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

Sangyup Choi† Myungkyu Shim‡

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Abstract

This paper empirically explores the impact of different types of uncertainty shocks on emerging economies, with a particular focus on South Korea. In doing so, 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 policy uncertainty (constructed by Baker, Bloom, and Davis (2015)). Interestingly, an increase in policy uncertainty is not associated with economic downturns, which is a finding that is inconsistent with the popular argument that policy uncertainty dampens the aggregate economy. By contrast, a substantial slowdown of the Korean economy typically follows an increase in financial uncertainty. In the U.S., however, both types of uncertainty shocks have similar real effects. This finding suggests that there exists a fundamental difference in the transmission mechanism of uncertainty shocks between advanced and emerging economies. Our main findings are robust to (1) various estimation techniques and identification methods and (2) estimating a panel VAR model of other emerging economies.

JEL classification: E20, E32
Keywords: Business Cycle Fluctuations, Policy Uncertainty, Financial Uncertainty, Emerging Economies, Sign-restriction VARs, Local Projections

*The views expressed in this paper are those of the author, and not necessarily those of the International Monetary Fund.
†Statistics Department, International Monetary Fund. Email: schoi2@imf.org
‡School of Economics, Shanghai University of Finance and Economics and School of Economics, Sogang University. Email: audrb917@gmail.com
1 Introduction

Literature that tries to explain the link between uncertainty and the aggregate economy has flourished since the Great Recession because this episode can be characterized by heightened uncertainty surrounding the economy’s future path. The most common finding is that rising uncertainty is associated with a slowdown of the aggregate economy, while issues related to the causality between uncertainty and economic activity and to the reasonable proxies for uncertainty are still open to debate (see Bachmann, Elstner, and Sims (2013), Baker, Bloom, and Davis (2015), Bloom (2009), Bloom, Floetotto, Jaimovich, Saporta-Eksten, and Terry (2014), Caggiano, Castelnuovo, and Groshenny (2014), Choi and Loungani (2015), Jo (2014), Jurado, Ludvigson, and Ng (2015), and Mathy (2014) for example).

Among others, Bloom (2009) shows that (financial) uncertainty measured by stock market volatility is an important driver of U.S. business cycles. Recently, Baker, Bloom, and Davis (2015) find that policy uncertainty proxied by the newspaper coverage frequency is also an important source of business cycle fluctuations. However, only a limited attempt has been made to study the effects of uncertainty shocks in the context of emerging economies (for example, Carrière-Swallow and Céspedes (2013)). Moreover, to the best of our knowledge, none of the earlier works on emerging economies studied the potential heterogeneity in the effects of the different uncertainty shocks on the aggregate economy. This paper fills this void; we examine comprehensively the extent to which different types of uncertainty shocks affect emerging economies, by focusing on South Korea (henceforth Korea) in particular.\textsuperscript{1} We find, unlike the U.S. economy, that only uncertainty about financial markets matters for Korean business cycles, while uncertainty regarding economic policy does not have any material effect. Our results are robust to (1) changing specifications in the Vector Autoregression (VAR, henceforth) model; (2) using data with different frequency; (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 methods by Jordà (2005); and (6) the panel VAR of selected emerging economies.

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 measure developed by Baker, Bloom, and Davis (2015)). We focus on Korea

\textsuperscript{1}We are not the first to analyze the effects of uncertainty shocks on the Korean economy. See Lee and Jung (2016); Kim and Kim (2012); and Yoon and Lee (2013) for example. However, we are the first to use the policy uncertainty index for Korea, constructed by Baker, Bloom, and Davis (2015), and compare the effects of different uncertainty shocks.
because it is essentially the only emerging economy allowing for an in-depth analysis. Although the EPU index is available for three other emerging economies (China, India, and Russia), there are important shortcomings in these countries that prevent us from drawing firm conclusions from their data; (1) the time series for Indian economic policy uncertainty is too short; (2) the financial markets in China are heavily regulated; and (3) the Russian economy heavily relies on commodity exports. Nevertheless, we still find supporting evidence from these economies by estimating an unbalanced panel VAR model.

