regarding financial markets and economic policy have different effects on the real economy. As most existing studies analyzing economic policy uncertainty have focused on the U.S. and other advanced economies,[2] we pay particular attention on emerging economies. Unfortunately, there are only six emerging countries (Brazil, Chile, China, India, Korea, and Russia) where the standardized policy uncertainty index is available as of April 2017. The data constraint might explain why no attempt has been made to study emerging economies in greater details.

To draw comparable results from the previous studies including Baker, Bloom, and Davis (2016), we should closely follow their identification specification. However, we should also take account of a small open economy nature into the Vector Autoregression (VAR, hereafter) model. To control for the dominant role of the U.S. in driving development in both global financial markets and global policy outlooks, we use the components of domestic financial and policy uncertainty that are orthogonal to their U.S. counterparts. This mitigates concerns that our results are simply driven by development in the U.S. economy, instead of the relative importance of uncertainty about financial markets and economic policy in emerging economies. After careful consideration of the data constraint to replicate Baker, Bloom, and Davis (2016), we choose Korea as a benchmark country for several reasons.[3]

[1] For example, during the recent episodes of the UK's referendum to leave the EU 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.

[2] For example, Baker, Bloom, and Davis (2016), Bernal, Gnabo, and Guilmin (2016), Choi, Furceri, Huang, and Loungani (Forthcoming), Gulen and Ion (2016), Pástor and Veronesi (2013), and Stockhammar and Österholm (2016) among others.

[3] To replicate the benchmark VAR model of Baker, Bloom, and Davis (2016), we need monthly data on industrial production, employment, the policy rate, and the stock market index, which are not necessarily available in emerging economies for sufficient periods. It is important to include pre-2000 data to avoid the dominance of the Global Financial Crisis in driving our results.

First, the Indian economic policy uncertainty index is too short to draw a meaningful conclusion (only available since 2003). Second, heavily controlled Chinese financial markets by its government makes it difficult to generalize the Chinese case to other emerging economies. Third, Brazil, Chile, and Russia heavily rely on commodity exports and the recent commodity price swings greatly affected their economic performance. Disentangling commodity price shocks from uncertainty shocks is beyond the scope of the paper, although some recent studies found a negative relationship between economic policy uncertainty and commodity prices (Antonakakis, Chatziantoniou, and Filis (2014); Kang, Ratti, and Vespignani (2017)).[4] We still estimate a country-by-country VAR model of these economies to confirm whether the results from Korea can be extended to other emerging economies.

Two particular measures of uncertainty are used in our paper; (1) a financial uncertainty measure constructed from the stock market; and (2) a measure of policy uncertainty (the economic policy uncertainty (EPU) index developed by Baker, Bloom, and Davis (2016)). For Korea, we construct a measure of financial uncertainty by combining the implied and realized volatility of the KOSPI (Korea composite stock price index), which corresponds to the widely used measure of U.S. uncertainty in Bloom (2009). To measure policy uncertainty, we use the EPU index for Korea, which is constructed by Baker, Bloom, and Davis (2016).[5] They use six newspapers to construct the EPU index for Korea by counting the number of newspaper articles appearing in relation to policy uncertainty.

By estimating the VAR model similar to that of Baker, Bloom, and Davis (2016), we find that policy uncertainty shocks do not appear to have any significant effects on real activity, such as employment, industrial production, and private investment, which does not support the common presumption that heightened policy uncertainty in Korea has been an important factor for the recent growth slowdown. It seems contradictory to earlier findings that policy uncertainty shocks have significant effects 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 have significant effects on real activity. Our results are robust to (1) changing specifications in the VAR model; (2) using data at different frequencies; (3) conducting sub-sample analyses; (4) using an alternative sign-restriction approach by Uhlig (2005); and (5) using a different estimation technique such as the local projection method by Jordà (2005).

[4]Moreover, the Chilean economic policy uncertainty index by Cerda, Silva, and Valente (2016) became available only during the revision of the draft.

[5]The EPU indices for various countries can be found at http://www.policyuncertainty.com.

The estimation results from other emerging economies, including Brazil, Chile, China, India, and Russia confirm the same pattern that financial uncertainty shocks have much stronger effects than policy uncertainty shocks except for China where financial markets are heavily controlled by the government. This finding is in sharp contrast to Stockhammar and Österholm (2016) who find that policy uncertainty shocks have larger effects than financial uncertainty shocks in a group of high-income small open economies with developed financial markets. Taken together, several implications can be drawn. First, it is important to identify the origin of uncertainty shocks to predict their effects on the economy. Second, the relative importance in uncertainty regarding financial markets and economic policy can differ between emerging and advanced economies.

Lastly, our findings highlight the importance of financial channels in understanding the link between uncertainty and the real economy. 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. The recent literature also highlights the role of financial frictions in amplifying the effect of uncertainty shocks on the real economy (Arellano, Bai, and Kehoe (2016); Bianchi and Schneider (2014); Caldara, Fuentes-Albero, Gilchrist, and Zakrajsek (2016); Carrière-Swallow and Céspedes (2013); Choi, Furceri, Huang, and Loungani (Forthcoming); Christiano, Motto, and Rostagno (2014); Gilchrist, Sim, and Zakrajšek (2014)). Whether financial markets act as a origin or a propagation mechanism of uncertainty shocks, we expect the dominance of financial uncertainty over policy uncertainty in the economy more subject to financial market imperfections. Combined with earlier studies on advanced economies, our findings underscore the importance of financial channels.

The rest of the paper is organized as follows. Section 2 describes the data and introduces the empirical models. Section 3 presents our findings on the Korean economy and Section 4 tests the robustness of these findings. Section 5 shows the results from estimating a country-by-country VAR model of the BRIC economies and Chile. Section 6 concludes.

2 Data and Empirical Models

This section describes the empirical strategies adopted in the paper. We explain data with a particular focus on two key measures of uncertainty and then introduce the empirical models used in the analysis.

2.1 Data Description For an analysis that is comparable to the existing works, we use essentially the same set of monthly data from Bloom (2009) and Baker, Bloom, and Davis (2016), which includes the Korean stock market index (KOSPI), the Nominal Effective Exchange Rate (NEER), the policy rate measured by the overnight call rate, employment, and industrial production. The only difference is the inclusion of the exchange rate to take account for a small open economy nature of a small open economy.[6] Due to the limited availability of data, most empirical studies on emerging economies use quarterly variables, but using monthly variables instead has three main advantages when studying the impact of uncertainty shocks in the context of structural VARs.

First, it helps discover relevant "short-run" dynamics found in Bloom (2009) because aggregation into a lower frequency necessarily smoothes out much of the variation. 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 difficult to justify. Finally, the quarterly GDP data may not correctly capture private sector behaviors due to cyclical government expenditure. Nevertheless, we further employ a set of quarterly data (year-on-year growth rate of investment and year-on-year CPI inflation rate) as a robustness check of our results in Section 4. All macroeconomic data used are taken from the Bank of Korea Economic Statistics System.

2.2 Measures of Uncertainty in Korea We use the following two proxies that represent different dimensions of uncertainty in the economy.

