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

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Abstract

This paper empirically examines the impact of different types of uncertainty shocks on emerging economies, with a particular focus on Korea. We consider two proxies for uncertainty: (1) a measure of financial uncertainty (implied and realized volatility from the Korean stock market) and (2) a measure of economic policy uncertainty (constructed by Baker, Bloom, and Davis (2016)). Whereas both types of uncertainty shocks have a similar size of negative real effects in the US, only financial uncertainty shocks have significant negative real effects in Korea. Estimating a panel Vector Autoregression model of the BRIC economies produces similar results, suggesting that financial uncertainty is far more important than policy uncertainty in driving business cycle fluctuations in these economies. We interpret our results as the relative importance of financial frictions in emerging economies compared to the US.

JEL classification: E20, E32

Keywords: Business Cycle Fluctuations, Policy Uncertainty, Financial Uncertainty, Emerging Economies, Sign-restriction VARs, Local Projections

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1 Introduction

The recent finding that recessions are often associated with heightened uncertainty has renewed interest in the link between uncertainty and the aggregate economy especially since the Great Recession (See Baker, Bloom, and Davis (2016); Bloom (2009); Bloom, Floetotto, Jaimovich, Saporta-Eksten, and Terry (2014); Caggiano, Castelnuovo, and Groshenny (2014); and Jurado, Ludvigson, and Ng (2015) among others).

Based on the high correlation among the countercyclical uncertainty measures, the literature has mostly focused on the general pattern, rather than heterogenous effects of different kinds of uncertainty shocks. For instance, Bloom (2009) shows that (financial) uncertainty measured by stock market volatility is an important driver of US business cycles while Baker, Bloom, and Davis (2016) find that policy uncertainty—mainly constructed by the newspaper coverage frequency—is also an important source of business cycle fluctuations.[1]

The recent observation that the two types of uncertainty greatly diverged from one another, however, suggests that two well-known proxies for uncertainty shocks can affect the aggregate economy in different manners; for example, during the episode of the UK's referendum to leave the EU, there has been an unprecedented increase in policy uncertainty in the UK economy, whereas financial uncertainty—measured by the UK stock market volatility—remained at the low level despite the initial concerns of investors.[2] We contribute to the literature by analyzing how two different types of uncertainty shocks (financial and policy uncertainty) affect the aggregate economy. Given that the most existing studies have focused on advanced economies,[3] we pay particular attention on emerging economies in this paper.

Unfortunately, there are only five emerging countries (Brazil, China, India, Korea, and Russia) where the standardized policy uncertainty index is available as of October, 2016. The data constraint might explain why no attempt has been made to study the emerging economy issue in greater details. To draw comparable results from Baker, Bloom, and Davis (2016), one should closely follow their identification specification. However, one should also take account of a small open economy nature into the Vector Autoregression (VAR, hereafter) model. After careful consideration of the data constraint to replicate Baker, Bloom, and Davis (2016) in the four emerging countries, we choose Korea as a benchmark country for several reasons.[4]

First, the Indian economic policy uncertainty index is too short to draw meaningful conclusion (only available since 2003). Second, financial markets in China are heavily regulated and its dominant size in the global economy makes it difficult to generalize the Chinese experience to other emerging economoes. Third, the Brazilian and Russian economies heavily rely on commodity exports and the recent commodity price swings overwhelmingly affected their economic performance. Disentangling commodity price shocks from uncertainty shocks is not the focus of the paper. Nevertheless, we still estimate an unbalanced panel VAR model of the other emerging economies and find consistent results with a benchmark Korean case.

We find that the effects of different types of uncertainty shocks on the Korean economy are substantially different, which is different from the previous findings on the US economy.[5] In particular, by estimating the VAR model to closely track the existing literature and identifying uncertainty shocks as in Baker, Bloom, and Davis (2016), we show that only the uncertainty about financial markets affects the Korean economy in a meaningful way, while uncertainty regarding economic policy does not have any material effect. 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); (5) using a different estimation technique such as the local projection method by Jordà (2005); and (6) estimating the panel VAR model of other emerging economies where data are available.

Two particular measures for uncertainty are used in our paper; (1) a financial uncertainty measure constructed from the Korean stock market; and (2) a measure of policy uncertainty (the economic policy uncertainty (EPU) index developed by Baker, Bloom, and Davis (2016)). 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 US uncertainty in Bloom (2009). Similarly to Bloom (2009), we combine the realized volatility (from 1991 to 2002) and the implied volatility (from 2003 to 2014) to extend the dataset. In order to measure policy uncertainty, we use the EPU index for Korea, which is constructed by Baker, Bloom, and Davis (2016).[6] They use six newspapers to construct the EPU index for Korea by counting the number of news articles that appear in relation to policy uncertainty. While this may not be a perfect proxy for true policy uncertainty, to our best knowledge, this is the only standardized index available to researchers. Furthermore, we confirm the credibility of the index for Korea by comparing the spikes observed in the proxy with the timing of the turbulent economic and political events that affected the Korean economy in Section 2.2.

Our finding that shocks to policy uncertainty do not appear to have any sizable impact on the Korean economy is inconsistent with the common presumption that economic policy uncertainty in Korea is an important factor in explaining the country's low investment rate and the slow growth since the Global Financial Crisis, and contradicts an earlier finding that the US economy responds negatively to innovations in policy uncertainty (Baker, Bloom, and Davis (2016)). Specifically, neither employment, nor industrial production, nor investment reveal any significant drops alongside policy uncertainty shocks in Korea. This result is consistent with Born and Pfeifer (2014) who found that policy risk, a concept comparable to policy uncertainty, does not play an important role in explaining business cycles by employing an estimated New Keynesian model.

