Global Uncertainty and the Global Economy:

Decomposing the Impact of Uncertainty Shocks

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Abstract

We constructed a new index of global uncertainty using the first principal component of the stock market volatility for the largest 15 economies. We evaluate the impact of global uncertainty on the global economy using the new global database from Global Economic Indicators (DGEI), Federal Reserve Bank of Dallas. Global uncertainty shocks are less frequent than those observed in data on the U.S. economy. Global uncertainty shocks are associated with a sharp decline in global inflation, global growth and in the global interest rate (based on official/policy interest rates set by central banks). Our decomposition of global uncertainty shocks shows that global financial uncertainty shocks are more important than non-financial shocks. Over the period 1981 to 2014 global financial uncertainty forecasts 18.26% and 14.95% of the variation in global growth and global inflation respectively. The non-financial uncertainty shocks have insignificant effects on global growth. The model for global variables shows more protracted and substantial negative effects of uncertainty on growth and inflation than does a panel model estimating associations of local country-level variables. This outcome is reversed for the effect of uncertainty on official interest rate.

Keywords: Global, Uncertainty shocks, Monetary Policy, FAVAR

JEL Codes: D80, E44, E66, F62, G10

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Global Uncertainty and the Global Economy: Decomposing the Impact of Uncertainty Shocks

1. Introduction

The impact of uncertainty on economic activity has generally been studied at country level.[1] The rapid and accelerating process of financial globalization and new technologies prompt the question as to whether or not economic uncertainty is best addressed as a global phenomenon rather than a country-specific occurrence. In this investigation, we aim to answer the following questions: How to measure global uncertainty? How does global uncertainty affect the global economy? Do global uncertainty shocks have different effects than U.S. uncertainty shocks on the global Economy? Does the source of uncertainty shocks matter for the global economy?

To answer these questions we developed a new index of global uncertainty using the first principal component of the stock market volatility of the largest 15 economies.[2] We also evaluated the impact of global uncertainty on global interest rate, inflation and industrial production using the new global Database from Global Economic Indicators (DGEI), Federal Reserve Bank of Dallas.

Most measures of country-specific uncertainty in the literature are related to the firm volatility on returns and/or profitability, assuming that high uncertainty causes firms to temporarily reduce investment and hiring, and consumers to delay important purchases. In a major paper, Bloom (2009) emphasizes the negative impact of uncertainty on employment and output for the U.S. after World War II. In his work, Bloom develops an uncertainty index based on firm stock return and/or firm profit growth.

Alternative measures of uncertainty, based on spreads between low-rated and highly rated corporate bonds, are discussed by a number of authors, including contributions by

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[1] See for example Bloom (2009), Gilchrist et al. (2010), Bachmann and Bayer (2011), Knotek and Khan (2011), Fernández-Villaverde et al. (2011), Bekaert et al. (2013), Bachmann et al. (2013), and Jurado et al. (2015).
[2] Note that Bloom et al. (2007) show that share-return volatility is significantly correlated with alternative measures of uncertainty proxies.

Favero (2009), Arellano et al. (2010) and Sim et al. (2010). Bredin and Fountas (2009) utilize a general bivariate GARCH-M model to generate the macroeconomic uncertainty associated with output growth and inflation in EU countries. Ferrara and Marsilli (2014) provide a timely indicator of the world GDP growth based on the Factor-Augmented Mixed Data Sampling (FAMIDAS) model. More recently, Jurado et al. (2015) argue that stock market volatility may not be closely linked to "true" economic uncertainty, and propose new time series measures of macroeconomic uncertainty. These time series based indicators are built with U.S macroeconomic data and are identified as the unforecastable component of the macroeconomic series. Rossi and Sekhposyan (2015) develop a more general approach to describe macroeconomic uncertainty. Their macroeconomic index is based on assessing the likelihood of the realized forecast error of macroeconomic variables. The more the difficulty of the realization of the forecast, the greater the uncertainty of the macroeconomic environment. Charemza et al. (2015) suggest a new measure of inflation forecast uncertainty that accounts for possible inter-country dependence.

Our measure of global uncertainty captures important political, war, financial and economic events over the period 1981 to 2014. Global uncertainty shocks are less frequent than those observed in data on the U.S economy. Global uncertainty shocks are associated with a sharp decline in global interest rate, global inflation and global industrial production. The maximum decline of global inflation and industrial production occurs six months after a global uncertainty shock, while the maximum decline in global interest rate occurs 16 months after a global uncertainty shock. Results are robust to both Factor Augmented Vector Autoregressive Model (FAVAR) and Factor Augmented Bayesian Vector Autoregressive Model (FABVAR) estimations.

Our decomposition of global uncertainty shocks shows that global financial uncertainty shocks are more important than non-financial shocks. Over 1981 to 2014 global

financial uncertainty forecasts 18.26% and 14.95% of the variation in global growth and global inflation respectively. The non-financial uncertainty shocks, in contrast, forecast statistically insignificant 7.75% and 2.15% of the variation in global growth and global inflation, respectively. During the global financial crisis, shocks to global uncertainty and to the global interest rate combine to reduce global growth.

This paper proceeds as follows. A new index of global uncertainty is introduced in Section 2. The effect of global uncertainty on the global economy is modelled in Section 3. In Section 4 preliminary results are examined with FAVAR. Section 5 compares the differences between the U.S. and global uncertainty shocks. In section 6, global uncertainty is decomposed in financial and non-financial shocks. Section 7 concludes.

2. A new index of global uncertainty

2.1. Methodology

The empirical literature on economic uncertainty has generally focused on the volatility of stock market returns and/or firm profitability as providing a measure of uncertain environments within which decisions are made.[3] Increased uncertainty can decrease the willingness to hire, invest and consume, with effects on firm profitability and therefore economic growth. In this investigation we build a global uncertainty index by extracting the first principal component of largest 15 economies stock market volatility.[4]

Let $R_{c,t}$ be the difference of the natural log of the stock market index of country c:

$$R_{c,t} = \ln \frac{S_{ct}}{S_{ct-1}}, \quad (1)$$

where s_{ct} denotes the average monthly stock price for a given country c at time t, with $t = 1, 2 \dots, T$. Let

$$V_{ct} = (R_{c,t} - \bar{R}_{c,t})^2, \quad (2)$$

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[3] An important thread in the literature is that uncertainty faced by the individual firm is embodied in its own stock price volatility (Leahy and Whited (1996), Bloom (2009), Bloom et al. (2007) and Baum et al. (2010)), among others.

[4] Note that this first principal component accounts for around 40% of the data variation.

where V_{ct} is the stock market volatility of country c at time t, $\bar{R}_{c,t}$ is the sample average of $R_{c,t}$. The stock market volatility index is then estimated for the largest 15 economies in 2013 according to the gross domestic product (based on purchase power parity). The countries are China, U.S., India, Japan, Russia, Germany, Brazil, France, UK, Italy, Mexico, South Korea, Saudi Arabia, Canada, and Spain.[5]

Given a data matrix with V_{ct} for the 15 largest economies and n samples, we first center on the means of V_{ct}. The first principal component for the global uncertainty index (GU_t) is given by the linear combination of all 15 volatility indices $V_{China,t}, V_{us,t}, ..., V_{Spain,t}$,

$$GU_t = a_1 V_{China,t} + a_2 V_{US,t} + \cdots + a_{15} V_{Spain,t}. \quad (3)$$

GU_t is calculated such that it accounts for the greatest possible variance in the data set. The weights (a_i) are the elements of an eigenvector with unit length and standardised by the restriction: $a_1^2 + a_2^2 + \cdots + a_{15}^2 = 1$.

2.2. Global and the U.S. uncertainty indices.

In Figures 1 and 2, we show the global uncertainty index developed in Equation (1) to (3) and the U.S. uncertainty index.[6] In each Figure the black line shows the 12-month moving average of the index and the horizontal broken line shows 1.65 standard deviations. We follow Bloom (2009) and Jurado et al. (2015) in defining uncertainty shocks as those events which exceed 1.65 standard deviations. By comparing Figure 1 with Figure 2, several points can be made.

The statistically significant global uncertainty shocks shown in Figure 1 are associated with Black Monday (October and November 1987), the Russian Default (September 1998), the 9/11 terrorist attack (September 2001), WorldCom (July 2002), the

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[5] Note that we attempt to estimate this index for G20 economies. However, data for Indonesia, Iran, Thailand Nigeria and Poland were not available for the full sample period.
[6] Note that the last is just the stock market volatility index constructed with only the data for the U.S. stock market.

Gulf War II (February 2003), and the Global Financial Crisis (GFC) between 2007-2008. The non-economic statistically significant global uncertainty shocks, the 9/11 attack and Gulf War II, are smaller than the economic statistically significant global uncertainty shocks in Figure 1. The statistically significant global uncertainty shocks shown in Figure 1 are also statistically significant U.S. uncertainty shocks in Figure 2.

On Monday, October 19, 1987 stock markets around the world collapsed. The fall started in Hong Kong, spread west to Europe, and in the United States the Dow Jones Industrial Average fell by 22.6%. Globally, stock market losses persisted, with markets in Hong Kong, the United Kingdom, and the United States down by 45.5%, 26.5%, and 22.7% respectively, at the end of October, 1987. Despite October 19, 1987 being the biggest daily percentage decline in the history of the Dow Jones Index, no major (news) event has been associated with the stock market crash. Both monthly U.S. stock market volatility and monthly global stock market volatility were high during October 1987, but higher still during November 1987.