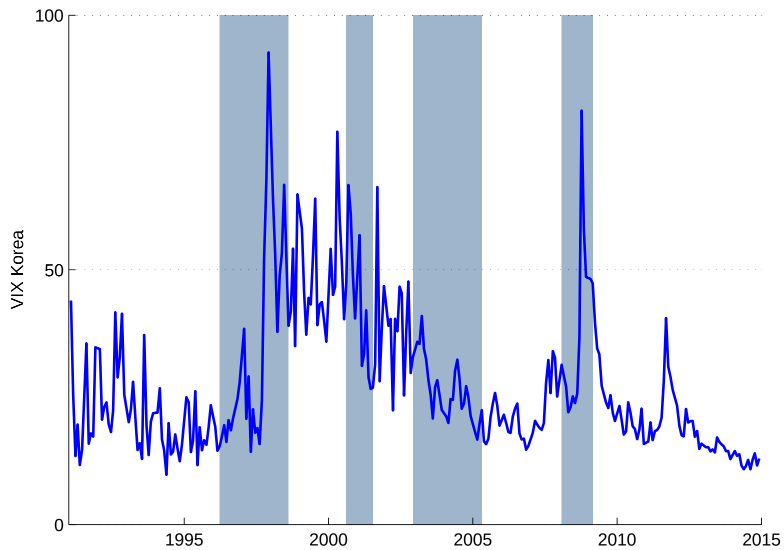
Financial uncertainty index: volatility from KOSPI. The VIX, which refers to the implied volatility of the S&P500 index, is often used as a proxy for uncertainty that arises in financial markets because it measures stock market volatility one month ahead, thereby capturing forward-looking information. Thus, the best counterpart for the VIX in Korea is the implicit volatility of the KOSPI (VKOSPI). Unfortunately VKOSPI is available only after 2003, so we use the realized volatility from January 1991 to December 2002 and the implied volatility after January 2003 to produce a consistent measure of financial uncertainty for Korea. Following Bloom (2009), the realized volatility is normalized to have the same mean and variance as the VKOSPI when they overlap from 2003 onward.[7] Figure 2.1

[6] In the earlier version of the paper, we used the exactly same specification from Baker, Bloom, and Davis (2016) without the exchange rate and obtained similar results. We conducted the same set of exercises and these results are available upon request.

[7] Using the realized volatility for the entire period changes none of the empirical results, as the two measures of volatility are highly correlated (at 0.92) at a monthly frequency (similar to 0.88 in the US data).

plots the volatility series for Korea during the sample period. The solid blue line represents the EPU index and the shaded regions are Korea's official recessionary periods declared by Statistics Korea. It is easy to observe that recessions are associated with heightened uncertainty in the financial market.

Figure 2.1: Korean financial uncertainty index



Note: The horizontal axis indicates the period between Jan 1991 and Dec 2014 and the vertical axis denotes the level of realized (1991-2002) and implied (2003-2014) volatility of the Korean stock market. Shaded regions are Korea's official recessionary periods as declared by Statistics Korea.

Economic policy uncertainty index. According to Baker, Bloom, and Davis (2016), policy uncertainty mainly 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." Following this criterion to capture uncertainty about economic policies, they construct the EPU index for various countries. In particular, they use six newspapers to construct the index for Korea: *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 they standardize each paper's EPU to unit standard deviation from 1995 to 2014, they average across the papers by month and then rescale the resulting series to a mean of 100 from January 1990 to December 2014.

Figure 2.2 plots the EPU index for Korea. Its correlation with the financial uncertainty index is only 0.15, suggesting a potentially different role of the two types of uncertainty shocks in explaining Korean business cycles. To confirm the credibility of the EPU index, we cross-check the key political or economical events that occurred during the sample period.[8] For example, the enactment of the Act on the Real Name Financial Transactions in August 1993 and the death of Kim Il-Sung (the first supreme leader of the Democratic People's Republic of Korea) in July 1994 are associated with spikes in the index in the early 1990s. During the recession in the late 1990s, two major spikes coincide with the bailout decision made by the government and the North Korean launch of the Daepo-dong missile. Other episodes noted in the heightened EPU index also correspond to major political or economic events, such as the bankruptcy of Daewoo Motors (November, 2000), the beginning of the Roh-regime and the arson at the subway station in Daegoo (early 2002), the impeachment of the president by the parliament (May, 2005), the Global Financial Crisis initiated by the collapse of Lehman Brothers (late 2008), and the serial bankruptcies of mutual saving banks in Busan and the death of Kim Jong-Il (the successor of Kim Il-Sung) in the end of 2011.

2.3 Empirical Models with Shock Identification

In the main analysis, we estimate a VAR model using the monthly Korean data from January 1991 to December 2014. The following general representation summarizes our VAR model:

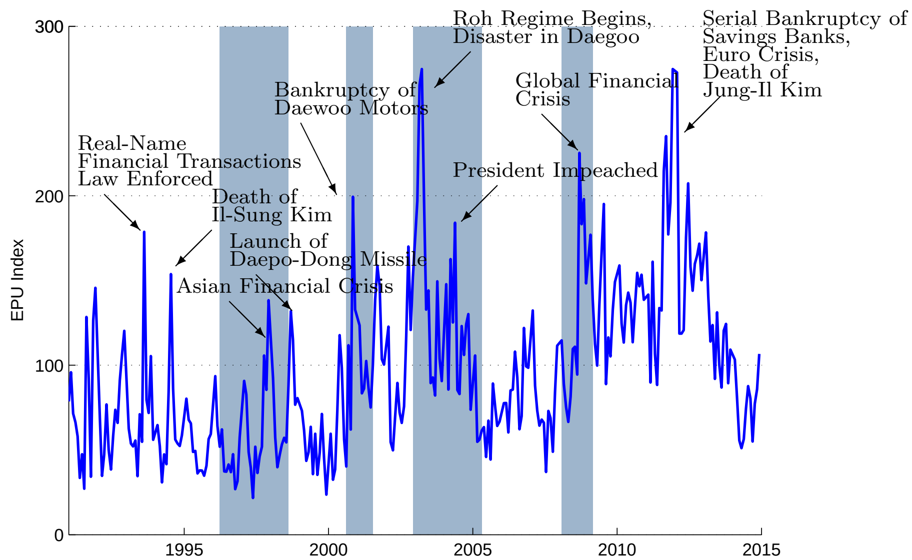
$$Y_t = \sum_{p=1}^{P} B_p Y_{t-p} + u_t, \tag{2.1}$$

$$u_t \sim N(0, \Sigma),$$

where Y_t is an $n \times 1$ vector of observed economic variables described earlier; B_p are $n \times n$ matrices of autoregressive coefficients; and u_t are an $n \times 1$ vector of reduced-form residuals with variance-covariance matrix Σ:

[8] Since Baker, Bloom, and Davis (2016) already scrutinized each of uncertainty events across countries, our evaluation serves as a supplement rather than innovation.

Figure 2.2: Korean policy uncertainty index



Note: The horizontal axis indicates the period between January 1991 and December 2014 and the vertical axis denotes the level of the Korean EPU index. Shaded regions are Korea's official recessionary periods as declared by Statistics Korea.

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

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

For a comparable analysis from Baker, Bloom, and Davis (2016), we use the same Cholesky decomposition (except for the exchange rate) with the following ordering to identify structural shocks in the main analysis: the EPU index, the log level of the Korean stock market index (KOSPI), the NEER, the level of the policy rate measured by the overnight call rate, the log level of employment, and the log level of industrial production. The Cholesky ordering implies that policy uncertainty shocks affect both financial and macroeconomic variables instantly, while these variables can feedback into policy uncertainty with a one period lag. Our baseline VAR specification includes three lags of all variables.[9]

[9] Akaike Information Criterion (AIC) and the Schwarz' Bayesian Information Criterion (BIC) suggest one and three lags respectively.

2.3.1 Sign Restriction

In Section 4.3, we adopt an alternative approach to identify shocks, a sign restriction approach as a robustness check. We briefly summarize a pure sign-restriction approach here, but further details are referred to as Uhlig (2005). We first estimate the equation (2.1) using Bayesian techniques, with prior and posterior distributions of the reduced-form VAR follow an n-dimensional Normal-Wishart distribution. Consider the $n \times n$ matrix A, which connects reduced-form residuals u_t to structural shocks ϵ_t,

$$u_t = A\epsilon_t, \tag{2.2}$$

where $\Sigma = E[u_t u_t'] = AE[\epsilon_t \epsilon_t']A' = AA'$.

For any orthogonal matrix Q such that $QQ' = I_n$ and $\Sigma = AQQ'A$, there is also an admissible decomposition for which $u_t = AQ\tilde{\epsilon}_t$ and $\tilde{\epsilon}_t \tilde{\epsilon}_t{}' = I_n$, where $\tilde{\epsilon}_t$ denotes the (many) different structural shocks implied by alternative identification. Although different orthogonal matrices Q produce different signs and magnitudes of the impulse responses, discriminating among them from data is practically impossible, as they imply identical VAR representations. Therefore, for any decomposition $\Sigma = AA'$, there exist infinitely many identification schemes $AQ^{(k)}$ for $k = 1, 2, ..., \infty$, such that $\Sigma = AQ^{(k)} Q^{(k)'} A'$.