There is a sizable negative impact on the aggregate economy, in contrast, when financial uncertainty in Korea suddenly increases, which is in line with the previous literature on the US economy (Bloom (2009) among others). For example, employment and industrial production substantially decrease after uncertainty shocks hit the Korean economy. Investment, a key variable in the transmission mechanism of uncertainty shocks, displays a clear "wait–and–see" mechanism to the innovation in financial uncertainty.

Several implications can be drawn from our findings. First, it is particularly important to identify the origin of uncertainty shocks in emerging economies. While the media often argue that uncertainty regarding the policy is one of the main drivers that sags the aggregate economy, our empirical findings do not support such a claim in the Korean context. On the contrary, uncertainty from the financial market can be an important channel for generating sizable economic fluctuations. One possible interpretation is that Korean policy uncertainty is mainly driven by domestic political events, while Korean financial uncertainty is sensitive to the development in the global economy. In an export-oriented country such as Korea, it is not surprising that the latter is more important than the former.

Second, Ludvigson, Ma, and Ng (2015) recently claim that uncertainty in the financial market is an "exogenous" driver of the economy while other types of uncertainty are "endogenous" responses to aggregate fluctuations. If so, our findings indicate that uncertainty shocks are still an important driver of emerging market business cycles, but the transmission is likely through a financial friction channel. The recent literature highlights the role of financial frictions in amplifying the effect of uncertainty shocks on the real economy (Arellano, Bai, and Kehoe (2010); Bianchi and Schneider (2014); Caldara, Fuentes-Albero, Gilchrist, and Zakrajsek (2016); Choi, Furceri, Huang, and Loungani (2016); Christiano, Motto, and Rostagno (2014); Gilchrist, Sim, and Zakrajšek (2014)). As long as financial frictions are more prevalent in emerging economies than the US economy, our findings are consistent with a financial friction channel.

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

2 Data and Empirical Models

This section describes the empirical strategies adopted in our paper. We explain the data used in our analysis 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 the Korean economy.[7] Primarily 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 countercyclical 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 were 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 Korean 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 the uncertainty that arises in financial markets because it measures stock market volatility one month ahead, thereby capturing forward-looking information (see Bloom (2009) and Carrière-Swallow and Céspedes (2013) for example). Thus, the best substitute 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.[8] Following Bloom (2009), the realized volatility is normalized to have the same mean and variance as the VKOSPI when they overlap from 2003 onward.[9] Figure 7.1 plots the volatility series for Korea during the sample period. It is easy to observe that recessions are associated with heightened uncertainty in the financial market.

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 7.2 plots the EPU index for Korea. The solid blue line represents the EPU index and the shaded regions are Korea's official recessionary periods declared by Statistics 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.[10] 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:

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

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. Unlike Choi (2016) who imposed block recursive identification by shutting down the feedback from domestic variables to US financial uncertainty using a small open economy assumption, the Cholesky ordering implies that policy uncertainty shocks affect both financial and macroeconomic variables instantly, while domestic variables can feedback into policy uncertainty with a one period lag. Our baseline VAR specification includes three lags of all variables.[11]

2.3.1 Sign Restriction In Section 4.3, we adopt an alternative approach to identify shocks, a sign restriction approach. 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 identifies 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 $\Sigma^{(j)} = \tilde{A}^{(j)}\tilde{A}^{(j)\prime}$.

(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 the key empirical findings from our main analysis.

3.1 Policy Uncertainty

We first study how policy uncertainty can affect the aggregate economy. Figure 7.3 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 EPU index in Korea.[12] An increase in policy uncertainty is followed by a sharp short-run decline in the stock market and sharp exchange rate depreciation, implying that financial markets quickly respond to an increase in policy uncertainty. However, its impact on real variables such as employment and industrial production is statistically insignificant at any horizon.

Overall, this result is in sharp contrast to Baker, Bloom, and Davis (2016) who found a strong negative impact of policy uncertainty shocks on output and employment in the US economy, but it is consistent with Born and Pfeifer (2014). Born and Pfeifer (2014) show that when policy risk, similar to the notion of policy uncertainty, is incorporated into a New Keynesian model and estimated using the US data, there is no substantial response of the aggregate variables to the shock to policy risk.

Comparison to the US Economy. To confirm that the insignificant impact of policy uncertainty 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 US data from January 1991 to December 2014. We use the monthly US 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 US employment, and the log level of US industrial production. Figure 7.4 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 US output after policy uncertainty shocks is consistent with an aggregate demand type of interpretation of uncertainty shocks in Leduc and Liu (2015) and Jones and Olson (2015), 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 US by estimating the variances of the four variables that are explained by a shock to the EPU index. Panel A in Table 7.1 shows that policy uncertainty shocks account for a much larger share of the macroeconomic variables in the US 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 findings from the last section with the ample empirical evidence demonstrating the importance of uncertainty shocks in the business cycle fluctuations of many other countries (such as the US by Bloom (2009) and Leduc and Liu (2015), Germany by Bachmann, Elstner, and Sims (2013), the UK and Japan by Jones and Olson (2015), and the G7 countries by Gourio, Siemer, and Verdelhan (2013))? Moreover, several studies conclude that the impact of uncertainty shocks on real activity is even greater in emerging economies than it is in advanced economies (Carrière-Swallow and Céspedes (2013); and Choi (2016)). However, it is worth noting that the measure of policy uncertainty is not necessarily a comprehensive measure of uncertainty surrounding emerging economies.