On August 17, 1998 the Russian Central Bank devalued the ruble and the Russian government defaulted on its debt. The background to these developments included high inflation (Russian inflation was over 80% during 1998) and the loss of foreign exchange reserves associated with decreased revenues from the export of crude oil and other commodities attendant on falling prices and weak demand in the aftermath of the Asian Financial Crisis in late 1997. The Russian devaluation and default caused the Long Term Capital Management hedge fund to default on financial contracts worth billions of dollars, leading the Federal Reserve Bank of New York to orchestrate a rescue effort to avert a major financial collapse. During this episode, monthly U.S. stock market volatility was highest during August 1998, as was global stock market volatility.

The 9/11 terrorist attack in September 2001 is associated with spikes in volatility in both monthly U.S. stock market volatility and monthly global stock market volatility. In July 2002 large overstated revenues were uncovered in an accounting scandal at WorldCom and monthly U.S. and global stock market volatility spike. A series of accounting scandals had started at Enron in December 2001 and at a number of large companies, including WorldCom, throughout 2002.

The Gulf War II started on March 19 and continued to May 1 in 2003. Monthly U.S. and global stock market volatilities increased sharply in February 2003 in anticipation of the U.S. invasion of Iraq. Over the next three months, global stock market volatility fell to somewhat less than half the value achieved in February 2003, before rising to about 73% of the February 2003 level in June 2003. By contrast, monthly U.S. stock market volatility fell to a very low value in March 2003, and achieved values from April to June 2003 of between 73% and 89% of the value in February 2003. The implications of this pattern of volatility is that, in the moving average plots of data in Figures 1 and 2, over the period September 2001 to June 2003, monthly U.S. stock market volatility peaks in June 2003 (in the aftermath of the Gulf War II), whereas monthly global stock market volatility peaks in September 2002 (during the accounting scandals).

The GFC includes several events described in detail in Appendix E1. The crisis is associated with subprime mortgage crisis and the consequent bankruptcy of Lehman Brothers in September 2008 and the bailout of several financial institutions including Northern Rock in UK (February 2008) and Fannie Mae and Freddie Mac (July 2008) and American International Group (September 2008) in U.S.

Standard & Poor downgraded U.S. sovereign debt from AAA to AA+ on August 5, 2011. Both U.S. stock market volatility and global stock market volatility spiked in August 2011. The 12-month moving average for volatility peaked in May 2012 in global stock

markets and in September 2011 for the U.S. stock market. This difference in timing is apparent in comparison of Figures 1 and 2.

2.3. Relative importance of high uncertainty events in U.S. and global data

The uncertainty associated with the Monetary Cycle turning point (October 1982), the Gulf War I (October 1990), and the Asian Crisis (November 1997) are statistically significant in the U.S. data depicted in Figure 2, but not in the global data represented in Figure 1. The market volatility during the Monetary Cycle turning point is identified with uncertainty over the effectiveness of policy during the Reagan administration at dealing with inflation and recession. The global uncertainty shock associated with the Monetary Cycle turning point is not statistically significant in Figure 1. Both the monthly volatility and the 12-month moving average volatility for the global stock markets peak in September 1982 and fall in the following months. The monthly volatility in the U.S. data also peaks in September 1982 and then falls in following months. The 12-month moving average volatility for the U.S. stock market has a peak in September 1982, a peak exceeded slightly in November 1982 and in January 1983, with high values over the whole period September 1982 to September 1983. Overall, the Monetary Cycle turning point is a much more important uncertainty event in the U.S. data than in the global data, as illustrated in Figure 3.

In Figure 3 the Global and U.S. volatility indices are scaled so that mean volatilities are equal. Figure 3 illustrates that the Monetary Cycle turning point, the Gulf War I, and the Asian Crisis are relatively less important in the global data, compared with other high uncertainty periods, than in the U.S. data.

In contrast, in Figure 3, Black Monday, the Russian Default, the 9/11 terrorist attack, and WorldCom and associated accounting scandals are relatively more important compared with other high uncertainty periods in the global data than they are in the U.S data. The last three major episodes, Gulf War II, GFC, and the downgrade of the U.S. sovereign debt are of

approximately equal relative importance compared to other high uncertainty periods in the U.S. and global data.

3. Modelling the effect of global uncertainty on the global economy

3.1. The FAVAR model

Following Bloom (2009) and Jurado et al. (2015), who run VAR models, we run a FAVAR model to estimate the impact of uncertainty on key macroeconomics variables. The endogenous variables in the model include the growth in global output $\Delta(GIP_t)$, global inflation $\Delta(GCPI)_t$, global interest rate (based on central bank official/policy interest rates) GIR_t and global uncertainty variable GU_t. The global macroeconomic variables are factors of variables available on the U.S., non-U.S. developed economies, and emerging economies from Global Economic Indicators (DGEI), Federal Reserve Bank of Dallas, for the G40 countries.

A structural VAR model of order p is utilized:

$$A_0 y_t = c_0 + \sum_{i=1}^{p} A_i y_{t-i} + \varepsilon_t, (4)$$

where $y_t = (\Delta(GIP_t), \Delta(GCPI_t), GIR_t, GU_t)$ is a $(m = 4) \times 1$ vector of endogenous variables, A_0 denotes the 4×4 contemporaneous coefficient matrix, c_0 represents a 4x1 vector of constant terms, A_i refers to the 4×4 autoregressive coefficient matrices, and ε_t stands for a 4×1 vector of structural disturbances.[7] To construct the structural VAR model representation, the reduced-form VAR model is consistently estimated using the least-squares method and is obtained by multiplying both sides of Equation (4) by A_0^{-1}. The reduced-form error term is $e_t = A_0^{-1} \varepsilon_t$ and $e_t \sim N(0, \Sigma)$.

The identifying restrictions on A_0^{-1}, is a lower-triangle coefficient matrix in the structural VAR model. This set up follows Christiano et al. (2005), Bekaert et al. (2014), and Jurado et al. (2015) in placing the output variable first, followed by global CPI, Global

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[7] We follow Bloom (2009) and Jurado et al. (2015) in setting p=12 which allows for a potentially long-delay in effects of uncertainty shocks on the economy and for a sufficient number of lags to remove serial correlation.

interest rate and global uncertainty.[8] The ordering of the variables assumes that the macroeconomic aggregates of output and CPI do not respond contemporaneously to shocks to the monetary policy of interest rate. The information of the monetary authority within a month t consists of current and lagged values of the macroeconomic aggregates and past values of the uncertainty. The uncertainty variable ordered last captures the fact that the uncertainty is a stock market based variable and responds instantly to monetary policy shocks. The structural shocks to the dynamic responses of an endogenous variable are then identified using a Cholesky decomposition. In Appendix B-C, for robustness analysis, we run both the FAVAR and FABVAR models using the reverse ordering of these variables that is proposed by Bloom (2009).

3.2. Data and global macroeconomic variables

The data for both the global uncertainty index and the VAR models are monthly from January 1981 to December 2014. Before 1981, data are not available on the stock markets from many developing countries.[9]

3.2.1. The global uncertainty index

The data for the largest 14 economies stock market are obtained from DataStream (Thomson Reuters). These economies are the largest economies worldwide according to the gross domestic product (purchase power parity version) in 2013. The countries are China, U.S., India, Japan, Russia, Germany, Brazil, France, UK, Italy, Mexico, South Korea, Saudi Arabia, Canada, and Spain.[i]

3.2.2. Global macroeconomic variables

GIR_t, $GCPI_t$, and GIP_t are factors estimated using data on emerging economies, advanced economies (excluding the U.S.), and the U.S. The data on interest rate, CPI and IP

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[8] Note we omitted the variables stock prices, wages, working hours and employment as these variables are not available at global level.
[9] Note that the DGEI data for emerging countries starts in January 2003. We extended this series until January 1981 using equal weighed data from China and India obtained from the People's Bank of China and the Federal Reserve Bank of Saint Louis respectively.

are taken from Global Economic Indicators (DGEI), Federal Reserve Bank of Dallas for the G40 countries. In DGEI weights (based on shares of world GDP (PPP)) are applied to the official/policy interest rates (determined by central banks) in levels and are applied to the indexes for industrial production and headline price indexes in growth rates to construct indices for emerging economies and advanced economies (excluding the U.S). In 2014 on a GDP PPP basis the G40 economies account for 83% of global GDP, and within the G40, the U.S., 19 advanced economies (excluding the U.S.), and 20 emerging economies account for 18%, 25%, and 40%, respectively, of global GDP. Combined, the 20 largest emerging economies on a PPP basis are now almost as big as the 20 largest developed economies. GIR_t, $GCPI_t$, and GIP_t are the leading principal components given by:

$$GIR_t = [IR_t^{Ad}, IR_t^{US}, IR_t^{Em}], \qquad (5)$$

$$GCPI_t = [CPI_t^{Ad}, CPI_t^{US}, CPI_t^{Em}], \quad (6)$$

$$GIP_t = [IP_t^{Ad}, IP_t^{US}, IP_t^{Em}], \qquad (7)$$

where the superscripts *US*, *Ad* and *Em* represent the United States, advanced economies (excluding the U.S) and emerging economies.

4. The FAVAR model results

The reduced-form VAR model of Equation (4) is consistently estimated by the ordinary least square method. We utilize the resulting estimates to construct the structural VAR representation of the model. The dynamic effect is examined by the impulse responses of global output growth, global inflation and interest rate to the structural global uncertainty shock. We present the responses to one-time global uncertainty shocks as well as to the historical episodes of the uncertainty shocks.

4.1. The effects of global uncertainty shocks on the economy

Figures 4 shows the impact of one standard deviation global uncertainty shocks on global industrial production growth, global CPI inflation and global interest rate, for the

FAVAR estimation. The dashed lines represent a one standard error confidence band around the estimates of the coefficients of the impulse response functions. We utilize the impulse response functions in Figure 4 to assess the timing and magnitude of the responses to one-time global uncertainty shock in the economy.