Unlike Uhlig (2005) who identified only one (monetary policy) shock, we attempt to simultaneously identify multiple structural shocks. The method to identify multiple structural shocks closely follows Peersman (2005):

(i) Draw $d = 1, ..., m$ models from the posterior distribution of the VAR (a model d consists of VAR parameters $B_j^{(d)}$ and a covariance matrix $\Sigma^{(d)}$).

(ii) For $j = 1, 2, ...,$ draw randomly from the m models.

(iii) Choose $A = \tilde{A}^{(j)}$, where $\tilde{A}^{(j)}$ is any Cholesky decomposition of $\Sigma^{(j)}$, such that $\Sigma^{(j)} = \tilde{A}^{(j)} \tilde{A}^{(j)'}$.

(iv) For each j, draw random matrices $Q^{(k(j))}$, $k(j) = 1, ..., K$ until the impulse response functions implied by B_p^j and the identification schemes $\tilde{A}^{(j)} Q^{(k(j))}$ satisfy the sign restrictions. If all the sign restrictions are satisfied, we define the combination of model j and identification scheme $\tilde{A}^{(j)} Q^{(k(j))}$ an accepted model.

(v) Iterate over (ii) - (iv) until 200 models are accepted.

2.3.2 Local Projection Following Choi and Loungani (2015), we briefly illustrate the computation of impulse response functions and refer to Jordà (2005) for details on the local projection method. 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:

$$IR(t, s, d_{i,t}) = \frac{\partial y_{t+s}}{\partial \delta_t} = E[y_{t+s}|\delta_t = d_{i,t}; X_t] - E[y_{t+s}|\delta_t = 0; X_t] \tag{2.3}$$

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:

$$y_{t+s} = \alpha^s + B_1^{s+1} y_{t-1} + B_2^{s+1} y_{t-2} + ... + B_p^{s+1} y_{t-p} + U_{t+s}^s, \tag{2.4}$$

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 impulse response functions 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 identification of structural shocks uses the same Cholesky ordering in Section 2.3.

3 Uncertainty Shocks in the Korean Economy

This section provides key empirical findings of the paper. Although a few studies examined the effects of uncertainty shocks on the Korean economy (Lee and Jung (2016); Kim and Kim (2012); Yoon and Lee (2013)), none of them compared different types of uncertainty shocks. As described earlier, we use the component of domestic policy uncertainty (financial uncertainty) that is orthogonal to U.S. policy uncertainty (financial uncertainty) to rule out the possibility that our results are simply driven by development in the U.S. economy.

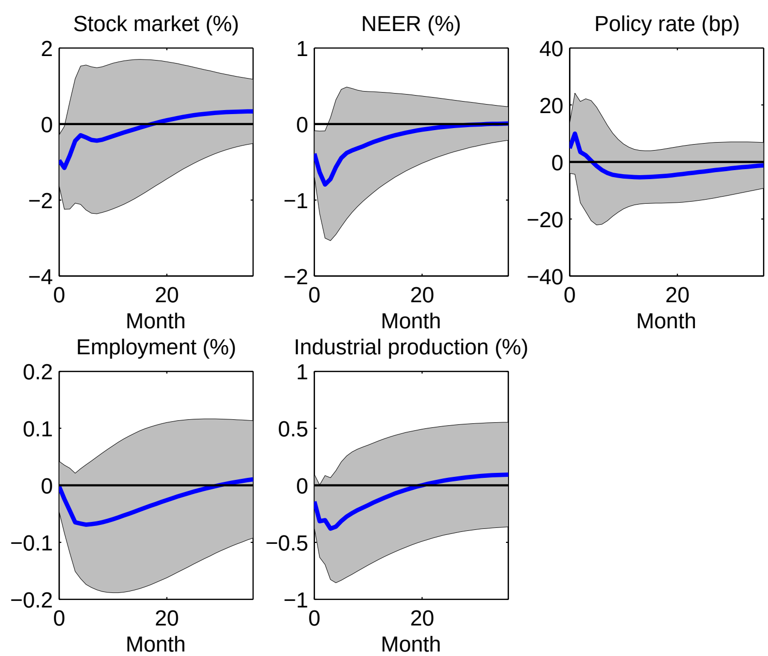
$$y_{korea,j,t} = y_{us,j,t} + e_{korea,j,t}, \tag{3.1}$$

where y is a measure of uncertainty for $j = \{policy, financial\}$. The residual $e_{korea,j,t}$ becomes a measure of domestic uncertainty that is not correlated with the U.S. measure of uncertainty. Figure 6.1

and 6.2 in the online appendix show the orthogonal components of both indices $e_{korea,j,t}$ together with the original Korean and U.S. indices $y_{korea,j,t}$ and $y_{us,j,t}$.

3.1 Policy Uncertainty We first study how policy uncertainty can affect the aggregate economy. Figure 3.1 shows the impulse response functions (IRFs) of the stock market, the exchange rate, the policy rate, employment, and industrial production to a one standard deviation shock to the orthogonalized EPU index in Korea.[10] An increase in policy uncertainty is followed by a decline in the stock market and a depreciation of the domestic currency in the short-run, implying that financial markets quickly respond to an increase in policy uncertainty. However, its effect on real variables such as employment and industrial production is not statistically significant at any horizon. This result is in sharp contrast to previous findings that policy uncertainty shocks have strong negative effects on output and employment in the U.S. (Baker, Bloom, and Davis (2016)) and the Euro area (Colombo (2013)).[11]

Figure 3.1: Impact of policy uncertainty shocks: Korea



Note: Each graph displays the IRFs with bootstrapped 90% confidence intervals to a one standard deviation policy uncertainty shock

Comparison to the U.S. Economy. To confirm that the insignificant impact of policy uncertainty

[10] 90% confidence intervals are plotted using 200 bootstraps.

[11] To be precise, Colombo (2013) studied the impact of U.S. policy uncertainty shocks on the Euro area. To obtain comparable results, we also estimate the effects of US policy uncertainty shocks on Korean output and employment and find insignificant effects even in this case.

shocks in Korea is not driven by a different sample period used in Baker, Bloom, and Davis (2016), we run the same VAR model using U.S. data from January 1991 to December 2014. We use the monthly U.S. policy uncertainty index from Baker, Bloom, and Davis (2016), the log level of the S&P500 index, the Federal Funds rate, the log level of U.S. employment, and the log level of U.S. industrial production. Figure 6.3 in the online appendix confirms that an increase in policy uncertainty is followed by statistically significant and persistent declines in every variable. A decline in the Federal Funds rate and U.S. output after policy uncertainty shocks is consistent with a negative aggregate demand type of interpretation of uncertainty shocks in Jones and Olson (2015) and Leduc and Liu (2016), although it is not the case for the Korean economy.

We also compare the importance of policy uncertainty shocks as a business cycle driver in Korea and the U.S. by estimating the variances of the four variables that are explained by a shock to the EPU index. Panel A in Table 3.1 shows that policy uncertainty shocks account for a much larger share of the macroeconomic variables in the U.S. as compared to Korea. For example, after one year, about 10% of the variances of employment and industrial production are explained by policy uncertainty shocks in the U.S economy while less than 3% are explained by the same shocks in the Korean economy. Taken together, we conclude that uncertainty regarding economic policy in Korea is not a major driver of its business cycle fluctuations.

3.2 Financial Uncertainty How do we reconcile our finding that policy uncertainty shocks have no significant effect on real activity in Korea with ample empirical evidence demonstrating the importance of uncertainty shocks in the business cycle fluctuations of many other countries? Especially, several studies found that the impact of uncertainty shocks on real activity is even greater in emerging economies than advanced economies (Carrière-Swallow and Céspedes (2013); Choi (2016)). However, it is worth noting that the measure of policy uncertainty is not necessarily a comprehensive measure of uncertainty surrounding emerging economies. Moreover, in an emerging economy where financial markets are imperfect, uncertainty about financial markets can have dominant effects via sudden capital outflows or an increase in external borrowing costs (Bernal, Gnabo, and Guilmin (2016); Carrière-Swallow and Céspedes (2013); Choi (2016); Forbes and Warnock (2012); Gourio, Siemer, and Verdelhan (2016)).