As shown in Figure 7.2, most of the spikes in the EPU index are associated with domestic political or economic events with the exception of the three events associated with financial crises. In an emerging economy, uncertainty about the state of global financial condition can be more important than uncertainty about domestic policies. To the extent to which Korean financial market is integrated with the rest of the world, uncertainty caused from international financial markets can have a significant real effect (Bacchetta and Van Wincoop (2013); Choi (2016); Gourio, Siemer, and Verdelhan (2014)).

We directly 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 stock market volatility index after the EPU index.[13] Figure 7.5 confirms the hypothesis. Overall, the size of the declines in employment and industrial production is more than double than after 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.[14]

We further conduct a similar test using the US data. As shown in Figure 7.6, policy uncertainty shocks have similar quantitative impacts as financial uncertainty shocks on the three macroeconomic variables, despite their much weaker impact on the stock market. Panel B in Table 7.1 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 types of uncertainty shocks are equally important in explaining US business cycles, financial uncertainty shocks play a dominant role in explaining Korean business cycles.

4 Robustness Analysis

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

4.1 Alternative Model Specifications We conduct several standard sensitivity 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 7.7 and 7.8 confirm the negligible impact of policy uncertainty shocks on real economic activity in Korea after changing the specifications in our baseline VAR model.

4.2 Subsample Analysis It is well recognized that the Asian financial crisis in 1997-1998 acts as a structural break in the trajectory of 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 7.9, Korean policy uncertainty shocks continue to have an insignificant impact on the real variables in both periods. However, the insignificant impact of the policy uncertainty shocks is not necessarily driven by the test's low power due to the smaller sample size, as Figure 7.10 shows a significant impact of financial uncertainty shocks on real variables in both periods.

We also run the same VAR model by dividing the sample based on political regimes (the Minjoo Party [left-wing party] from 1998 to 2007 vs. the Saenuri Party [right-wing party] from 2008 to 2014) in order to analyze if the market responds differently according to political regime; while the result is not reported here, we find no meaningful difference between the two regimes.[15]

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 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.[16] In order to separate financial uncertainty from policy uncertainty shocks, we impose heuristic restrictions on both the measures of uncertainty and the stock market index.

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. 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 7.11 clearly indicates that contrasting dynamic effects between financial and policy uncertainty shocks survive with an alternative shock identification procedure.[17]

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 7.12 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.

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 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)).

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 monthly 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 7.13 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

As a final robustness check, we estimate an unbalanced panel VAR model of the BRIC economies (Brazil, Russia, India, and China) to check whether our main findings from the Korean context can be generalized to other emerging economies. In order to maximize the time series coverage of the sample, we only include five variables in the following order: policy uncertainty index, financial uncertainty index, stock market index, the exchange rate (NEER), and industrial production. The individual country coverage of the data starts in January 2002 (Brazil), 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 the daily returns of the Bovespa index (Brazil), Shanghai Stock Exchange Composite Index (China), the NIFTY 50 Index (India), and the MICEX Index (Russia). All financial data are taken from Bloomberg. The policy uncertainty indices are downloaded from www.policyuncertainty.com. Figure 7.14 shows the evolution of two uncertainty indices from each of the BRIC economies.

We estimate the panel VAR model with country fixed effects by closely following the procedure in Love and Zicchino (2006). We generate confidence intervals of the IRFs using 200 Monte Carlo simulations. Although the differences are less stark than in the case of Korea, Figure 7.15 shows that financial uncertainty shocks have substantial negative effects on both financial and real variables in the BRIC economies, whereas policy uncertainty shocks have much weaker effects. Variance decomposition in Table 7.2 is consistent with the results from the analysis of the Korean economy; financial uncertainty shocks explain a much larger share of variation in the three macroeconomic variables than policy uncertainty shocks.

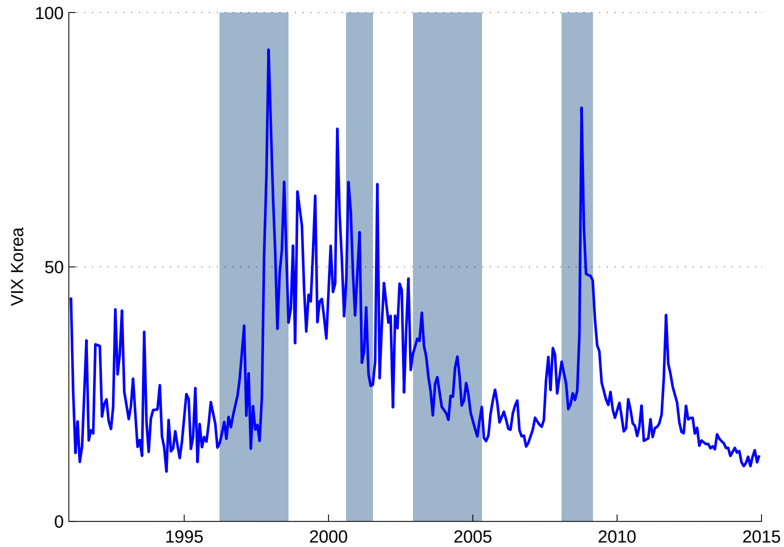
6 Conclusion

The claim that uncertainty over economic policies has prevented the economic recovery in the aftermath of the Global Financial Crisis has a popular appeal. However, until now, there has been no systematic analysis of emerging economies to test this claim due to a lack of reliable measures of economic policy uncertainty. To address this, we critically examine the impact of uncertainty shocks on emerging economies using two proxies for uncertainty: (1) a measure of policy uncertainty and (2) a measure of financial uncertainty. Our finding that an increase in policy uncertainty is not followed by a slowdown in economic activity is in sharp contrast to the most commonly accepted argument presented in the literature. Our findings, however, do not necessarily reject the uncertainty-based explanation of business cycles, as a shock to financial uncertainty does have a substantial impact on emerging economies. This is consistent with Caldara, Fuentes-Albero, Gilchrist, and Zakrajsek (2016) who find that uncertainty shocks carry a quantitatively small effect unless they are transmitted through a financial market.