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). 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 (2015). 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 index is the only proxy 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 empirical analysis closely tracks that of the existing literature to obtain comparable findings; we estimate the VAR model, using monthly Korean and U.S. data from January 1991 to December 2014. In particular, uncertainty shocks are identified as in Baker, Bloom, and Davis (2015). We consistently find that shocks to policy uncertainty do not appear to have any sizable impact on the Korean economy. This observation is inconsistent with the common prevailing assumption that economic policy uncertainty in Korea is an important factor in the country’s currently low investment and slow growth, and contradicts an earlier finding that the U.S. economy responds negatively to innovations in policy uncertainty (Baker, Bloom, and Davis (2015)). Specifically, neither employment, nor industrial production, nor investment reveal any significant drops alongside policy uncertainty shocks in Korea. This finding is consistent with Born and Pfeifer (2014); using an estimated New Keynesian model, they show that policy risk, a concept comparable to policy uncertainty, does not play an important role in generating business cycles.

There is a sizable negative impact on the aggregate economy, in contrast, when financial uncertainty

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2 The EPU indices for various countries can be found at http://www.policyuncertainty.com.
in Korea suddenly increases, which is in line with the previous literature on the U.S. economy (Bloom (2009) among others). For instance, 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 origins of uncertainty shocks in emerging economies. While newspaper articles or non-academic economic reports usually 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. The fact that both types of uncertainty shocks have similar real effects on the U.S. economy implies that there exists a fundamental difference in the transmission mechanism of uncertainty shocks between advanced and emerging economies.

Second, following the recent finding by Ludvigson, Ma, and Ng (2015) who 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, our finding that financial uncertainty can drive down the aggregate economy indicates that uncertainty shocks could still be an important driver of emerging economies.

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 the robustness of these findings is tested in Section 4. Section 5 provides our concluding remarks.

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 our analysis.

2.1 DATA DESCRIPTION For an analysis that is comparable to the existing papers on the effects of uncertainty shocks, we first use the same set of monthly data from Bloom (2009) and Baker, Bloom, and Davis (2015), which includes the Korean stock market index (KOSPI), the policy rate measured by the overnight call rate, employment, and industrial production. 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 can represent a level 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 instance). 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. Following Bloom (2009), the realized volatility is normalized to have the same mean and variance as the VKOSPI when they overlap from 2003 onward. Figure 2.1 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 (2015), 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

\[^3\] 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 (compared to 0.88 in the U.S. data).
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 consider 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, “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
Figure 2.2 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, already suggesting that a potentially different role is played by the two types of uncertainty when it comes to in shaping fluctuations in the Korean economy. To confirm the credibility of the EPU index, we cross-check the key political or economical events that occurred during the sample period.\footnote{Since this exercise was already done by Baker, Bloom, and Davis (2015), our evaluation serves as a supplement.} For instance, the enactment of the Real-name financial transactions in August 1993 under the Kim regime and the death of Kim Il-Sung 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 disaster at a 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 bankruptcy of savings banks and the death of Kim Jung-II (late 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:

\[ Y_t = \sum_{p=1}^{P} B_p Y_{t-p} + u_t, \]

\[ u_t \sim N(0, \Sigma), \]

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 \( \Sigma \):

\[
\Sigma = \begin{pmatrix}
\sigma_1 & 0 & \ldots & 0 \\
0 & \sigma_2 & \ldots & 0 \\
\ldots & \ldots & \ldots & 0 \\
0 & \ldots & 0 & \sigma_n
\end{pmatrix},
\]

where \( \sigma_i \) is the standard deviation of each of the structural shocks.

For a comparable analysis from Baker, Bloom, and Davis (2015), we use the same Cholesky decomposition 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 level of the policy rate measured by the overnight call rate, the log level of employment, and the log level of industrial production. Our baseline VAR specification includes three lags of all variables.\(^5\)

\(^5\)Akaike Information Criterion (AIC) and the Schwarz' Bayesian Information Criterion (BIC) suggest one and three
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 relates reduced-form residuals $u_t$ to structural shocks $\epsilon_t$,

$$u_t = A\epsilon_t,$$

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

For any orthogonal matrix $Q$ such that $QQ' = I_n$, $\Sigma = AQQ'A$ is also an admissible decomposition for $\Sigma$ 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 not possible, as they imply identical VAR representations. Therefore, for any decomposition $\Sigma = AA'$, there exist infinitely many identification schemes $AQ(k)$ for $k = 1, 2, \ldots, \infty$, 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) and Busch, Scharnagl, and Scheithauer (2010):

(i) Draw $d = 1, \ldots, m$ 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 $j = 1, 2, \ldots$, 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 $Q^{(k(j))}$, $k(j) = 1, \ldots, K$ until the impulse response functions implied by $B_j^{(d)}$ 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.

lags respectively.
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:

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

for \( i = 0, 1, 2, ..., n \); \( s = 0, 1, 2, ..., h \); \( X_t = (y_{t-1}, y_{t-2}, ..., )' \), where operator \( E[\cdot | \cdot] \) 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 \( y_t \).\(^6\) The expectations are formed by linearly projecting \( y_{t+s} \) onto the space of \( X_t \):

\[
y_{t+s} = \alpha^s + B^{s+1}_1 y_{t-1} + B^{s+1}_2 y_{t-2} + ... + B^{s+1}_p y_{t-p} + U_t^s,
\]  

where \( \alpha^s \) is a vector of constants and \( B^{s+1}_j \) 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 \( B^{s+1}_j \). The estimated impulse response functions are denoted by \( \hat{IR}(t, s, d_i) = \hat{B}_i^s d_{i,t} \), with the normalization \( B^0_1 = I \). Thus, an innovation to the \( i \)-th variable in the vector \( y_t \) produces an impulse response of \( \hat{B}_i^s \). The impulse responses from local approximations are calculated from univariate least squares regressions for each variable at every horizon.

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 3.1 shows the impulse response functions (IRFs) of the stock market, the policy rate, employment, and industrial production to a one standard deviation shock to the EPU index in Korea.\(^7\) An increase in policy uncertainty is followed by a sharp short-run decline in the stock market, implying that a financial market quickly responds to news regarding policy uncertainty. However, its impact on real variables (such as employment and industrial production) is statistically insignificant at any horizon. In order to

\(^6\)Shocks are identified from the VAR.

\(^7\)90% confidence intervals are plotted using 200 bootstraps.
Figure 3.1: 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

deal with the issue of whether U.S. policy uncertainty is important for small open economies, we test this hypothesis by estimating the VAR using the U.S. policy uncertainty index instead, which yields a similar finding.\(^8\)

Overall, this result is in sharp contrast to Baker, Bloom, and Davis (2015), but it is consistent with Born and Pfeifer (2014); using the empirical method described in detail below, the former finds that the U.S. economy slows down when there is a positive shock to policy uncertainty. The latter, on the other hand, shows that when policy risk, which is a concept that corresponds to the notion of policy uncertainty as used in our paper, is incorporated into a New Keynesian model and estimated using the U.S. data, there is no substantial response of the aggregate variables to the shock to policy risk. Hence, our finding indicates the possibility that either the size of the shock to the policy uncertainty in the Korean economy is small or that the amplification mechanism through the shock does not fully work. For instance, because the Korean economy is a small open economy that is heavily reliant on international trade\(^9\), uncertainty about Korean economic policy, per se, may not be an important factor for most economic agents.

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\(^8\)Results are available upon request.

\(^9\)For instance, the ratio of merchandise trade and GDP is greater than 80% between 2011 and 2014 on average (http://data.worldbank.org/indicator/TG.VAL.TOTL.GD.ZS).
Comparison to the U.S. 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 (2015), 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 (2015), 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 3.2 shows 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 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 U.S. by estimating the variances of the four variables that are explained by a shock to the EPU index. Figure 3.3 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, at their peak, about 10% of the variances of employment and industrial production are explained by the shock to policy uncertainty in the U.S economy while less than 3% are explained in the Korean economy. Taken together, we
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 U.S. by Bloom (2009) and Leduc and Liu (2015), Germany by Bachmann, Elstner, and Sims (2013), the U.K. 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 (2015)). 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 2.2, 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 a typical emerging economy such as Korea, uncertainty about the state of global financial condition can be more important than uncertainty about domestic policies. As long as the Korean financial market is well integrated with the rest of the world, uncertainty caused by
international financial markets can have a significant real effect via various mechanisms (Bacchetta and Van Wincoop (2013) and Gourio, Siemer, and Verdelhan (2014)).

Figure 3.4: 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).

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 volatility index after the EPU index. Figure 3.4 shows that our hypothesis is indeed confirmed. Overall, the size of the declines in employment and industrial production is more than double that 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 U.S. monetary policies.

We further conduct a similar test using the U.S. data. As shown in Figure 3.5, 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. Lastly, Figure 3.6 shows the relative importance of two types of uncertainty when it comes to explaining Korean and U.S. business cycles.