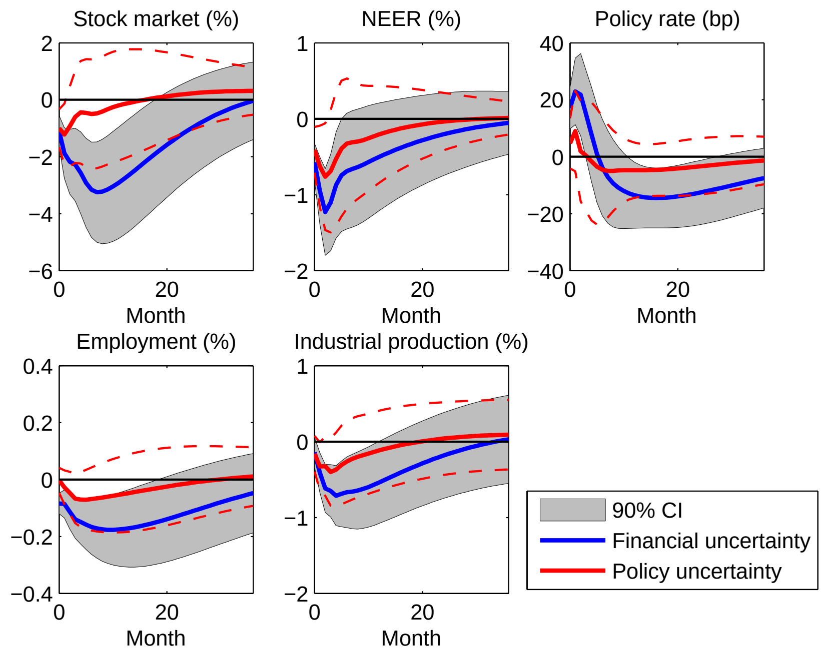
We test this hypothesis by re-estimating the baseline VAR model with an inclusion of the measure of financial uncertainty. To obtain conservative results, we place the orthogonalized policy uncertainty

Table 3.1: Forecast error variance decomposition: Korea vs. the U.S.

Panel A: policy uncertainty only									
			Korea				U.S.		
Horizon	Stock	NEER	Policy rate	Employ ment	Output	Stock market	Policy rate	Employ ment	Output
1	2.69	2.21	0.40	0.01	0.48	11.44	0.45	0.06	1.02
6	1.08	3.22	0.37	1.67	2.42	9.43	15.90	4.58	7.52
12	0.68	2.65	0.55	1.66	1.82	5.83	22.43	9.85	10.76
24	0.44	2.21	0.87	1.05	1.06	3.76	27.81	11.63	9.56
36	0.49	2.09	0.82	0.79	0.83	2.90	29.83	9.65	7.35
Panel B: both financial and policy uncertainty									
Panel B.1: financial uncertainty									
			Korea				U.S.		
Horizon	Stock	NEER	Policy rate	Employ ment	Output	Stock market	Policy rate	Employ ment	Output
1	3.64	4.83	5.05	4.88	0.47	46.01	2.55	11.83	0.03
6	9.71	7.67	4.18	9.80	8.14	35.05	4.56	9.93	3.38
12	14.26	7.15	4.63	11.43	9.14	29.34	9.43	6.60	6.77
24	13.86	6.66	7.43	10.36	7.07	25.04	11.39	4.77	7.67
36	12.78	6.44	7.92	8.94	5.25	23.87	12.31	3.86	6.49
Panel B.2: policy uncertainty									
			Korea				U.S.		
Horizon	Stock	NEER	Policy rate	Employ ment	Output	Stock market	Policy rate	Employ ment	Output
1	2.98	2.47	0.38	0.01	0.62	1.06	2.50	0.41	0.88
6	1.34	2.99	0.32	1.82	2.60	1.73	3.31	15.36	6.85
12	0.80	2.41	0.56	1.67	1.82	0.94	6.41	22.13	9.89
24	0.53	2.03	0.80	1.10	1.13	0.60	8.98	28.05	9.19
36	0.55	1.89	0.77	0.77	0.82	1.15	10.81	30.29	7.41

Notes: The share of forecast error of each variable explained by policy uncertainty shock in the baseline model (Panel A), financial uncertainty shock in the augmented model (Panel B.1), and policy uncertainty shock in the augmented model (Panel B.2).

Figure 3.2: Impact of financial uncertainty shocks: Korea



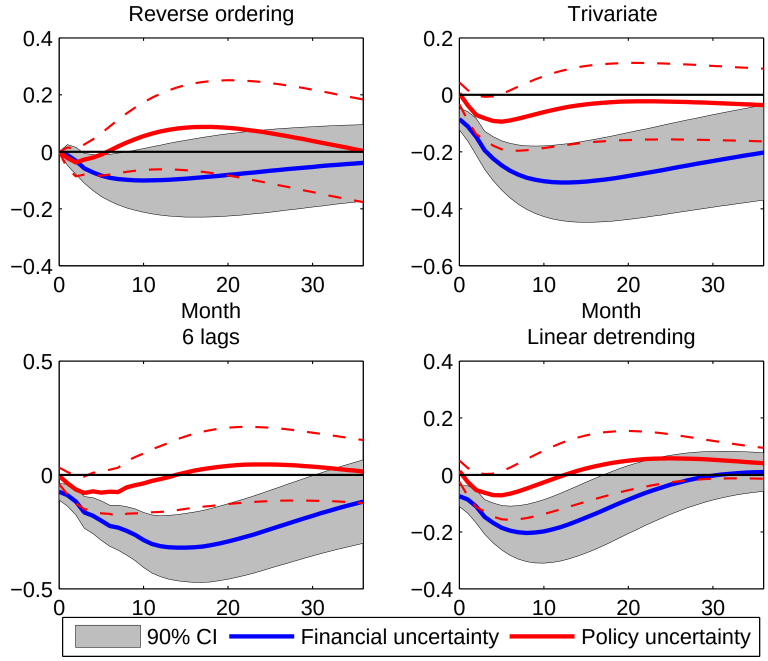
Note: Each graph displays the IRFs with 90% bootstrapped confidence intervals to a one standard deviation financial uncertainty (blue) and policy uncertainty shock (red).

index after the orthogonalized EPU index.[12] Figure 3.2 supports the hypothesis. Overall, the size of the declines in employment and industrial production is more than double of policy uncertainty shocks and these effects are highly significant. It is clear that the central bank sharply increases its policy rate in response to financial uncertainty shocks, implying a fundamental difference between Korean and US monetary policies. In an integrated international financial market system, an increase in uncertainty induces "flight to safety" types of capital flows from emerging economies to the U.S. economy since international investors consider it a safe haven. Despite deteriorating domestic economic conditions, central banks in emerging economies often raise the policy rate to prevent capital outflows. See Choi (2016), Gourio, Siemer, and Verdelhan (2016), and Rey (2016) for further details.

We also conduct a similar test using the U.S. data. As shown in Figure 6.4 in the online appendix, policy uncertainty shocks have similar quantitative effects as financial uncertainty shocks on the three macroeconomic variables, despite their much weaker effects on the stock market. Panel B in Table 3.1 further shows the relative importance of two types of uncertainty shocks in explaining the variance of macroeconomic variables in each economy, which reinforces the results from the IRFs. Whereas two

[12]Reversing the ordering between the two uncertainty indices only strengthens our conclusion.

Figure 4.1: Robustness check: employment



Note: Each graph displays the response of employment with 90% bootstrapped confidence intervals to a one standard deviation financial uncertainty and policy uncertainty shock under different specifications.