The contrasting effects between policy and financial uncertainty shocks deserve further analysis. To fully understand these findings, one needs to employ a theoretical framework that explicitly incorporates different types of uncertainty. By estimating such a structural model, one can quantitatively analyze the importance of uncertainty from different sources in order to explain the business cycles. However, we will leave this for future research.

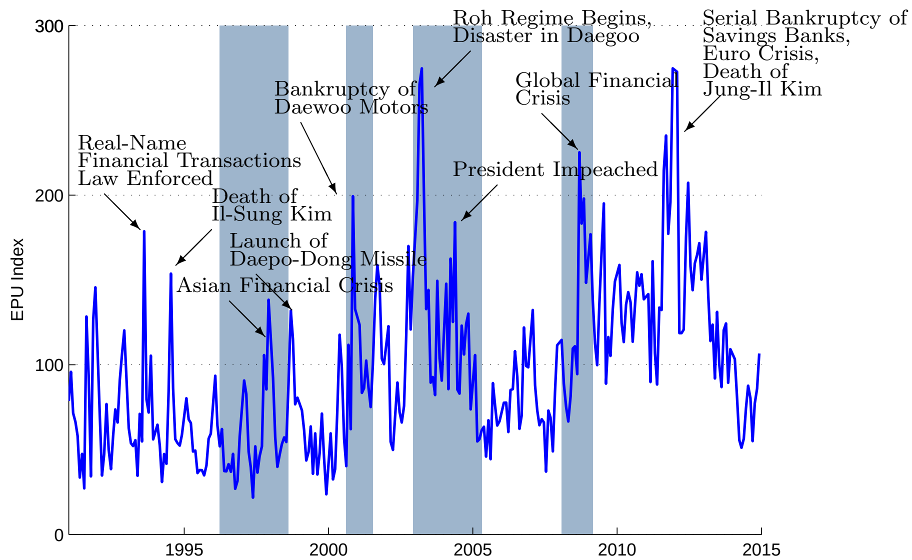
7 Figures and tables

Figure 7.1: Korean financial uncertainty index



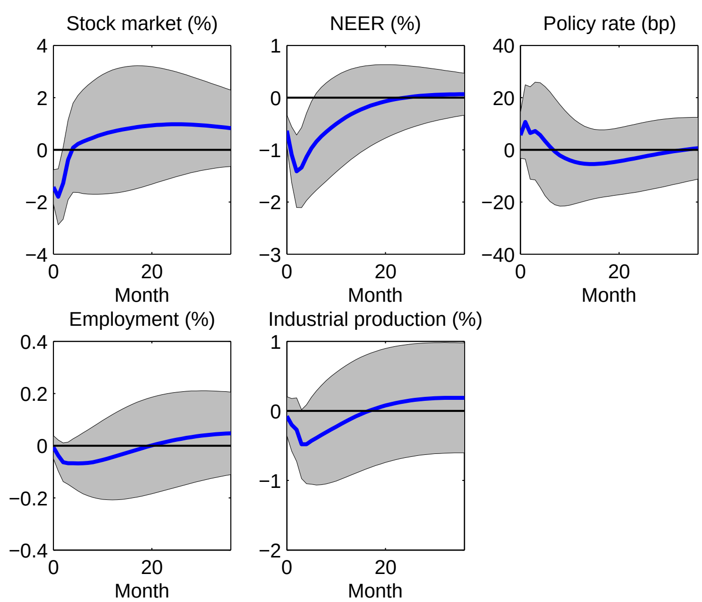
Note: The horizontal axis indicates the period between Jan 1991 and Dec 2014 and the vertical axis denotes the level of realized (1991-2002) and implied (2003-2014) volatility of the Korean stock market. Shaded regions are Korea's official recessionary periods as declared by Statistics Korea.

Figure 7.2: Korean policy uncertainty index



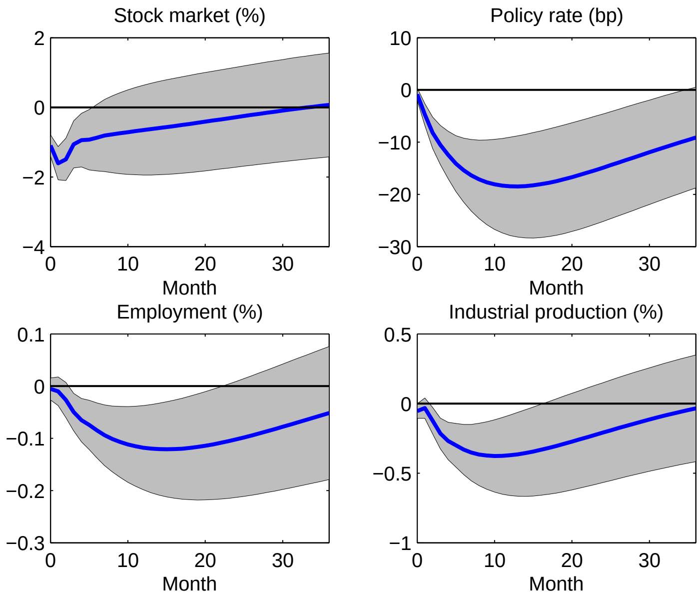
Note: The horizontal axis indicates the period between January 1991 and December 2014 and the vertical axis denotes the level of the Korean EPU index. Shaded regions are Korea's official recessionary periods as declared by Statistics Korea.