On the left hand side of Figure 4, the lags in the VAR system estimated are indicated. The FAVAR model is estimated with 3, 6 and 12 lags. The second, third and fourth columns in Figure 4 show responses of global interest rate, global CPI inflation and global industrial production growth to global uncertainty shocks. The results are summarized as follows:

- Global uncertainty shocks are associated with a quick and sharp decline in global industrial production growth, which is greatest after 4 to 8 months depending on the specification.

- Global uncertainty shocks are associated with a quick and sharp decline in global CPI reaching the greatest point of decline after 6 months. However, when 12 lags are used in the VAR system, greatest point of decline occurs after 10 months.

- Global uncertainty shocks are associated with a decline in global interest rate; when 3 and 6 lags are used in the VAR systems the greatest decline in the global interest rate is observed after 16 months.[10]

4.1.1. Global uncertainty and local uncertainty proxy for each country

We investigate the question of whether a VAR with the local uncertainty proxy for each country does better or worse than using the global measure for all of them. This investigation will shed light on whether the global measure tracks the US because there is a global measure, or because world stock-markets all tracked the US.

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[10] Note that when the models are specified with 12 lags, the greatest response occurs after 6 months, with a quick return to positive values after 12 months. This pattern is only observed for FAVAR model and for the FABVAR model Wishart type of priors in models with a 12 month lag. Even with a 12 month lag structure, the FABVAR model with Minnesota and Sims-Zha priors results are similar to those obtained in the FAVAR and FABVAR models with 3 month and 6 month lags.

In this estimation we used unbalanced panel data for the largest 14 economies used in our global approach. A local uncertainty proxy is constructed by the stock market volatility of each country. The other endogenous variables are growth in industrial production, CPI inflation, and official/policy interest rate for each country. In total 3936 observations are used in this estimation. Observations with inflation greater than 10% per month are excluded. When inflation is greater than 10% per month (or an annual of inflation over 310%), uncertainty in the economy is likely to be dominated by the inflation process itself and likely to render proxy measures of uncertainty (that exclude inflation) redundant. In the data, Russia and Brazil have periods of substantial high inflation. Experimentation with restrictions on the sample with other monthly inflation cut-offs (including 5%) does not affect results.

In Figure A1 we show the impact of one standard deviation local uncertainty shocks on local industrial production growth, local CPI inflation and local interest rate, for the panel FAVAR estimation. The dashed lines represent a one standard error confidence band around the estimates of the coefficients of the impulse response functions. The first, second and third rows of Figure A1 report results for 3, 6 and 12 lags in the panel VAR system.

The second column in Figure A1 show responses of local industrial production growth to positive local uncertainty shocks. Following a local uncertainty shock, local industrial production growth falls sharply for the first two months, recovers abruptly in the third month, then undergoes small damped oscillations in the following months, before stabilizing after about 12 months. The time-period over which there is a negative effect of the local shock on local growth is much attenuated compared to the time-period over which there is a negative effect of the global uncertainty shock on global industrial production growth, which was over one year duration. The absolute value of the negative effect of the local shock on local growth is also much smaller than the absolute value of the negative effect of the global uncertainty shock global industrial production growth.

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In the third column in Figure A1, in response to a local uncertainty shock, local inflation falls sharply for about six months before recovering. The model for global variables also shows a more protracted and substantial negative effect of uncertainty on inflation than does the panel model estimating associations of local variables.

In the fourth column in Figure A1 the effect of local uncertainty shocks on local/official interest rates is reported. A local uncertainty shock is associated with a sharp decline in local interest rate in the first month that is reversed over the next few months, before resulting in a statistically significant decline in the interest rate after about six months which extends throughout the remainder of the 48-month horizon. In contrast to the results for growth and inflation, the model for local variables shows more protracted and substantial negative effects of uncertainty on the official interest rate than does the model estimating associations of global variables.

4.2. Historical decomposition of global uncertainty shocks

In this subsection we construct a historical decomposition of the dynamics effect of structural global uncertainty shocks on the global macroeconomic variables. It helps us to assess the timing and magnitude of the responses to a vector sequence of the uncertainty shocks that often involves different signs at each point of time. We expect that the global uncertainty shocks have very different effects on the economy at different points in time.

The cumulative contributions of structural global uncertainty shocks from estimating the structural FAVAR model in equation (4) to global output growth, global inflation and global interest rate are reported in Figure 5. The cumulative contributions of structural shocks to each variable reported in Figure 5 are for each month and are not annual averages. The vertical axes for global growth and global inflation are in percentage changes per month (with

1% equal to 12.68% at an annual rate). The vertical axis for global interest rate is the annual rate.

The three largest declines in the cumulative contributions of uncertainty shocks to global growth in Figure 5 are associated with Black Monday (October 1987), the Russian Default (August 1998), and the global financial crisis (in late 2008). Large declines in the cumulative contribution of global uncertainty to global inflation and global interest rate also appear in Figure 5, roughly during these periods. We examine these three episodes in detail. In Figure 5, the cumulative contribution of global uncertainty to global growth takes negative values from September 1987 through December 1989, with the largest negative value in absolute terms in March 1988. Over the period from February 1987 through June 1989 (with the exception of one month) global industrial growth is positive. In results shown in Appendix E, cumulative contributions of global output growth and global interest to global output growth are mostly positive and substantial. The cumulative contributions to global output growth, of global output growth and of global interest rate, are positive from May 1987 to April 1989 and from August 1987 to January 1991 respectively. The latter two effects offset the negative effect of the global uncertainty on global output growth over the period 1987 through 1989.

In Figure 5, the cumulative contribution of global uncertainty shocks to global growth takes a series of negative values from May 1998 through August 2000, with the largest negative value in absolute terms in December 1999. Global growth is negative in most months from July 1998 to February 1999, and positive thereafter until December 2000. In Appendix C it is shown that cumulative contributions of global output growth and global interest to global output growth are positive from March 1999 to September 2000 and from June 1999 to December 2001, respectively.

The role of global uncertainty in the period encompassing the global financial crisis when cumulative contribution of global uncertainty to global growth is negative, October 2007 to December 2010, is examined. Actual global growth is negative from March 2008 until December 2009. In Appendix C, cumulative contributions of global output growth to global output growth is negative from February 2007 to October 2009, and there is a cumulative negative effect on global growth by the global interest rate from April 2008 to December 2009. During the period of the global financial crisis, the negative effect of global uncertainty reinforces the own effect of shocks and that of shocks in the official/policy interest rates set by central banks in reducing global growth.

5. Are global uncertainty shocks different from U.S. uncertainty shocks for the global economy?

Given that the U.S. is the largest financial centre worldwide, we disaggregate further the US uncertainty (USU_t) estimated as volatility index of the U.S. stock market and global uncertainty. The new vector of endogenous variables is a $(m = 5) \times 1$ vector of endogenous variables: $y_t = (\Delta(GIP_t), \Delta(GCPI_t), GIR_t, USU_t, GU_t$), and A_0 denotes the 5×5 contemporaneous coefficient matrix. More precisely, the Cholesky lower triangle contemporaneous matrix is estimated by postulating the following $A_0 y_t$ matrix form:

$$\begin{bmatrix} 1 & 0 & 0 & 0 & 0 \\ a_{11} & 1 & 0 & 0 & 0 \\ a_{21} & a_{22} & 1 & 0 & 0 \\ a_{31} & a_{32} & a_{33} & 1 & 0 \\ a_{41} & a_{42} & a_{43} & 0 & 1 \end{bmatrix} \begin{bmatrix} \Delta(GIP_t) \\ \Delta(GCPI_t) \\ GIR_t \\ USU_t \\ GU_t \end{bmatrix}, (8)$$

where USU_t represents the U.S uncertainty shock derived from the volatility of the U.S. stock market. Note that coefficient a_{44} is set to be zero, implies that we do not have

preference in terms of ordering both U.S and global uncertainty first in the Cholesky decomposition.[11]

Figure 6 shows the responses of global IP, CPI and interest rate to global uncertainty shocks (first row) and U.S uncertainty shocks (second row). In the first column a one-standard deviation shock to global uncertainty decreases global industrial production by -0.13 and a one-standard deviation shock to U.S. uncertainty reduces Global IP by less than -0.6. The global uncertainty shock is statistically significant over a more extended period of time. The global and U.S uncertainty shocks are statistically significant over 1 to 16 month and 1 to 10 month horizons, respectively. The impact of global and U.S uncertainty shocks also differ in effects on Global CPI. While the response of global CPI to global uncertainty shocks is statistically significant and reaches a minimum of -0.08, the impact of U.S. uncertainty shocks on global CPI is much smaller and is not statistically significant at conventional levels.

Finally, the global interest rate is negatively affected by a positive global uncertainty shock but the effect is only marginally statistically significant. The response of global interest rate to U.S uncertainty shocks is much smaller and is not statistically significant.

6. Does the source of uncertainty shocks matter for the global economy?

The central result in Section 4.2 is that the global uncertainty shocks have very different effects on the economy at different points in time. In this section we show that global uncertainty shocks have different sources. We analyse the impact of global uncertainty shocks by source on the global economy. In particular, we decompose global uncertainty shocks into global financial and non-financial shocks, where all the shock considered are those shocks which exceed 1.65 standard deviations in terms of monthly observations.

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[11] We also estimate the Cholesky contemporaneous restriction matrix allowing a_{44} to be estimated and order both U.S and Global uncertainty first and be estimated in separate models. Results are almost identical to those presented in Figure 6.