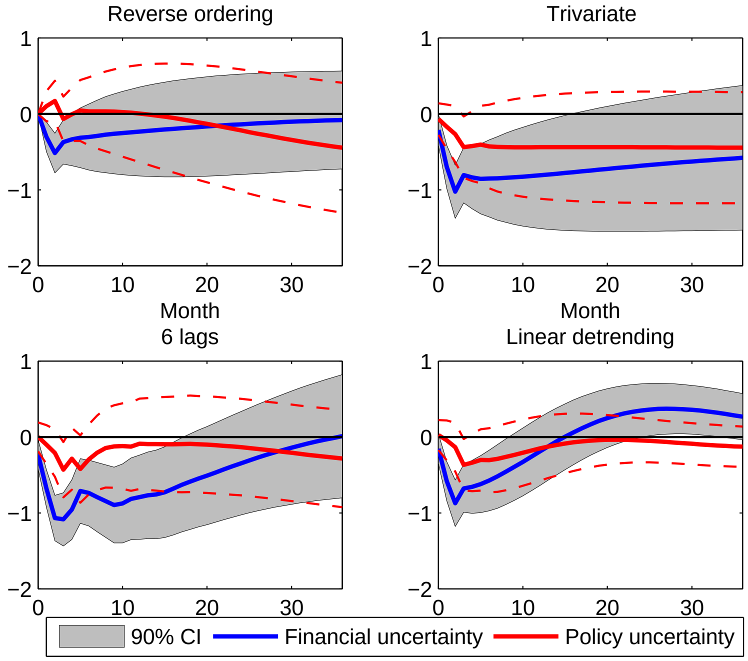
types of uncertainty shocks are equally important in explaining U.S. business cycles, only financial uncertainty shocks play an important role in explaining Korean business cycles.

4 Robustness Checks

In this section, we run an array of sensitivity tests to confirm the contrasting pattern between policy and financial uncertainty shocks found in the last section.

4.1 Alternative Model Specifications We conduct several tests following Baker, Bloom, and Davis (2016), which include: 1) the reverse ordering of the variables in the system; 2) employing a four-variable VAR model (policy uncertainty, financial uncertainty, employment, and industrial production); 3) using more lags in the VAR system; and 4) linear de-trending of the variables. Figures 4.1 and 4.2 confirm the negligible impact of policy uncertainty shocks on real economic activity in Korea after changing the specifications in our baseline VAR model.

Figure 4.2: Robustness check: industrial production

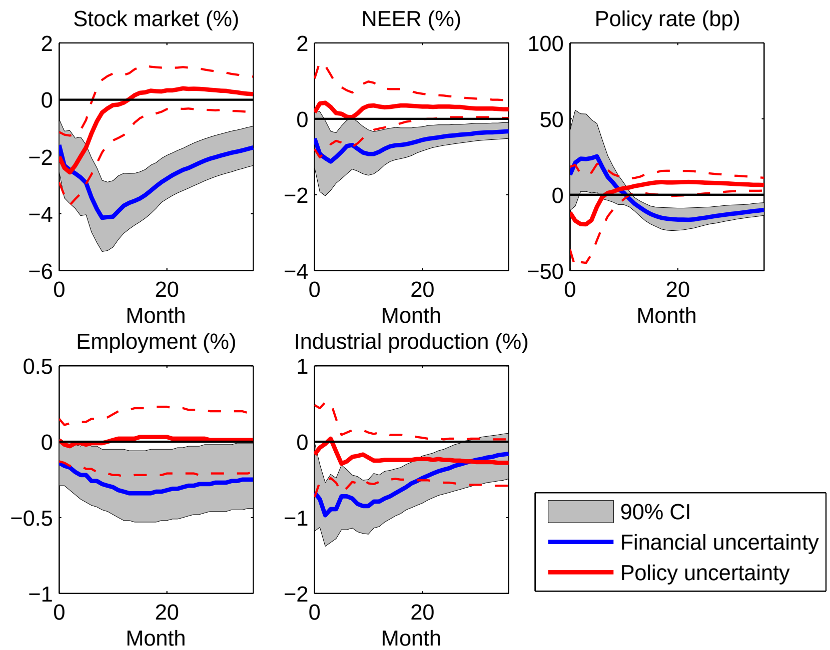


Note: Each graph displays the response of industrial production with 90% bootstrapped confidence intervals to a one standard deviation financial uncertainty and policy uncertainty shock under different specifications.

4.2 Subsample Analysis It is well recognized that the Asian financial crisis in 1997-1998 acts as a structural break in the Korean economy. Ignoring the presence of this structural break in the data may result in biased results. To mitigate this risk, we estimate the pre- (1991:01-1997:09) and post- (1999:01-2014:12) crisis sample periods separately. As shown in Figure 6.5 in the online appendix, Korean policy uncertainty shocks continue to have insignificant effects on the real variables in both periods. However, the insignificant effects of the policy uncertainty shocks are not necessarily driven by the test's low power due to the smaller sample size, as Figure 6.6 shows significant effects of financial uncertainty shocks on real variables in both periods.

4.3 Alternative Shock Identification: A Sign-restriction Approach In this section we test the robustness of our results by applying an alternative sign-restriction approach to identify structural shocks. Recently, the sign-restriction approach by Peersman (2005) and Uhlig (2005) has been widely used in the area of empirical macroeconomics because this approach seeks identification based on heuristic economic reasoning rather than the (often) arbitrary timing assumption used in standard recursive identification. This arbitrary timing assumption becomes a particular issue when studying

Figure 4.3: Robustness check: sign-restriction VARs



Note: Each graph displays the median IRFs with 68% confidence intervals to a one standard deviation financial uncertainty and policy uncertainty shock based on 200 draws using a sign-restriction approach.

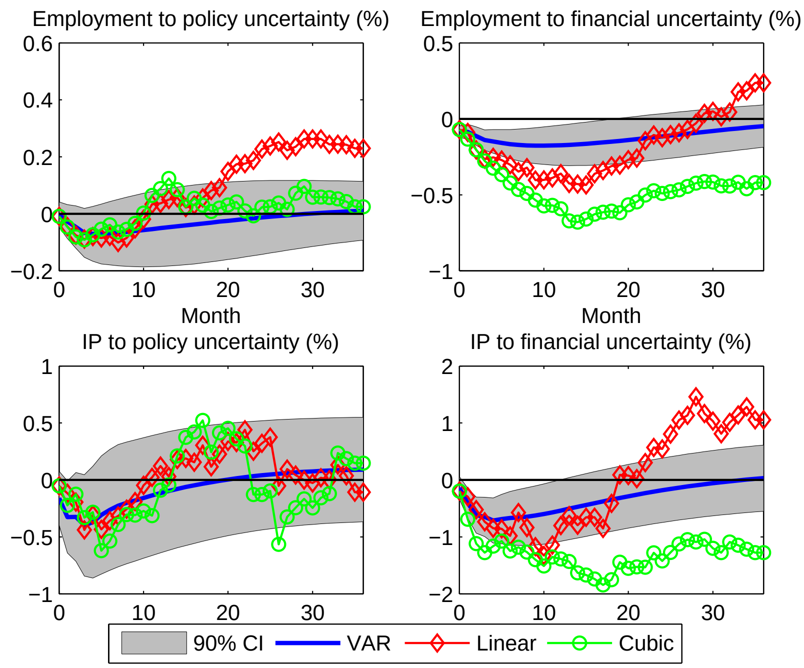
uncertainty shocks because no theories clearly guide the relative timing of the arrival of shocks to uncertainty and macro variables and not all existing studies agree with the identifying assumptions used in our main analysis.[13]

We do not attempt to identify every structural shock to the economic system, since the full identification of underlying shocks requires further sign restrictions and is not necessarily desirable (see, Christiano, Eichenbaum, and Evans (1999) and Uhlig (2005)). This approach identifies a financial uncertainty shock and a policy uncertainty shock by imposing sign restrictions on three variables. While both types of uncertainty shocks must be followed by a decline in the stock market index, they should have the opposite effect on the measures of each uncertainty.[14] Following Uhlig (2005), all the restrictions are imposed for six months following the initial shock, but the qualitative results hardly change when imposing restrictions for three or twelve months. Figure 4.3 clearly indicates that contrasting dynamic

[13]For example, Jurado, Ludvigson, and Ng (2015) place a measure of uncertainty after macroeconomic variables in the process of recursive identification.

[14]In other words, financial uncertainty shocks should not decrease the financial uncertainty index and should not increase the EPU index and the stock market index, whereas policy uncertainty shocks should not decrease the EPU index and should not increase the financial uncertainty index and the stock market index.