Figure 7.3: The impact of policy uncertainty shocks: Korea



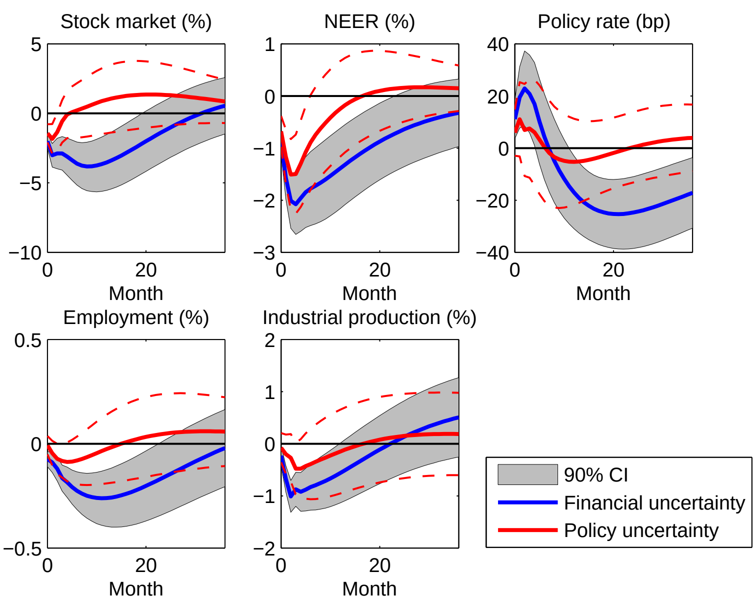
Note: Each graph displays the IRFs with bootstrapped 90% confidence intervals to a one standard deviation policy uncertainty shock

Figure 7.4: The impact of policy uncertainty shocks: US



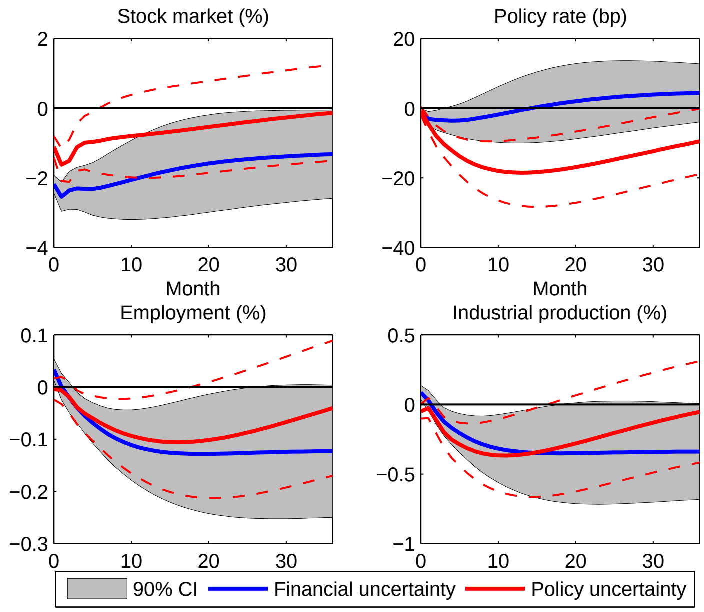
Note: Each graph displays the IRFs with bootstrapped 90% confidence intervals to a one standard deviation policy uncertainty shock

Figure 7.5: The impact of financial uncertainty shocks: Korea



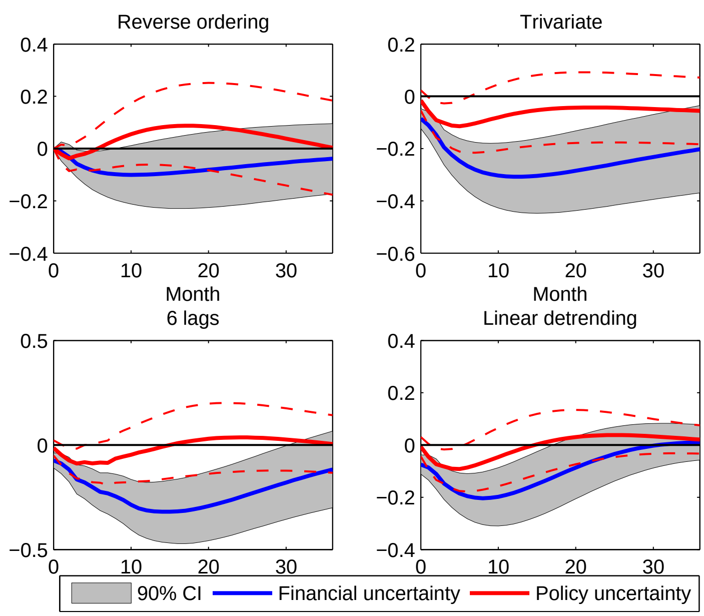
Note: Each graph displays the IRFs with 90% bootstrapped confidence intervals to a one standard deviation financial uncertainty (blue) and policy uncertainty shock (red).

Figure 7.6: The impact of financial uncertainty shocks: US



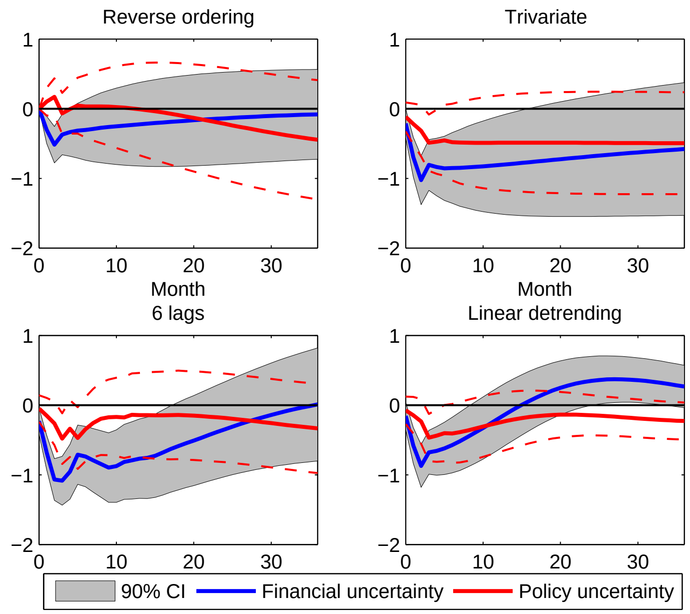
Note: Each graph displays the IRFs with 90% bootstrapped confidence intervals to a one standard deviation financial uncertainty (blue) and policy uncertainty shock (red).