6.1. Financial vs. non-financial uncertainty shock

In this subsection, we distinguish between financial and non-financial shocks and estimate the impact effects of both shocks on the global economy. Shocks originating in economic or financial disruption may have been amenable to better economic policy design whereas those due to war or terrorism are not (although political policies might have an impact). Examination of uncertainty shocks with an economic/financial source might lead to a better understanding of how economic policy might be designed to both avoid and mitigate the effects of future shocks.

Our definition of global financial shocks comprises the following events which exceeded 1.65 standard deviations: Black Monday, Russian Default, WorldCom, and the GFC. The global financial crisis includes the four main events described in Table D1. These are North Rock emergency funding in September 2007 and the nationalisation in February 2008, the bailout of Fannie Mae and Freddie Mac, the Lehman Brothers bankruptcy and the bail out of American International Group (AIG) in the U.S in the period July 2008, September 2008 and October 2008 (respectively). The Non-financial uncertainty shocks which exceed 1.65 standard deviations are the Gulf War II and 9/11 terrorist attack.

To disaggregate global uncertainty shocks we modify the system of equations presented in equation by subtitling the unique variable GU_t into two different uncertainty shocks: $DF * GU_t$ and $DNF * GU_t$, where the first variable the global financial uncertainty shock is constructed by interacting the GU_t index with a dummy variable DF_t, which takes the value of 1 when a financial shock occurs and 0 otherwise (details of the period dummies can be found in Appendix D, Table D1).[12] The second variable (the non-financial uncertainty shocks) is constructed by interacting the GU_t index with a dummy variable DNF_t, which

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[12] Note that the dummy variables only take the value of 1 when the identified shock exceeds 1.65 standard deviations following Bloom (2009).

takes the value of 1 when a non-financial shock occurs and 0 otherwise.[13] The new vector of

endogenous variables is a $(m = 5) \times 1$ vector, that is $y_t = (\Delta(GIP_t), \Delta(GCPI_t), GIR_t, FDF_t * GU_tU_t, DNF_t * GU_t$). The Cholesky lower triangle

contemporaneous matrix is estimated using the following A_0y_t matrix:

$$\begin{bmatrix} 1 & 0 & 0 & 0 & 0 \\ a_{11} & 1 & 0 & 0 & 0 \\ a_{21} & a_{22} & 1 & 0 & 0 \\ a_{31} & a_{32} & a_{33} & 1 & 0 \\ a_{41} & a_{42} & a_{43} & 0 & 1 \end{bmatrix} \begin{bmatrix} \Delta(GIP_t) \\ \Delta(GCPI_t) \\ GIR_t \\ DF_t * GU_t \\ DNF_t * GU_t \end{bmatrix} . (9)$$

We set a_{44} to be zero, since there is no good reason to impose an order on financial and

non-financial uncertainty.

Figure 7 compare the impacts of financial and non-financial uncertainty shocks on

key global macroeconomic variables. In the first and second rows we show the impact of

financial and non-financial uncertainty shocks (respectively) on global industrial production

(first column), CPI (second column) and interest rate (third column).

Results in the first column suggest that financial uncertainty shocks have a much

larger impact in absolute value than the non-financial shocks in reducing global industrial

production (up to -0.17 and -0.10, respectively). It is also observed that the impact of

financial shocks on global industrial production is faster. The greatest impact of financial

shocks on global industrial production is observed between 6 to 10 months later, compared to

11 to 16 months later for non-financial shocks. More remarkable are the differences between

the responses of Global CPI to those shocks. Financial uncertainty shocks have a negative

effect on global CPI that is statistically significant at conventional levels. By contrast, non-

financial shocks do not have a statistically significant effect on Global CPI. In the third

---

[13] Note that we slightly innovate with respect of Bloom (2009), who uses only a single dummy variable which takes the value of 1 when the uncertainty shock occurs and 0 otherwise. The reason for doing that is because Bloom (2009)'s definition does not capture the magnitude of the shock. By interacting the GU_t and a dummy variable the shocks now also capture the dimension of the shock.

column of Figure 7, it is observed that central banks eventually reduce interest rates by similar amounts after both financial and non-financial shocks.

6.2. Variance decomposition of global macroeconomic variables to financial and non-financial uncertainty shocks

Table 1 a), b) and c) report the fractions of forecast error variance decomposition (FEVDs) for the global industrial production, global CPI and global interest rate (respectively) contributed by all the variables, including global financial uncertainty and global non-financial uncertainty. Global industrial production growth, global inflation, global interest rate and global financial uncertainty each make statistically significant contributions to forecasting the variation in global industrial production. The contribution of global financial uncertainty explains 18.26% of the variation in global growth after 48 months. By contrast, global non-financial uncertainty explains only 7.75% of the variation in global growth (that is not statistically significant) after 48 months. After 48 months, global inflation and global interest rate forecast 19.74% and 3.67% of variation in global growth.

Global industrial production growth, global interest rate, and global financial uncertainty each make statistically significant contributions to forecasting the variation in global inflation, while global non-financial uncertainty does not. The contribution of global financial uncertainty explains 14.95% of the variation in global inflation after 48 months. In contrast to the effect on global industrial production, the global interest rate explains a large fraction variation (25.20%) in global inflation after 48 months. Only global growth explains a statistically significant fraction (10.60% after 48 months) of the variation in global interest rate.

In summary, the forecast error variance decomposition results indicate that global financial uncertainty explains statistically significant fractions of the variation in global growth and global inflation over 48-month horizons, while global non-financial uncertainty

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does not. At the 48-month horizon, global financial uncertainty accounts for 18.26% and 14.95% of the variation in global growth and global inflation, respectively.

7. Conclusions

We constructed a new index of global uncertainty using the first principal component of the stock market volatility for the largest 15 economies. We also evaluate the impact of global uncertainty on the global economy using the new global Database from Global Economic Indicators (DGEI), Federal Reserve Bank of Dallas. Our measure of global uncertainty captures important political, war, financial and economic events over the period 1981 to 2014. Global uncertainty shocks are less frequent than those observed in data on the U.S economy. Global uncertainty shocks are associated with a sharp decline in global interest rate, global inflation and global industrial production. The maximum decline of global inflation and industrial production occurs six months after a global uncertainty shock, while the maximum decline in global interest rate occurs after 16 months after a global uncertainty shock.

Global uncertainty had a cumulative negative effect on global growth in the period embracing the global financial crisis from October 2007 to December 2010. Within this period there is a cumulative negative effect on global growth by the global interest rate from April 2008 to December 2009. The two effects contribute to actual global growth measured by global industrial production being negative from March 2008 until December 2009. The observed correlation between global uncertainty and global growth is particularly marked during the global financial crisis because of spikes in global uncertainty coinciding with cumulative negative effects of monetary policy on global growth. The VAR's results are robust to both Factor Augmented Vector Autoregressive (FAVAR) and Factor Augmented Bayesian Vector Autoregressive (FABVAR) models.

Our decomposition of global uncertainty shocks shows that global financial uncertainty shocks are more important than non-financial uncertainty shocks associated with the 9/11 and Gulf War II events. From 1981 to 2014 global financial uncertainty forecasts 18.26% and 14.95% of the variation in global growth and global inflation, respectively. The non-financial uncertainty shocks forecast statistically insignificant 7.75% and 2.15% of the variation in global growth and global inflation, respectively.

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Table 1: Variance decomposition of global macroeconomic variables

a. Forecast error variance decomposition of Global industrial production

| Contribution from/months	Global IP	Global CPI	Global IR	Financial uncertainty shock	Non-financial uncertainty shock
1	100.00***	0.00	0.00	0.00	0.00
6	85.99***	0.82	0.05	12.25***	0.88
12	64.71***	10.86*	0.83	18.95***	4.66
18	52.48***	19.78**	2.70**	17.26***	7.78
24	51.21***	20.51***	3.43**	16.85***	8.00
30	51.44***	19.54***	3.28**	18.11***	7.63
36	50.71***	19.75***	3.46**	18.35***	7.73
48	50.58***	19.74***	3.67**	18.26***	7.75

b. Forecast error variance decomposition of global CPI

Contribution from/months	Global IP	Global CPI	Global IR	Financial uncertainty shock	Non-financial uncertainty shock
1	0.19	99.81***	0.00	0.00	0.00
6	7.02	85.77***	0.24	5.44*	1.53
12	14.95**	66.66***	2.75	13.02**	2.63
18	18.95**	54.21***	8.02*	16.64**	2.17
24	18.90***	47.68***	14.35**	16.88**	2.19
30	18.02***	44.15***	19.52**	16.08**	2.22
36	17.45***	41.99***	22.98**	15.40**	2.18
48	17.31***	40.40***	25.20**	14.95**	2.15

c. Forecast error variance decomposition of global interest rate

| Contribution from/months	Global IP	Global CPI	Global IR	Financial uncertainty shock	Non-financial uncertainty shock
1	2.86	0.03	97.11***	0.00	0.00
6	4.20	0.09	95.24***	0.34	0.14
12	6.95	0.07	91.06***	0.94	0.99
18	9.21	0.10	87.51***	1.72	1.46
24	10.36	0.23	85.21***	2.28	1.92
30	10.64	0.36	84.27***	2.49	2.24
36	10.62*	0.41	84.03***	2.53	2.41
48	10.60*	0.42	83.97***	2.52	2.49