Figure 4.4: Robustness Check: Local Projections



Note: Each graph displays the IRFs computed by VAR (blue), local linear projections (red), and cubic projections (green).

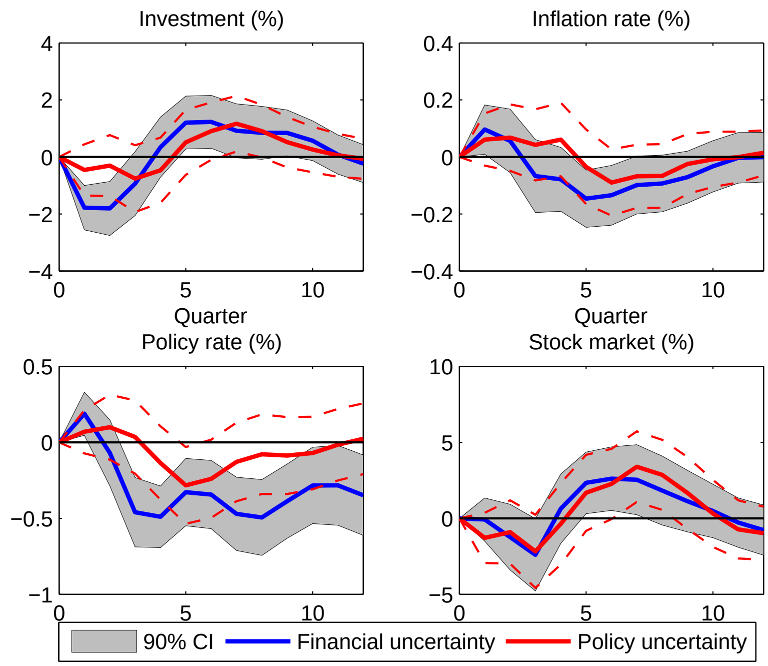
effects between financial and policy uncertainty shocks survive with an alternative shock identification procedure.[15]

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

Figure 4.4 shows the responses of employment and industrial production to the two types of uncertainty shocks when linear and cubic projections are applied. Our key findings do not depend on any particular estimation technique, as the alternative method yields even greater differences in the effects of the two types of uncertainty shocks.

[15]We do not provide forecast error variance decomposition exercises here, as we do not identify every structural shock in the model.

Figure 4.5: Robustness check: quarterly VAR model



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

4.5 Investment in Quarterly Data A weak linkage between policy uncertainty and economic activity such as industrial production and employment, can be overturned when we measure economic activity using investment data. For example, substantial heterogeneity in the degree of employment protection or the bargaining power of labor unions across countries make an international comparison of the effect of uncertainty shocks on employment difficult. In an export-driven economy such as Korea, a large part of industrial production is directly related to exports in which exchange rate movements play a dominant role. Moreover, option value theories often predict a strong negative link between investment and uncertainty given its irreversible nature (Bernanke (1983); Dixit (1994)).

Given that investment data are only available at a quarterly frequency, we modify the baseline VAR model accordingly. It is difficult to justify the Cholesky ordering used in a quarterly VAR model, which assumes that uncertainty does not respond to shocks to real economic activity or a policy variable within a quarter. Following more conventional identifying assumptions in most VAR models using quarterly data (Bernanke, Boivin, and Eliasz (2005); Choi and Loungani (2015); Jurado, Ludvigson, and Ng (2015)), we include five variables in the following order: growth rate in investment, annualized CPI inflation rate, the policy rate, the NEER, the EPU index, and the financial uncertainty index with four lags. Figure 4.5 shows that the impact of financial uncertainty shocks is much greater than that of the policy uncertainty shocks and that the response of investment to financial uncertainty shocks clearly shows a "wait–and–see" pattern, which supports the claim that financial uncertainty is an important driver of Korean investment dynamics.

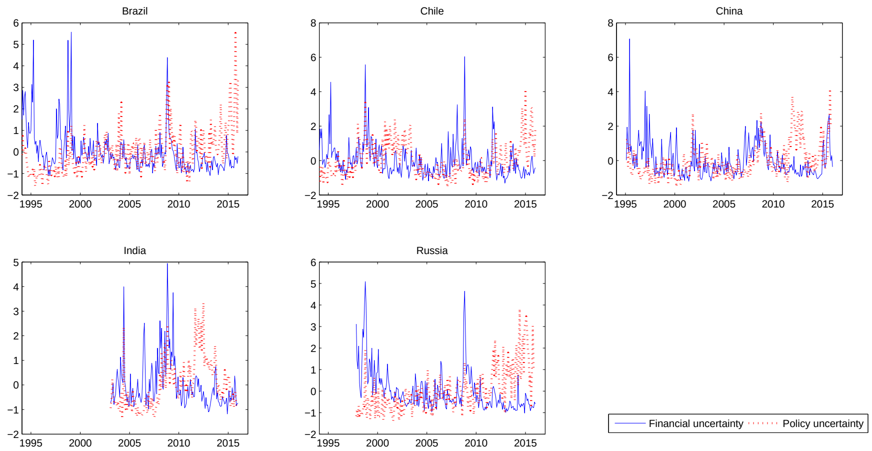
5 Evidence from the BRIC economies

To confirm whether the empirical findings from Korea can be generalized to other emerging economies, we estimate a VAR model of the BRIC economies (Brazil, Russia, India, and China) and Chile. We only include five variables in the following order to maximize the time series coverage of the sample: the policy uncertainty index, the financial uncertainty index, the stock market index, the exchange rate (NEER), and industrial production. The individual country coverage of the data starts in January 2002 (Brazil), January 1994 (Chile), January 1997 (China), January 2003 (India), and October 1997 (Russia), which is solely determined by the availability of the main variables. We construct the financial uncertainty indices by estimating the monthly realized volatility of daily returns of the Bovespa index (Brazil), the Santiago Stock Exchange IPSA Index (Chile), the Shanghai Stock Exchange Composite Index (China), the NIFTY 50 Index (India), and the MICEX Index (Russia). Stock market data are taken from Bloomberg and other macroeconomic data are taken from IMF International Financial Statistics. The policy uncertainty indices are downloaded from www.policyuncertainty.com. Figure 5.1 shows the evolution of two uncertainty indices from each of five emerging economies.

The individual estimation results for each variable are shown in Figure 5.2 to 5.4. By construction, financial uncertainty shocks are expected to have stronger effects on the stock market than policy uncertainty shocks, which is confirmed in Figure 5.2. Interestingly, Figure 5.3 shows that both financial and policy uncertainty shocks have similar quantitative effects on the exchange rates. Consistent with the case of Korea, however, only financial uncertainty shocks have significantly negative effects on output. Except for China, policy uncertainty shocks do not have any significant effects (Figure 5.4).

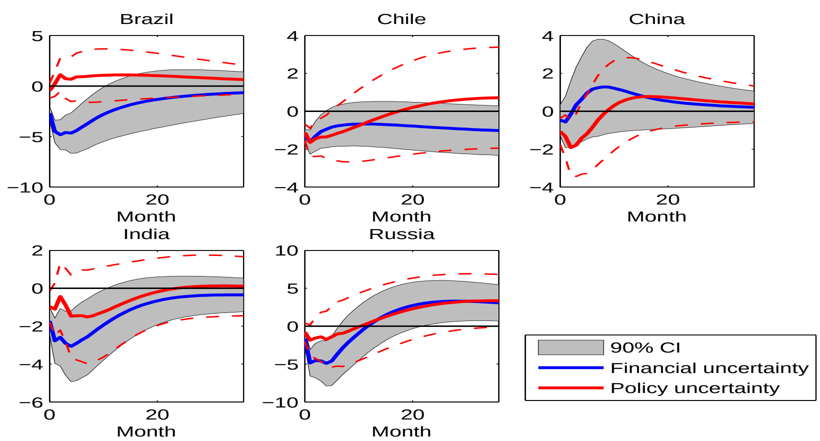
Variance decomposition in Table 5.1 further supports the relative importance of financial uncertainty shocks in explaining output fluctuations with an exception of China. In sum, the results from other emerging economies confirm that financial uncertainty shocks are far more important in explaining output fluctuations than policy uncertainty shocks. Our findings are also consistent with Caldara,

Figure 5.1: Uncertainty indices: five emerging economies



Note: Blue solid lines display the financial uncertainty indices and red dotted lines display the policy uncertainty indices. For better visualization, each of the indices is normalized.