Figure 7.7: Robustness check: employment



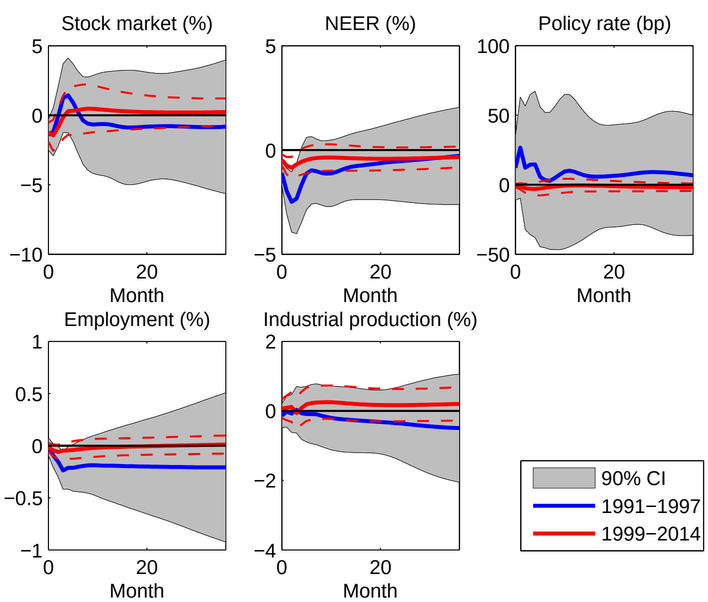
Note: Each graph displays the response of employment with 90% bootstrapped confidence intervals to a one standard deviation financial uncertainty and policy uncertainty shock under different specifications.

Figure 7.8: Robustness check: industrial production



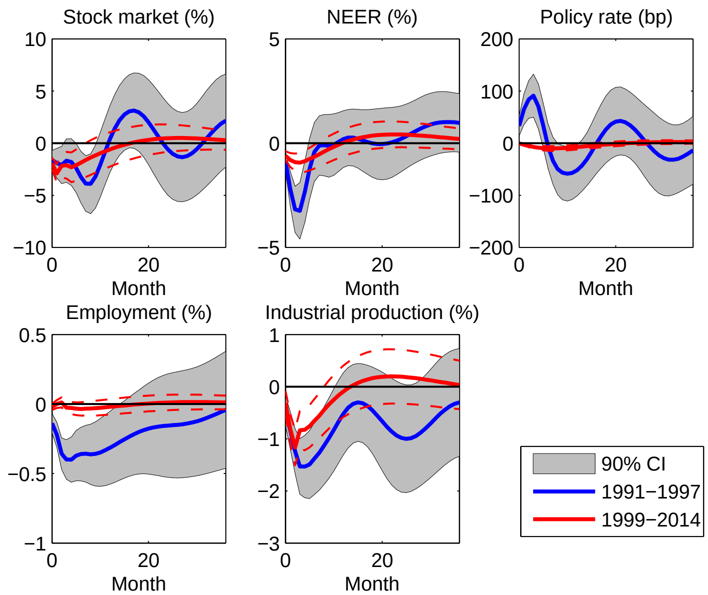
Note: Each graph displays the response of industrial production with 90% bootstrapped confidence intervals to a one standard deviation financial uncertainty and policy uncertainty shock under different specifications.

Figure 7.9: Subsample analysis: policy uncertainty



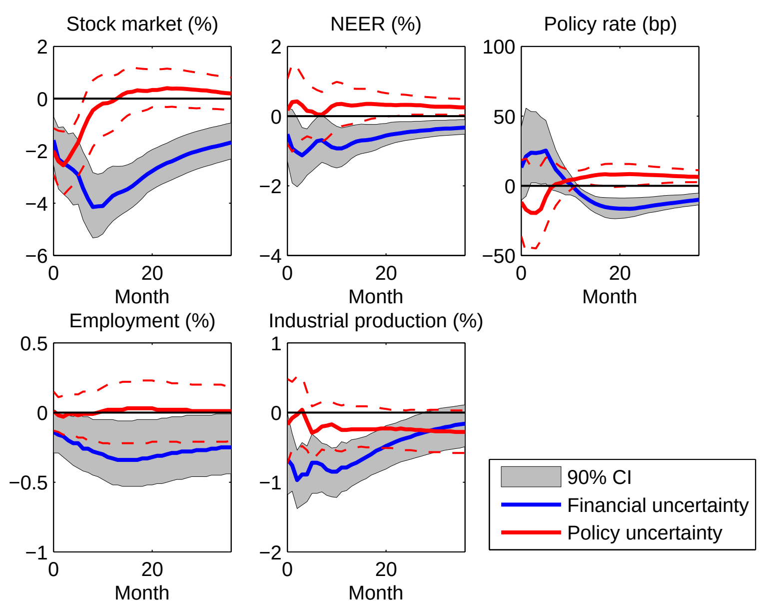
Note: Each graph displays the IRFs with 90% bootstrapped confidence intervals to a one standard deviation policy uncertainty shock during the pre- (blue) and the post- (red) Asian financial crisis periods.