**Figure 1. Global volatility index: 12-month moving average standard deviation**
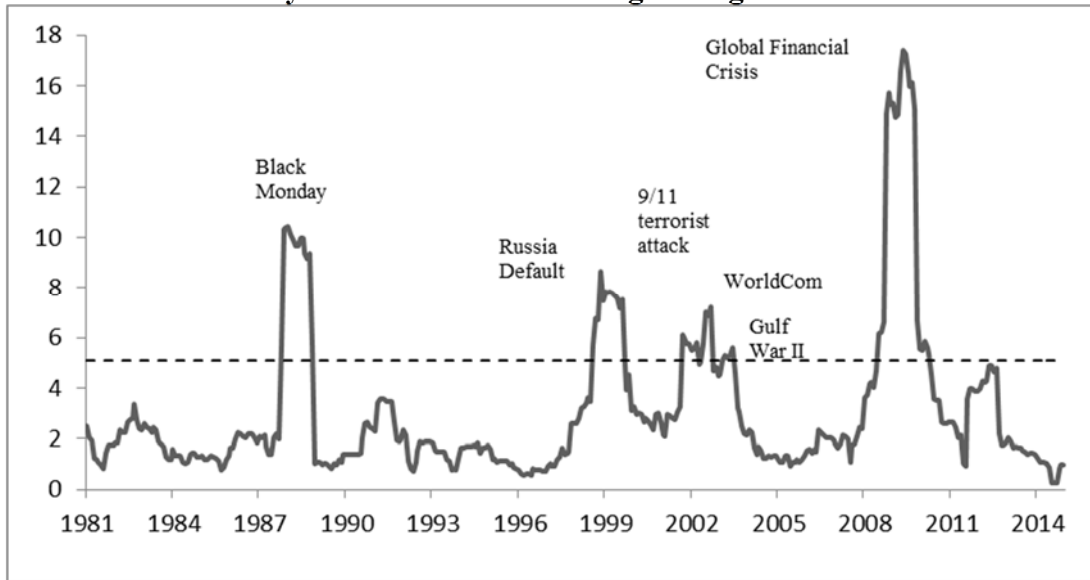
Figure 2. U.S. volatility index: 12-month moving average standard deviation
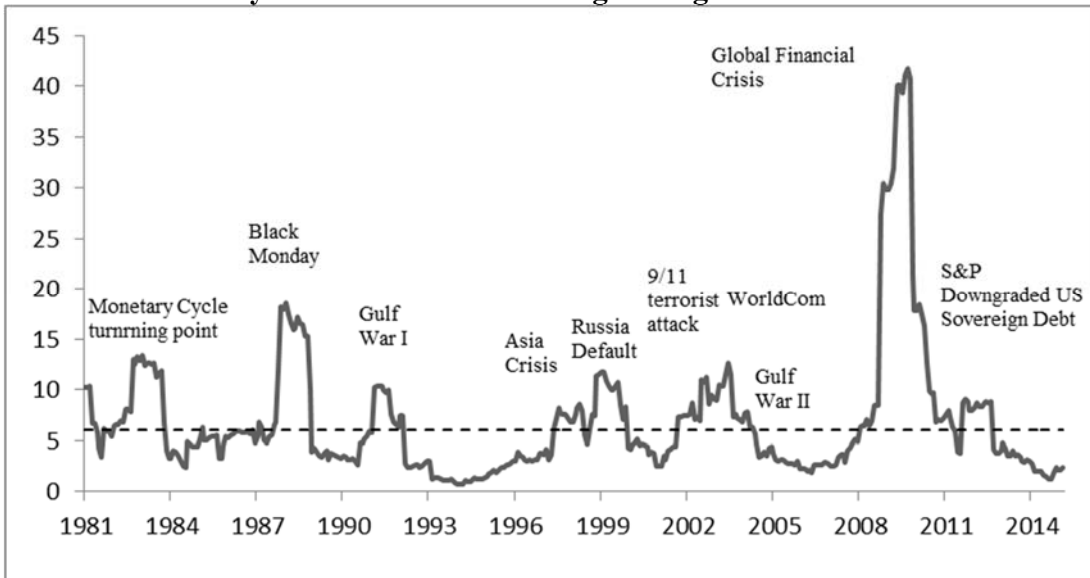
**Figure 3. Global and U.S volatility indices scaled so that mean volatilities are equal.**
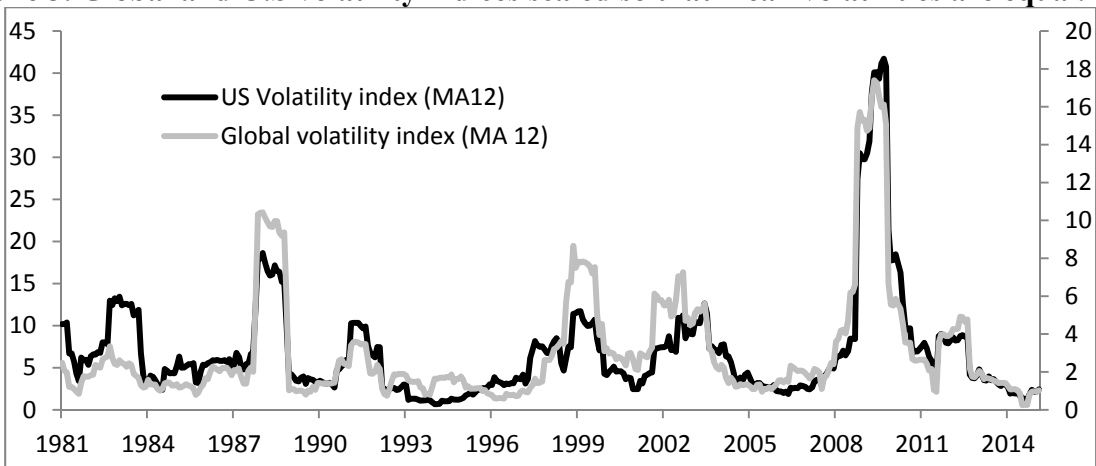
Figure 4. Responses of global industrial production, global inflation and global interest rate to global uncertainty shocks
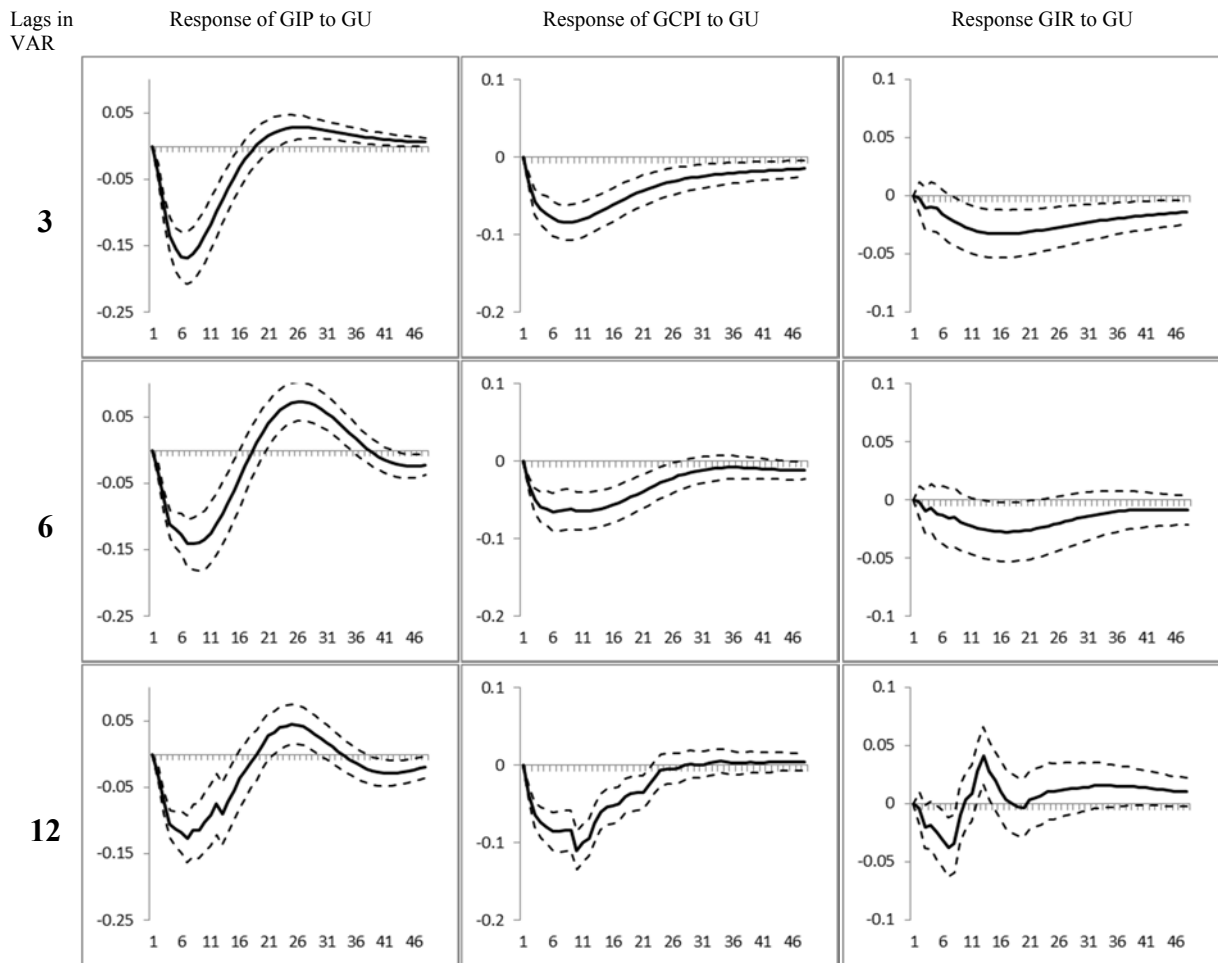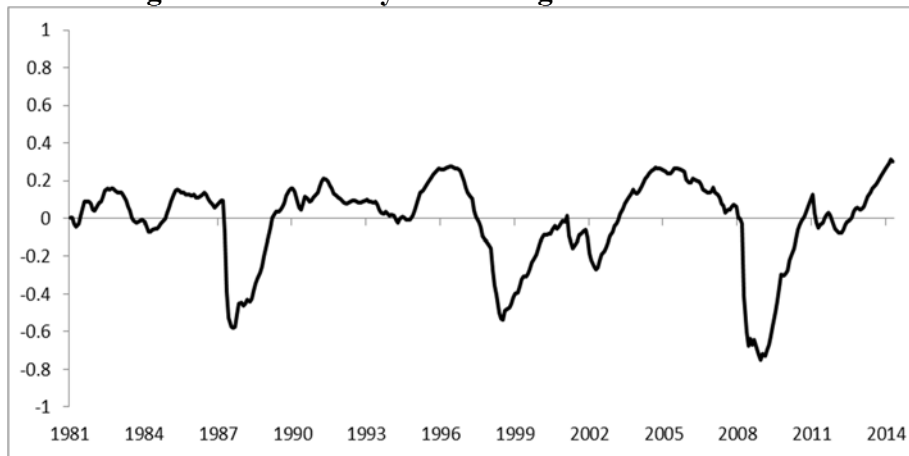