Figure 5.2: Responses of stock markets

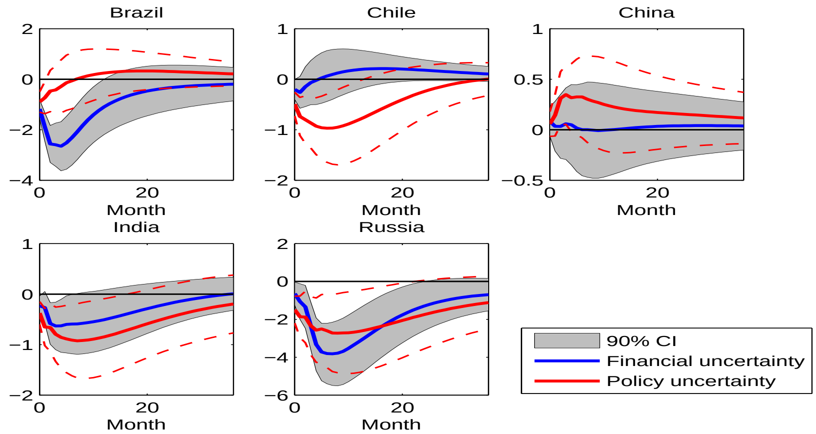


Note: Each graph displays the IRFs with 90% bootstrapped confidence intervals to a one standard deviation financial uncertainty (blue) and policy uncertainty shock (red).

Fuentes-Albero, Gilchrist, and Zakrajsek (2016) who find that uncertainty shocks carry a quantitatively small effect unless they are transmitted through financial markets.

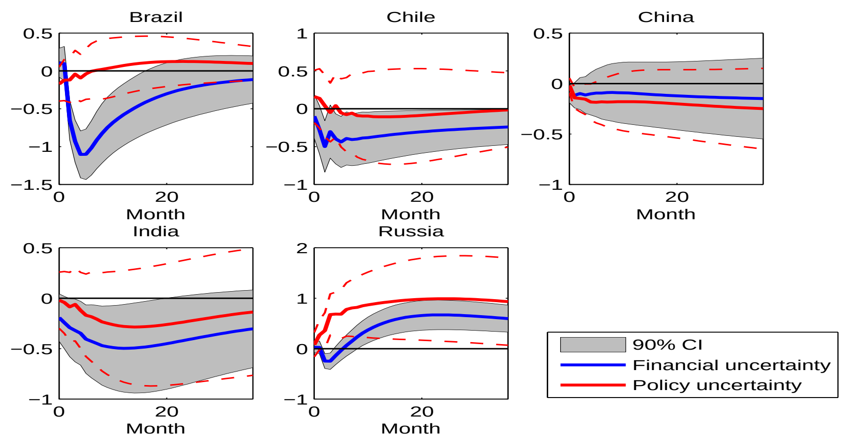
The insignificant effect of financial uncertainty shocks on output in China does not necessarily undermine our claim that financial channels are important in understanding the link between uncertainty and the real economy. While uncertainty about financial markets can affect the real economy via sudden capital outflows or an increase in external borrowing costs, the Chinese government controls capital flows and interest rates. In such an economy, it is not surprising that uncertainty regarding the government's

Figure 5.3: Responses of the exchange rates



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

Figure 5.4: Responses of output



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

policy is a more important factor in explaining business cycles.

6 Conclusion

Using different measures of uncertainty (financial vs. policy), we find that policy uncertainty shocks do not have significant effects on output of emerging economies, which is in sharp contrast to the findings from advanced economies (Baker, Bloom, and Davis (2016); Colombo (2013)). Nevertheless, our findings do not necessarily reject the uncertainty-based explanation of business cycles, as financial uncertainty shocks still have substantial effects on output of emerging economies. To the extent that

Table 5.1: Forecast error variance decomposition in emerging economies

Horizon	Stock market		NEER		output	
	Financial uncertainty	Policy uncertainty	Financial uncertainty	Policy uncertainty	Financial uncertainty	Policy uncertainty
Brazil	29.14	1.53	43.95	1.69	48.14	0.49
Chile	4.94	6.89	0.59	21.79	6.28	0.38
China	1.70	2.24	0.07	3.94	1.33	3.79
India	19.33	4.81	9.80	22.28	10.87	2.26
Russia	8.86	0.95	29.18	18.75	13.51	8.26

Notes: The share of forecast error of each variable explained by financial and policy uncertainty shocks in the panel VAR model.

financial frictions are more severe in emerging economies than advanced economies, our findings are compatible with Stockhammar and Österholm (2016) who find the opposite results from a group of high-income small open economies with developed financial markets. By providing empirical evidence that financial channels play a major role in the link between uncertainty and the real economy, we contribute to the recent literature on the transmission channel of uncertainty shocks.