Figure 7.10: Subsample analysis: financial uncertainty



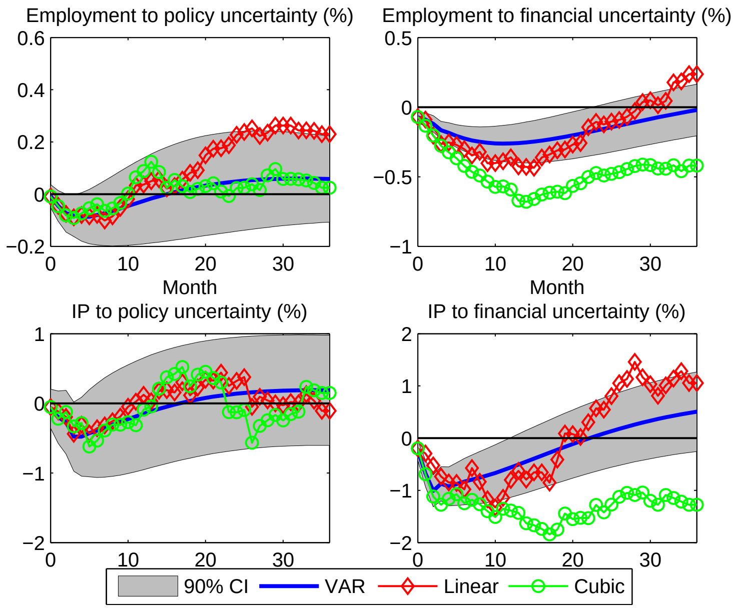
Note: Each graph displays the IRFs with 90% bootstrapped confidence intervals to a one standard deviation financial uncertainty shock during the pre- (blue) and the post- (red) Asian financial crisis periods.

Figure 7.11: Robustness check: sign-restriction VARs



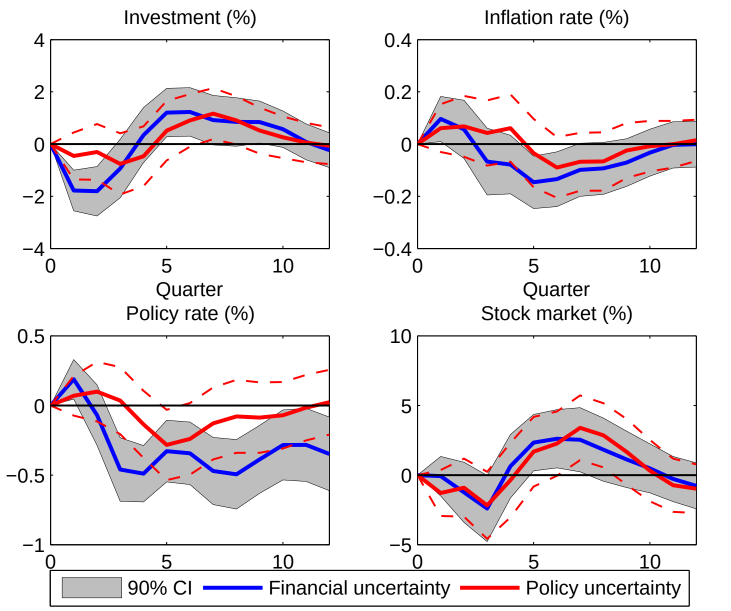
Note: Each graph displays the median IRFs with 68% confidence intervals to a one standard deviation financial uncertainty and policy uncertainty shock based on 200 draws using a sign-restriction approach.

Figure 7.12: Robustness Check: Local Projections



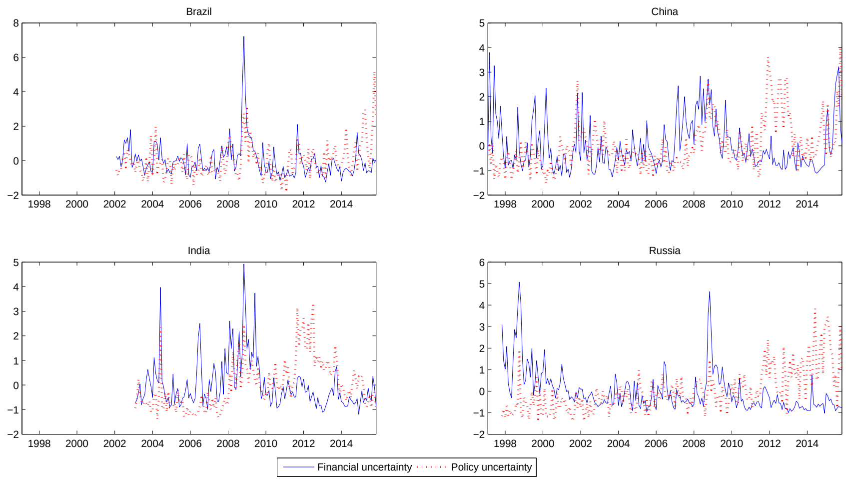
Note: Each graph displays the IRFs computed by VAR (blue), local linear projections (red), and cubic projections (green).