Notes: The dashed lines represent a one standard error confidence band around the estimates of the coefficients of the impulse response functions. The confidence bands are obtained using Monte Carlo integration as described by Sims (1980), where 5000 draws were used from the asymptotic distribution of the VAR coefficient.

Figure 5. Historical contributions of global uncertainty shocks
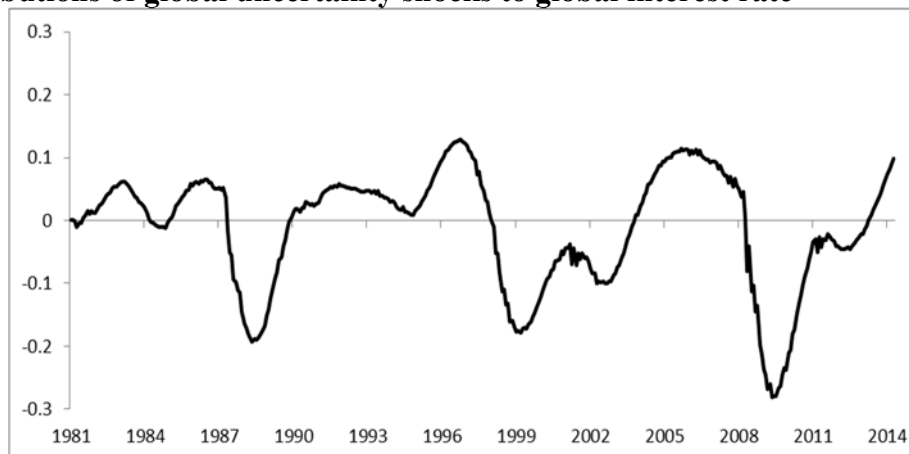
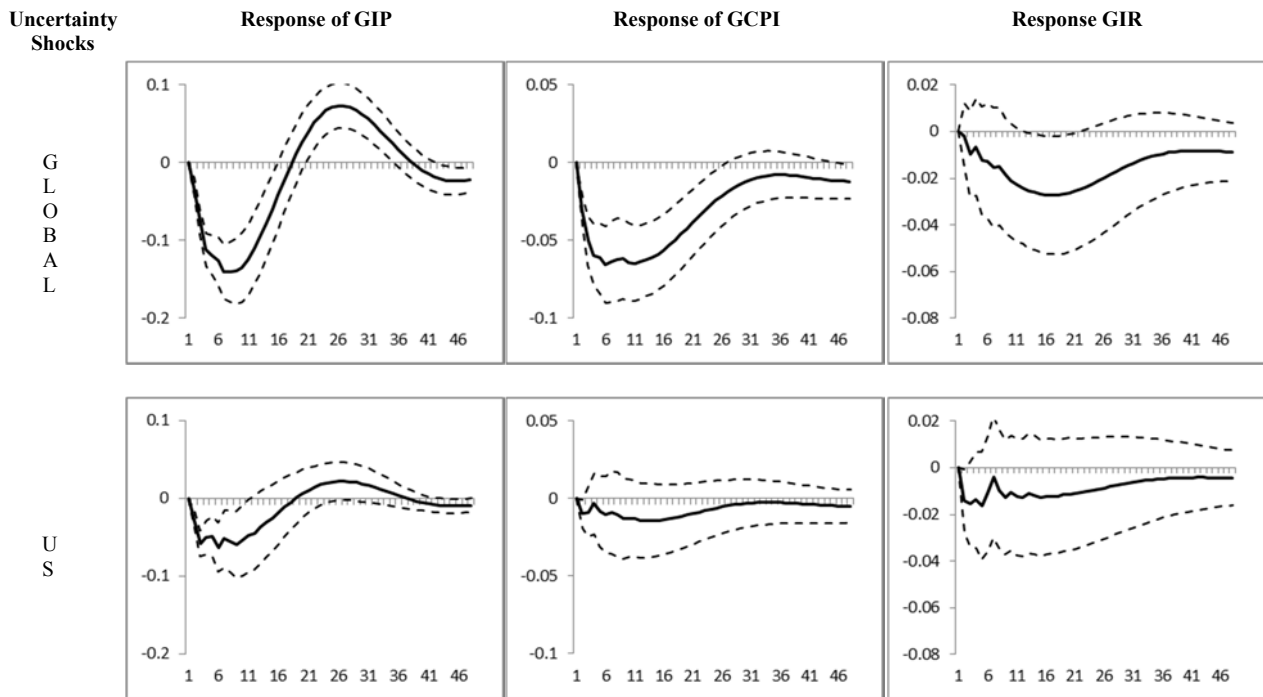**a. Contributions of global uncertainty shocks to global industrial production**
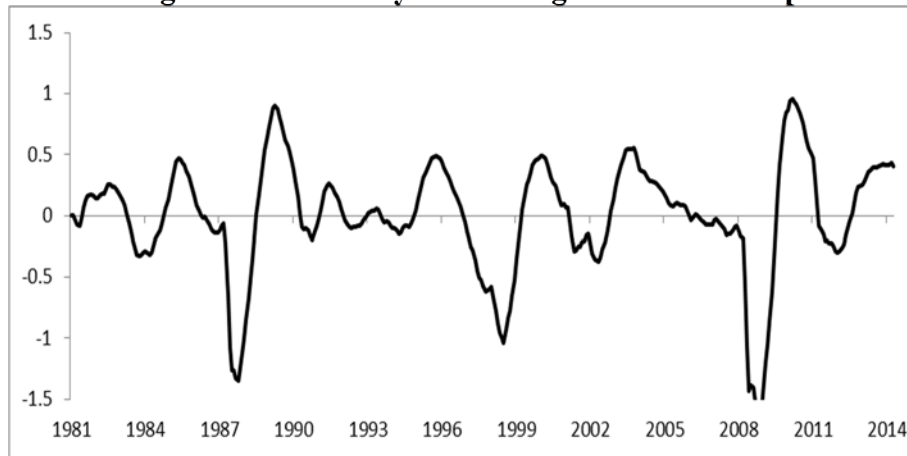
b. Contributions of global uncertainty shocks to global CPI

c. Contributions of global uncertainty shocks to global interest rate
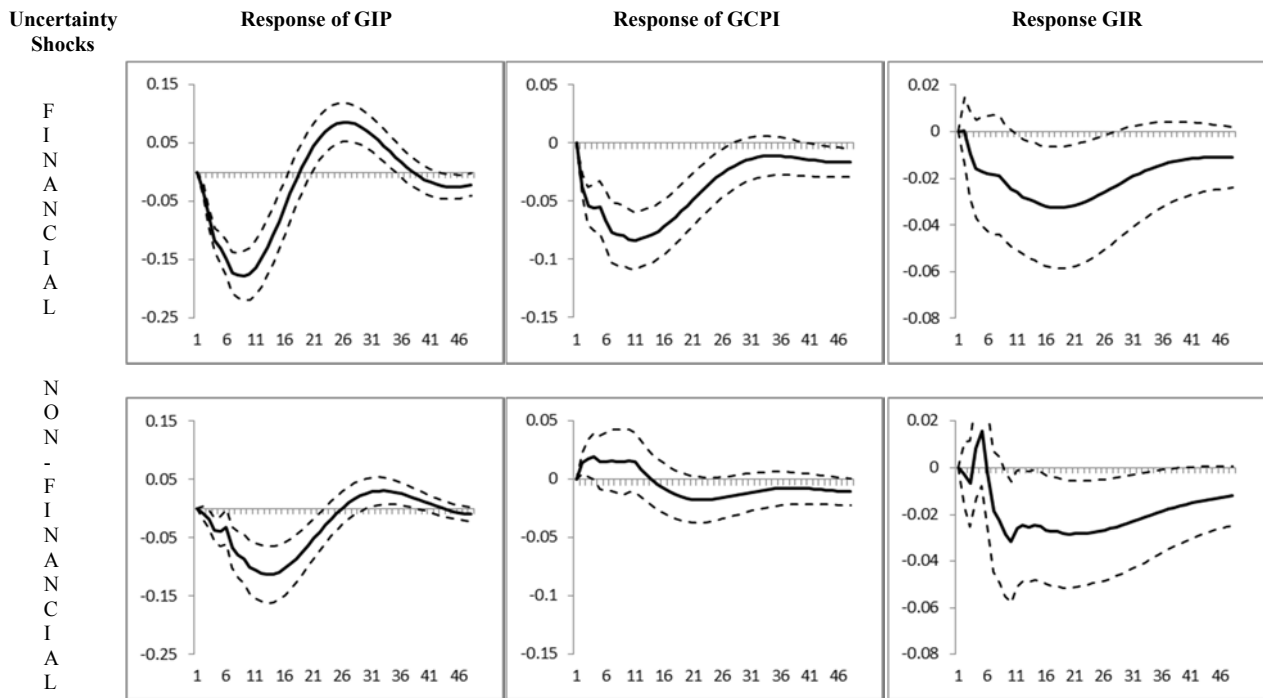
Figure 6. Responses of global variables to U.S and global uncertainty shocks

Notes: The dashed lines represent a one standard error confidence band around the estimates of the coefficients of the impulse response functions. The confidence bands are obtained using Monte Carlo integration as described by Sims (1980), where 5000 draws were used from the asymptotic distribution of the VAR coefficient.