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Online Appendix

Figure 6.1: Decomposition of policy uncertainty

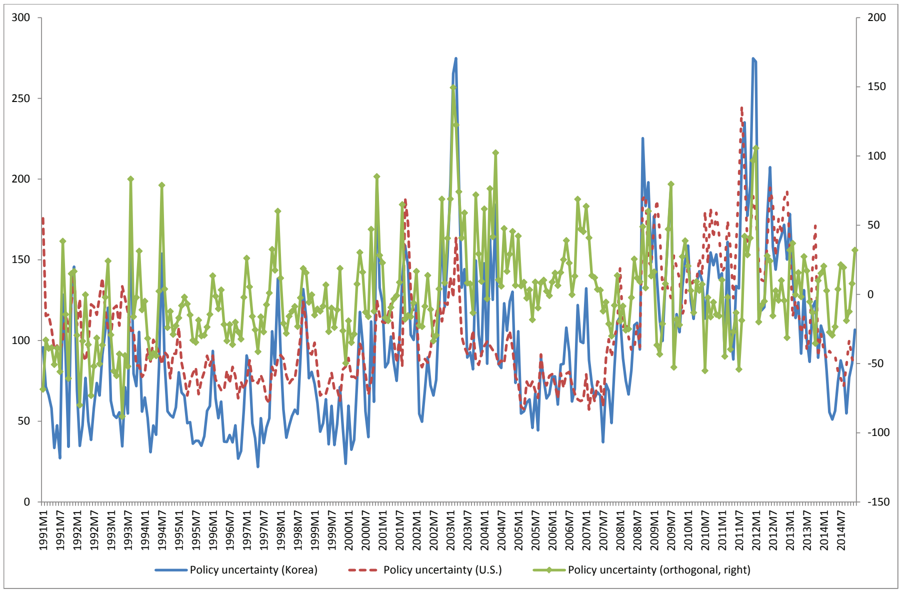


Figure 6.2: Decomposition of financial uncertainty

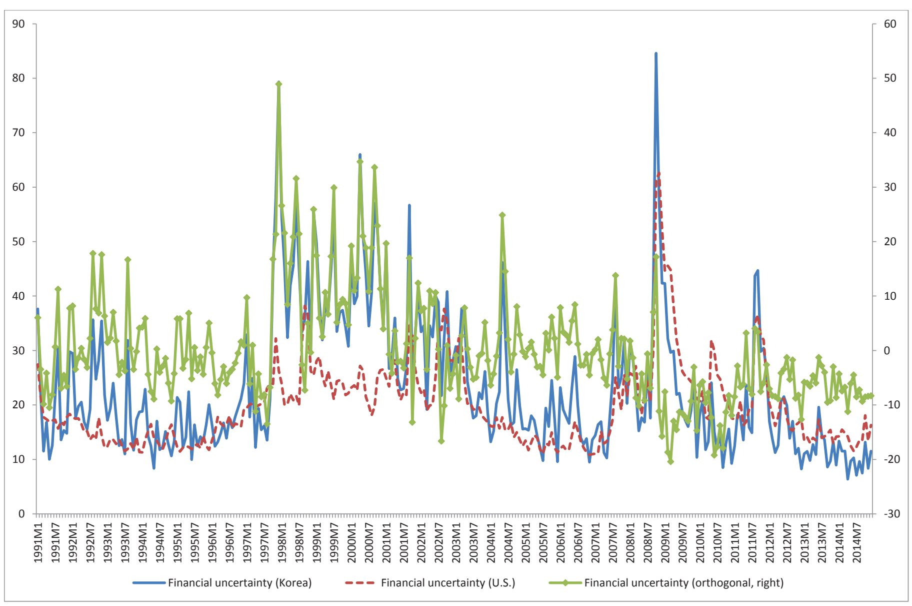
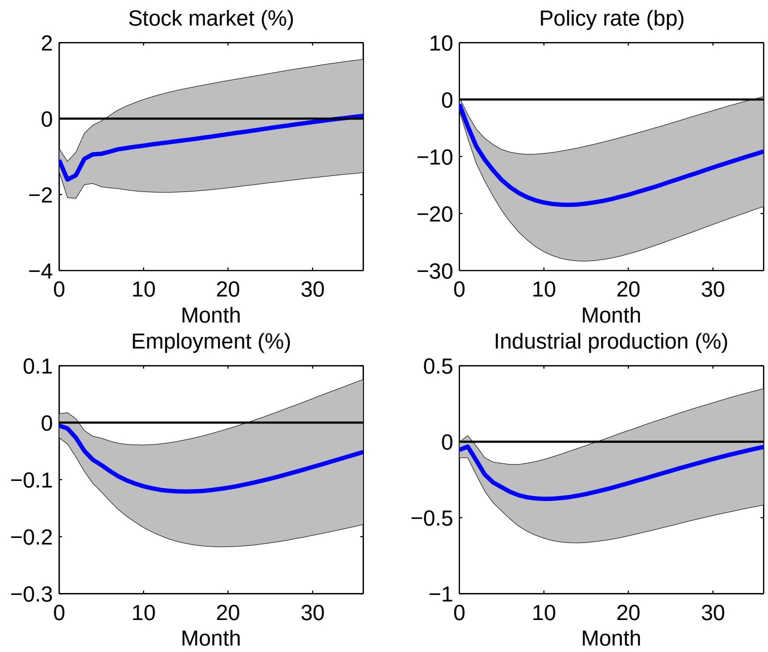
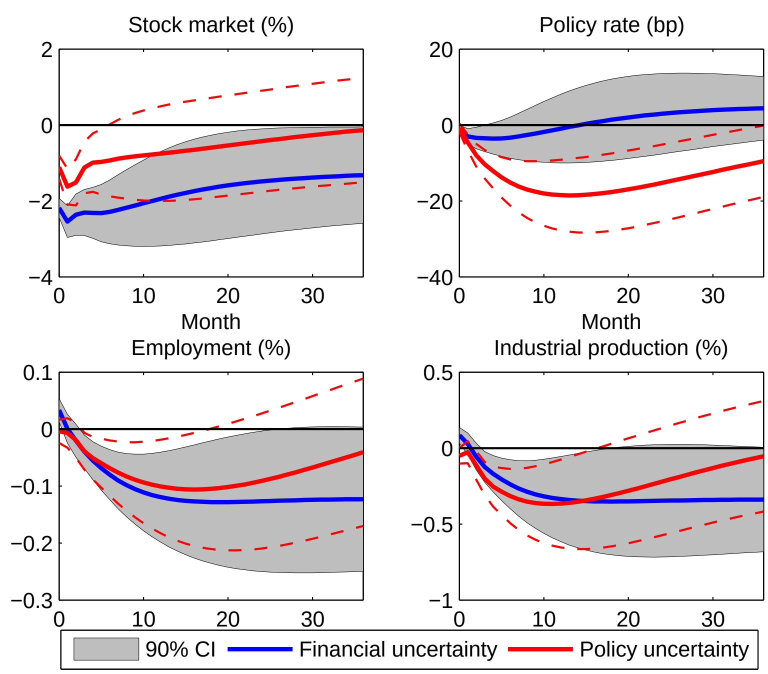


Figure 6.3: Impact of policy uncertainty shocks: the U.S.



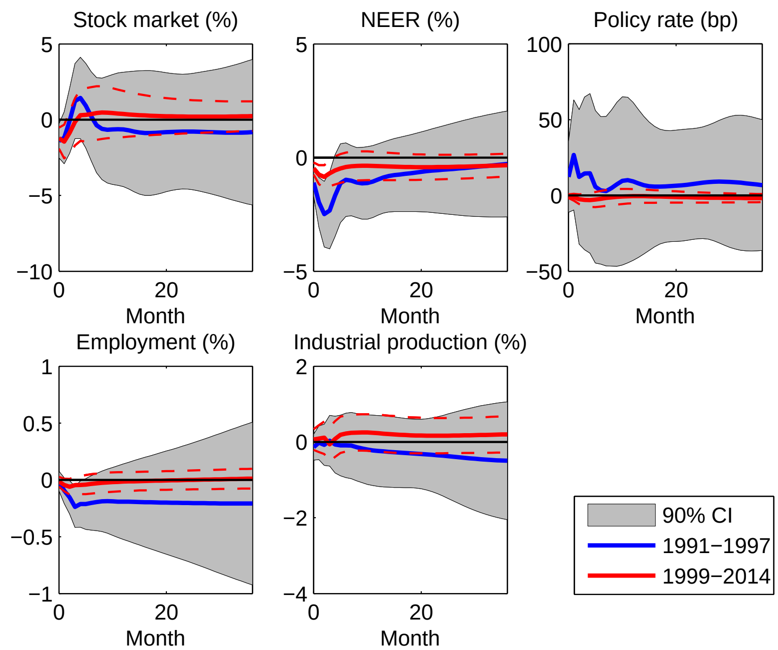
Note: Each graph displays the IRFs with bootstrapped 90% confidence intervals to a one standard deviation policy uncertainty shock

Figure 6.4: Impact of financial uncertainty shocks: the U.S.



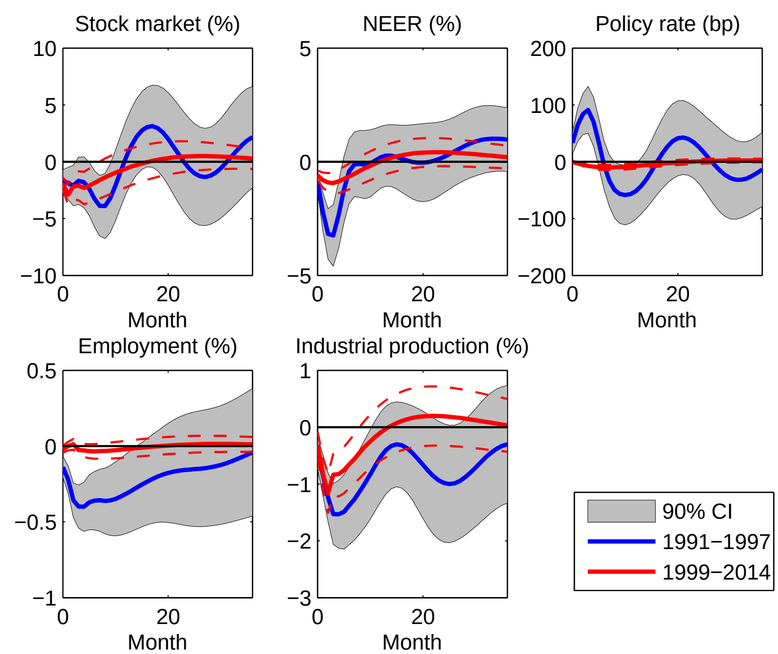
Note: Each graph displays the IRFs with 90% bootstrapped confidence intervals to a one standard deviation financial uncertainty (blue) and policy uncertainty shock (red).

Figure 6.5: Subsample analysis: policy uncertainty



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

Figure 6.6: Subsample analysis: financial uncertainty



Note: Each graph displays the IRFs with 90% bootstrapped confidence intervals to a one standard deviation financial uncertainty shock during the pre- (blue) and the post- (red) Asian financial crisis periods.