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10Reversing of the ordering between the two uncertainty indices only strengthens our results.
11In 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 the deteriorating domestic economic conditions, an emerging economy’s central bank often raises the policy rate to prevent capital outflows. See Choi (2015) and Gourio, Siemer, and Verdelhan (2014) for further details.
which reinforces the results from the IRFs. Whereas two types of uncertainty shocks are equally important in U.S. business cycles, financial uncertainty shocks play a dominant role in Korean business cycles. In particular, at its peak, more than 20% (resp. 10%) of the variation in employment (resp. industrial production) is explained by financial uncertainty in Korea, which is even greater than it is in the U.S.

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 (2015), 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 six 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 activities in Korea after changing the specifications in our baseline VAR model.
Figure 3.6: Forecast error variance decomposition: financial vs. policy uncertainty

Note: Each graph displays the portion of the variance of the forecasting error in variables explained by financial and policy uncertainty shocks in Korea (blue) and in the U.S. (red)

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.
4.2 **Subsample Analysis**  It is 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 might lower the efficiency of the estimation, and result in insignificant responses for every variable. 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 4.3, 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 its having a smaller sample size, as Figure 4.4 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.\(^\text{12}\)

\(^\text{12}\)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.
Figure 4.3: 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 4.4: 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.
4.3 Alternative Shock Identification: a Sign-restriction Approach  In this section we test the robustness of our results by applying an alternative identification scheme in the form a sign-restriction approach. 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 on 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. 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 level.

Figure 4.5: 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.

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 un-

\footnote{For example, Jurado, Ludvigson, and Ng (2015) places a measure of uncertainty after macroeconomic variables in the process of recursive identification following the underlying assumptions found in Christiano, Eichenbaum, and Evans (2005).}
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 nine months. Evidence from Figure 4.5 clearly indicates that contrasting dynamic effects between financial and policy uncertainty shocks are aligned with the alternative shock identification procedure, which is a sign-restriction approach. Figure 4.6 further supports our main conclusions by showing that financial uncertainty shocks, on average, explain three times of the amount of variation in macroeconomic variables than policy uncertainty shocks.

Figure 4.6: Forecast error variance decomposition: sign-restriction VARs

Note: Each graph displays the portion of the variance of the forecasting error in variables explained by financial and policy uncertainty shocks using a sign-restriction approach.

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 4.7 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 by investment. This can be explained by the substantial heterogeneity in the degree of employment protection or the bargaining power of labor unions across countries, both of which make an international comparison of the effect of uncertainty shocks more difficult. In an export-driven economy such as Korea’s, 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 with 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 EPU index, and the financial uncertainty index with four lags. Figure 4.8 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.

4.6 Evidence from Other Emerging Economies As a final robustness check, we estimate an unbalanced panel VAR model on other emerging economies (China, India, and Russia) to check whether our main findings from the Korean context can be generalized to emerging economies. In order to maximize the time series coverage of the sample, we only include four variables in the following order: policy uncertainty index, financial uncertainty index, stock market index, and industrial production. The individual country coverage of the data starts in January 1997 (China), January 2003 (India), and October 1997 (Russia), which is solely determined by the availability of the main variables. We
measure financial uncertainty by estimating the monthly realized volatility of the daily returns of the Shanghai Stock Exchange Composite Index (China), the NIFTY 50 Index (India), and the MICEX Index (Russia). All financial data are taken from Bloomberg.

Figure 4.9: Robustness check: IRFs from a panel VAR model

![Figure 4.9: Robustness check: IRFs from a panel VAR model](image)

Note: Each graph displays the IRFs with 90% confidence intervals from an unbalanced panel VAR model to financial and policy uncertainty shocks using 1,000 Monte Carlo simulations.

Figure 4.10: Robustness check: forecast error variance decomposition from a panel VAR model

![Figure 4.10: Robustness check: forecast error variance decomposition from a panel VAR model](image)

Note: Each graph displays the portion of the variance of the forecasting error in variables explained by financial and policy uncertainty shocks from an unbalanced panel VAR model.

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 1,000 Monte Carlo simulations. Although the differences are less stark than in the case of Korea, Figure 4.9 shows that financial uncertainty shocks have substantial negative effects on output in other emerging economies, whereas policy uncertainty shocks do not have significant effects. Variance decomposition in Figure 4.10
reinforces our conclusions, nevertheless, these results should be taken with caution due to the limited availability of data for these economies.

5 Conclusion

The claim that uncertainty over economic policies is what has been preventing the economy from recovering 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. Most significantly, our finding that an increase in policy uncertainty is not associated with economic downturns is in contrast to the most commonly accepted argument presented in the literature. Our findings, however, do not entirely 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 (2014) 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.
References