Figure 7. Responses of global variables to financial and non-financial uncertainty shocks

| Uncertainty Shocks	Response of GIP	Response of GCPI	Response GIR

Notes: The dashed lines represent a one standard error confidence band around the estimates of the coefficients of the impulse response functions. The confidence bands are obtained using Monte Carlo integration as described by Sims (1980), where 5000 draws were used from the asymptotic distribution of the VAR coefficient.

Appendix A: The panel data approach

In this estimation we used unbalanced panel data the largest 14 economies (same countries used in our global approach). In total 3936 observations are used in this estimation. Observations of periods of very high inflation (higher than 10% per month) are excluded.

Figure A1. Responses of country-level variables to local uncertainty shocks: Panel data
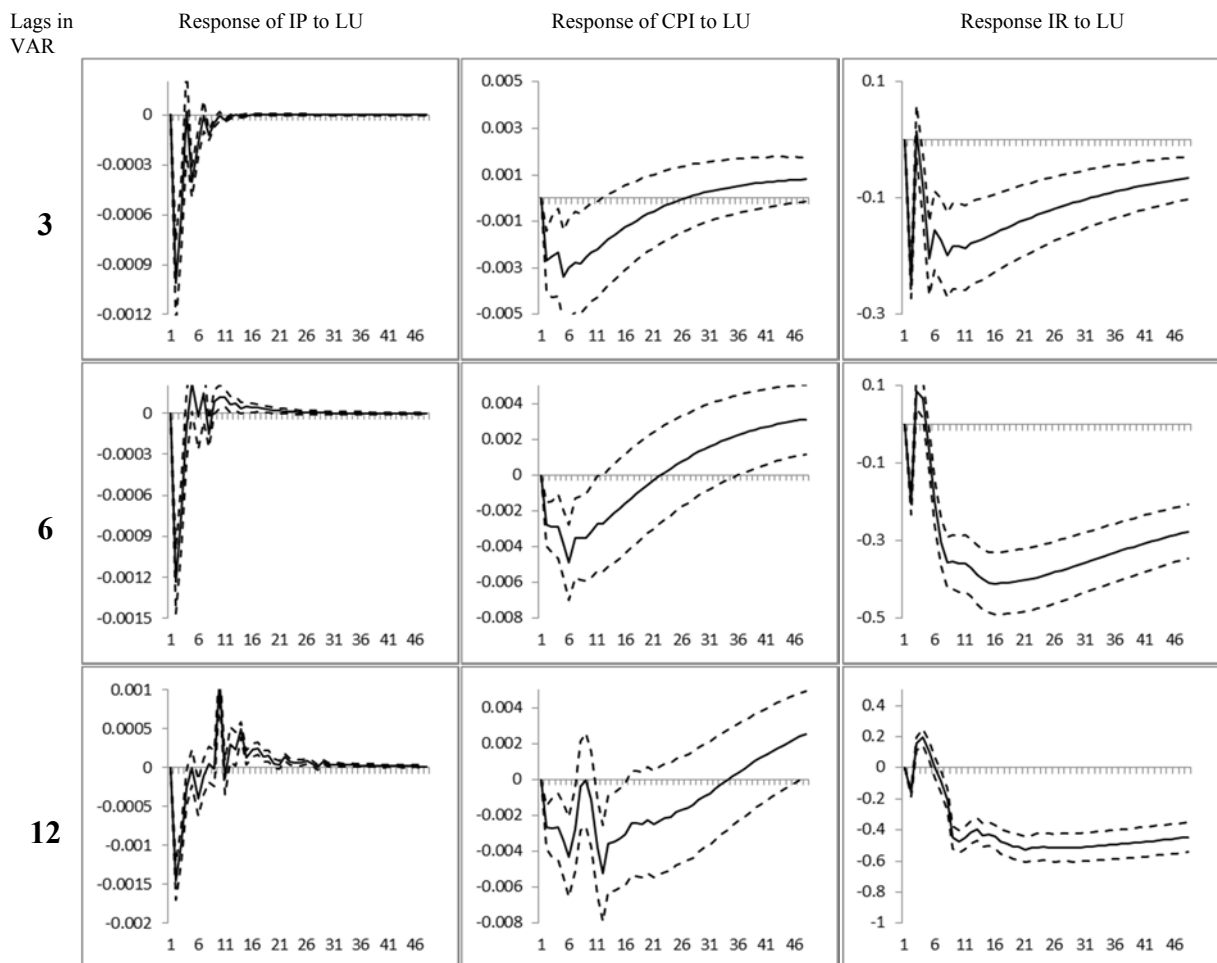
Appendix B: A robustness check by the FABVAR estimation

The VAR model in Equation (4) is conventionally estimated by ordinary least square (OLS) or maximum likelihood estimator (MLE). For the economic application of the VAR model, accurate estimation of finite sample distributions of (A, Σ) is important (such as the approximation of nonlinear impulse-response functions). However, the VAR model includes $(p + 1)m$ unknown parameters for the vector of regression coefficient and $m \times m$ unknown elements of the variance-covariance matrix. In the OLS/MLE estimation, the number of unknown parameters are relatively large relative to the data at hand. To assess the robustness, we utilize the Bayesian analysis to capture the uncertainty in the parameter estimation and in the valuation for the precision of inference and the reliability of prediction.

A Bayesian version of the FAVAR model in Equation (4) is now described. For compactness we may rewrite the model in Equation (4) as

$$Y = XA + E, \text{(A.1)}$$

or

$$y = (I_m \otimes X)\theta + e, \text{(A.1')}$$

where Y and E are $T \times m$ matrices, $X = (x_1, \ldots, x_t)'$ is a $T \times (mp + 1)$ matrix for $x = (1, y'_{t-1}, \ldots, y'_{t-q})$, I_m is the identify matrix of dimension m, $\theta = vec(A)$, and $e_t \sim N(0, \Sigma_\epsilon \otimes I_T)$. The likelihood function is:

$$l(\theta, \Sigma_\epsilon) \propto |\Sigma_\epsilon \otimes I_T|^{-0.5} \exp\left\{-0.5(y - (I_m \otimes X)\theta)'^{(\Sigma_\epsilon \otimes I_T)^{-1}}(y - (I_m \otimes X)\theta)\right\}. \text{(A.2)}$$

To derive the posterior moments in the Bayesian analysis, let assume that Σ_ϵ is known and a multivariate normal prior for θ is

$$\Pi(\theta) \propto |V_o|^{-0.5} \exp\left\{-0.5(\theta - \theta_0)'V_0^{-1}(\theta - \theta_0)\right\}, \text{(A.3)}$$

where θ_0 is the prior mean and V_o is the prior variance-covariance matrix. When we combine this prior with the likelihood function, the posterior density can be written as

$$\Pi(\theta|y) = \exp\{-0.5((V_0^{-0.5}(\theta - \theta_0)'V_0^{-0.5}(\theta - \theta_0)$$

$$+\{(\Sigma_\epsilon^{-0.5} \otimes I_T) - (\Sigma_\epsilon^{-0.5} \otimes X)\theta\}'\{(\Sigma_\epsilon^{-0.5} \otimes I_T)y - (\Sigma_\epsilon^{-0.5} \otimes X)\theta\})\} \,, \text{(A.4)}$$

a multivariate normal probability density function. Define

$$\omega \equiv \begin{bmatrix} V_0^{-0.5}\theta_0 \\ (\Sigma_\epsilon^{-0.5}\otimes I_T)y \end{bmatrix},$$

$$W \equiv \begin{bmatrix} V_0^{-0.5} \\ (\Sigma_\epsilon^{-0.5}\otimes X) \end{bmatrix}.$$

The posterior density is

$$\Pi(\theta|y) \propto \exp\{-0.5((\omega - W\theta)'(\omega - W\theta)\} \propto$$

$$exp\{-0.5(\theta - \bar{\theta})'W'W(\theta - \bar{\theta}) + (\omega - W\bar{\theta})'(\omega - W\bar{\theta})\}, \quad \text{(A.5)}$$

where the posterior mean $\bar{\theta}$ is:

$$\bar{\theta} = (W'W)^{-1}W'\omega = [V_0^{-1} + (\Sigma_\epsilon^{-1} \otimes X'X)]^{-1}[V_0^{-1}\theta_0 + (\Sigma_\epsilon^{-1} \otimes X)'y] \,. \text{(A.6)}$$

We utilize a Minnesota prior that involves setting the elements of θ_0 to be zero to ensure shrinkage of the VAR coefficients toward zero and reduce the over-fitting risk. It assumes the prior covariance matrix V_o to be diagonal, in the sense that own lags of endogenous variables are more likely to be important predictors than lags of other variables. The error variance-covariance matrix is the standard OLS estimate of the error terms $\widehat{\Sigma_\epsilon} = S/T$.