Figure 7.13: Robustness check: quarterly VAR model



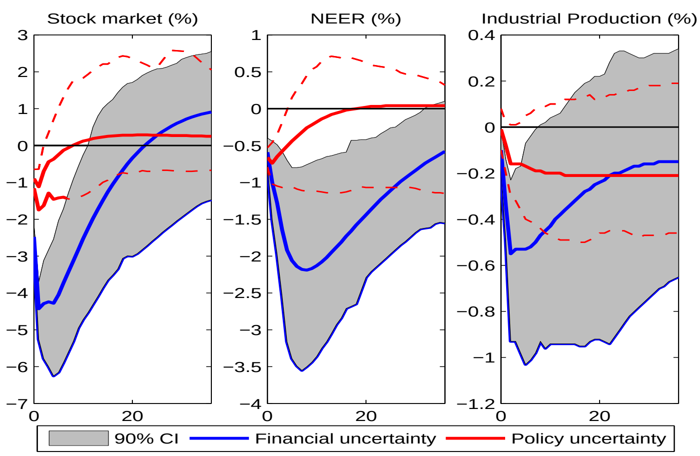
Note: Each graph displays the IRFs with 90% bootstrapped confidence intervals to a one standard deviation financial uncertainty (blue) and policy uncertainty shock (red).

Figure 7.14: Uncertainty indices: BRIC 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 7.15: IRFs from a panel VAR model



Note: Each graph displays the IRFs with 95% confidence intervals from an unbalanced panel VAR model to financial and policy uncertainty shocks using 200 Monte Carlo simulations.

Table 7.1: Forecast error variance decomposition: Korea vs. US

Panel A: policy uncertainty only									
	Korea					US			
Horizon	Stock	NEER	Policy rate	Employ ment	IP	Stock	Policy rate	Employ ment	IP
1	6.09	5.87	0.54	0.03	0.14	11.44	0.45	0.06	1.02
6	2.41	10.99	0.73	2.02	3.13	9.43	15.90	4.58	7.52
12	1.48	9.51	0.70	1.72	2.68	5.83	22.43	9.85	10.76
24	1.85	7.80	0.99	0.90	1.59	3.76	27.81	11.63	9.56
36	2.59	7.41	0.87	0.89	1.48	2.90	29.83	9.65	7.35
Panel B: both financial and policy uncertainty									
Panel B.1: financial uncertainty									
	Korea					US			
Horizon	Stock	NEER	Policy rate	Employ ment	IP	Stock	Policy rate	Employ ment	IP
1	12.33	11.42	2.11	3.80	1.35	46.01	2.55	11.83	0.03
6	17.31	27.75	4.76	14.15	16.33	35.05	4.56	9.93	3.38
12	22.96	33.18	4.83	21.13	15.03	29.34	9.43	6.60	6.77
24	22.59	35.81	14.23	21.23	9.75	25.04	11.39	4.77	7.67
36	20.35	36.01	19.64	17.70	8.21	23.87	12.31	3.86	6.49
Panel B.2: policy uncertainty									
	Korea					US			
Horizon	Stock	NEER	Policy rate	Employ ment	IP	Stock	Policy rate	Employ ment	IP
1	6.31	6.91	0.59	0.04	0.31	1.06	2.50	0.41	0.88
6	2.60	13.56	0.79	3.11	3.66	1.73	3.31	15.36	6.85
12	1.65	10.96	0.82	2.15	2.85	0.94	6.41	22.13	9.89
24	2.99	8.68	0.88	1.15	1.68	0.60	8.98	28.05	9.19
36	4.08	8.43	0.85	1.42	1.42	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).

Table 7.2: Forecast error variance decomposition from a panel VAR model

Horizon	Stock		NEER		IP	
	Financial uncertainty	Policy uncertainty	Financial uncertainty	Policy uncertainty	Financial uncertainty	Policy uncertainty
1	11.30	1.73	2.18	3.99	0.14	0.00
6	17.68	0.75	15.78	1.83	5.94	0.50
12	14.78	0.58	28.63	1.02	6.23	0.67
24	11.26	0.55	35.63	0.72	4.92	0.85
36	11.75	0.54	36.94	0.67	4.27	0.86

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

Notes

[1]The recent work by Choi and Loungani (2015) is an exception. They focused on the different effects of aggregate and sectoral uncertainty shocks on the US labor market.

[2]The daily UK Economic Policy Uncertainty index is available since 2002 and downloadable from www.policyuncertainty.com. As of October 2016, the UK Economic Policy Uncertainty index is nearly three times higher than its historical average, while the UK implied volatility index (VFTSE) remained even below the historical average.

[3]See Carrière-Swallow and Céspedes (2013) and Choi (2016) for few exceptions.

[4]To replicate the benchmark VAR model of Baker, Bloom, and Davis (2016), one needs 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 crucial to include pre-2000 data to avoid the dominance of the Global Financial Crisis in driving our results.

[5]Although a few studies analyzed the effects of uncertainty shocks on the Korean economy (Lee and Jung (2016); Kim and Kim (2012); Yoon and Lee (2013)), none of them focused on different types of uncertainty.

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

[7]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.

[8]None of the results in the paper changes in a meaningful way when we only used realized volatility for the whole sample period.

[9]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).

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

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

[12]90% confidence intervals are plotted using 200 bootstraps.

[13]Reversing the ordering between the two uncertainty indices only strengthens our results.

[14]In an integrated international financial market system, an increase in uncertainty induces "flight to safety" types of capital flows from emerging economies to the US economy since international investors consider it a safe haven. Despite the deteriorating domestic economic conditions, an emerging economy's central bank often raises the policy rate to prevent capital outflows. See Choi (2016), Gourio, Siemer, and Verdelhan (2014), and Rey (2016) for further details.

[15]One possible explanation for this result is that the newspapers that are used to construct the EPU index for Korea are equally divided between left- and right-leaning perspectives.

[16]For example, Jurado, Ludvigson, and Ng (2015) place a measure of uncertainty after macroeconomic variables in the process of recursive identification following the underlying assumptions found in Christiano, Eichenbaum, and Evans (2005).

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

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