Alternatively, we estimate the FABVAR model using two different non-informative priors, in that the Minnesota prior ignores any uncertainty in the elements of error variance-covariance matrix Σ_ϵ. The first is the natural conjugate prior that treats Σ_ϵ as an unknown parameter, $\Sigma_\epsilon^{-1} \sim W(S^{-1}, v)$, where S is the prior hyper-parameters. Here we choose small degree of freedom parameters, $v = m(m-1) + 1$ and $S = 0.01 \times m(m-1) \times I_{m(m-1)}$, in order to put a small weight on the priors that makes the priors to contain small amount of information relative to the sample. The second is the Sims-Zha normal-Wishart prior for Σ_ϵ using the fictitious observations (Sim and Zha (2008)), for example $\widehat{\Sigma_\epsilon} = (X'X)^{-1}$.

The results show that Sims-Zha/normal-Wishart priors lead to the prediction similar to the FAVAR estimates, in that the non-informative priors do not do any of the shrinkage. The impulse response functions show smoother patterns by utilizing Minnesota shrinkage priors which show very important in the VAR modelling. Overall these results are robust to the finding by the FAVAR model.

Figure B. FABVAR model: Response of global industrial production, global inflation and global interest rate to global uncertainty shocks
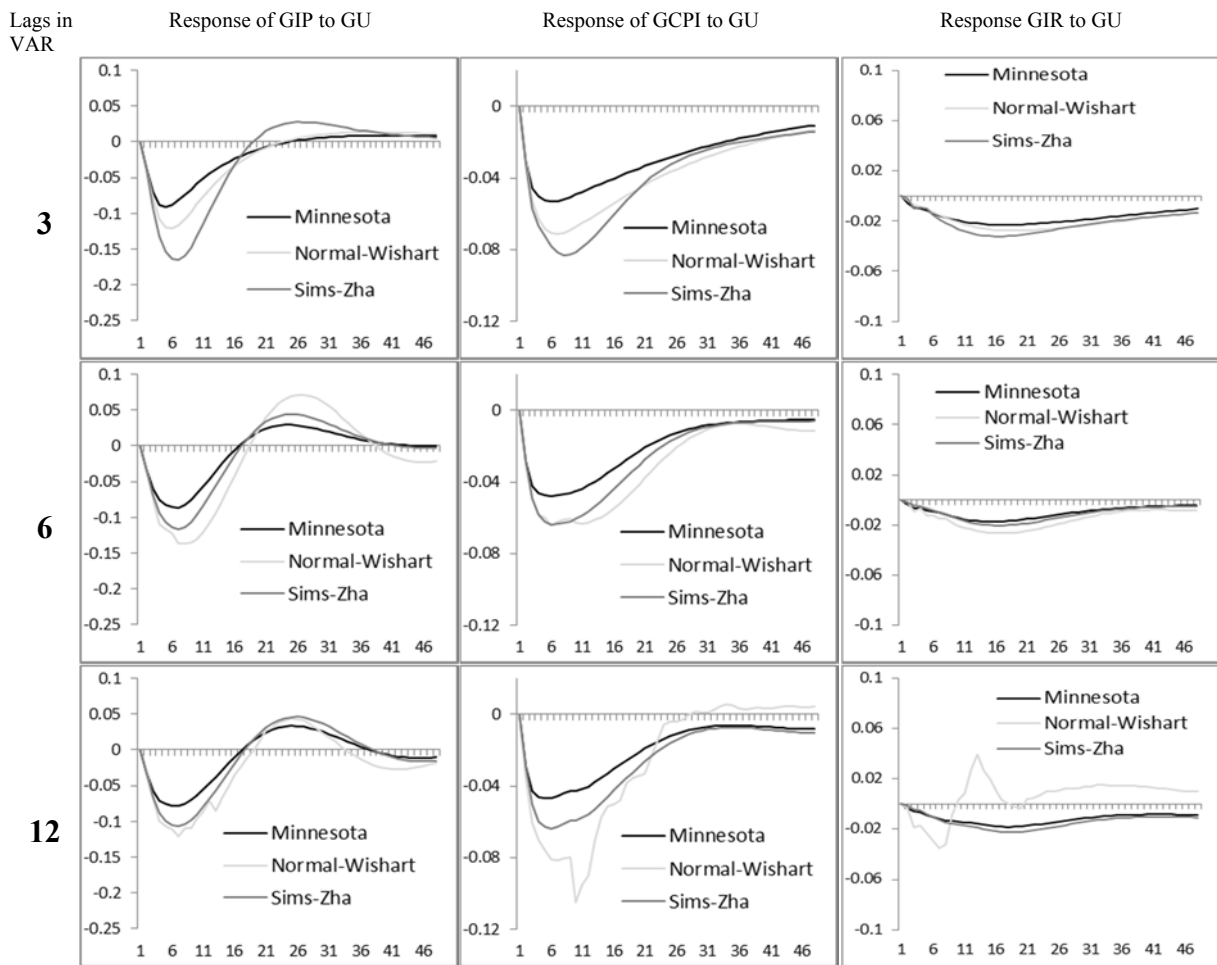
Appendix C. FAVAR and FABVAR estimation with reverse variable order in VAR system

We also specified both the FAVAR and FABVAR systems using the reverse lower triangle order of the variables.[14] More precisely, the order of the variables is as follows: $y_t = (GU_t, GIR_t, \Delta(GCPI_t), \Delta(GIP_t))$. Figure C1 and Figure C2 present results for the FAVAR and FABVAR systems (respectively). Results are quite consistent to those observed in Figure 4 and Appendix A.

Figure C1 FAVAR model (inverse order in VAR): Response of global industrial production, global CPI and global interest rate to global uncertainty shocks
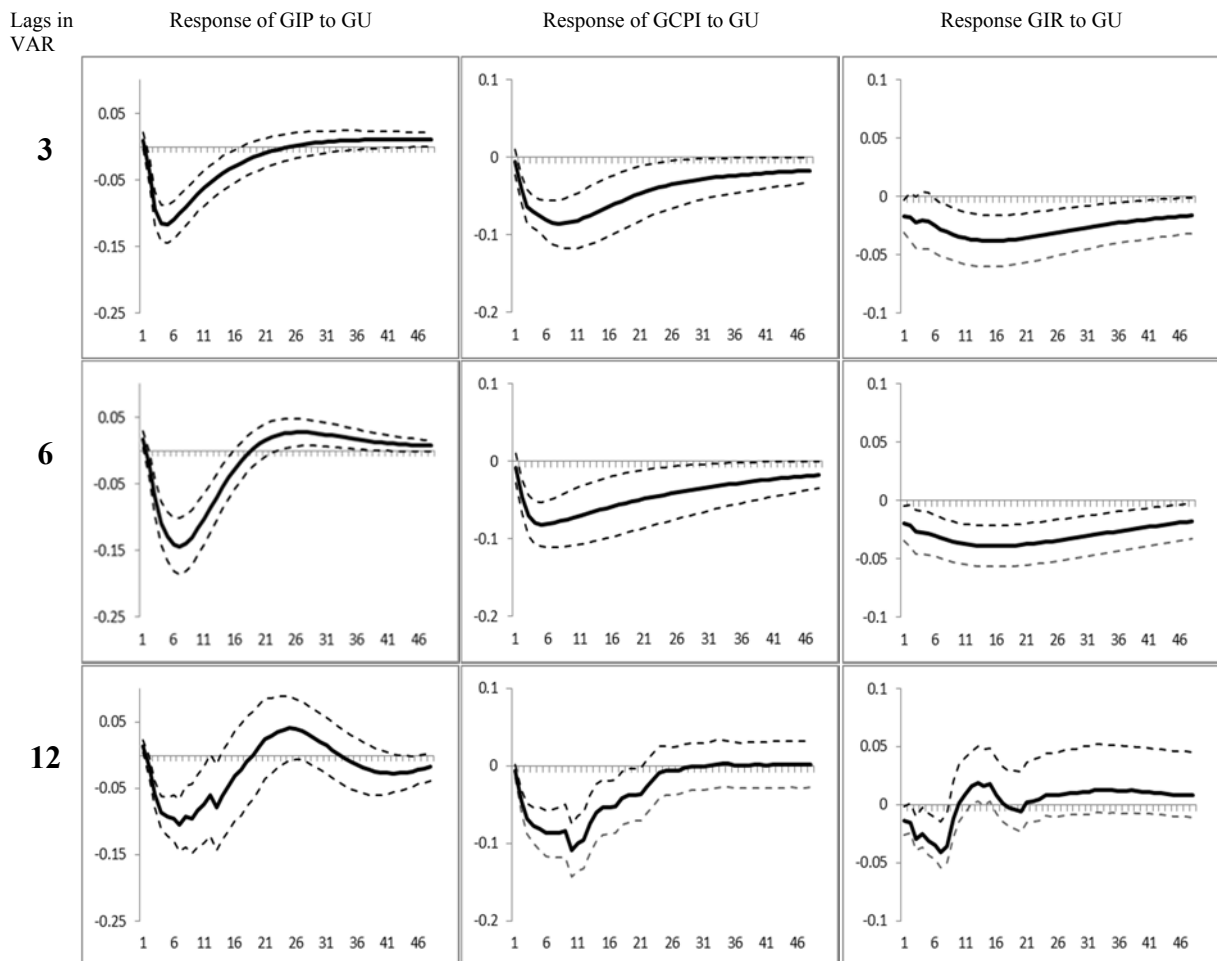
Notes: The dashed lines represent a one standard error confidence band around the estimates of the coefficients of the impulse response functions. The confidence bands are obtained Using Monte Carlo integration as described by Sims (1980), where 5000 draws were used from the asymptotic distribution of the VAR coefficient.
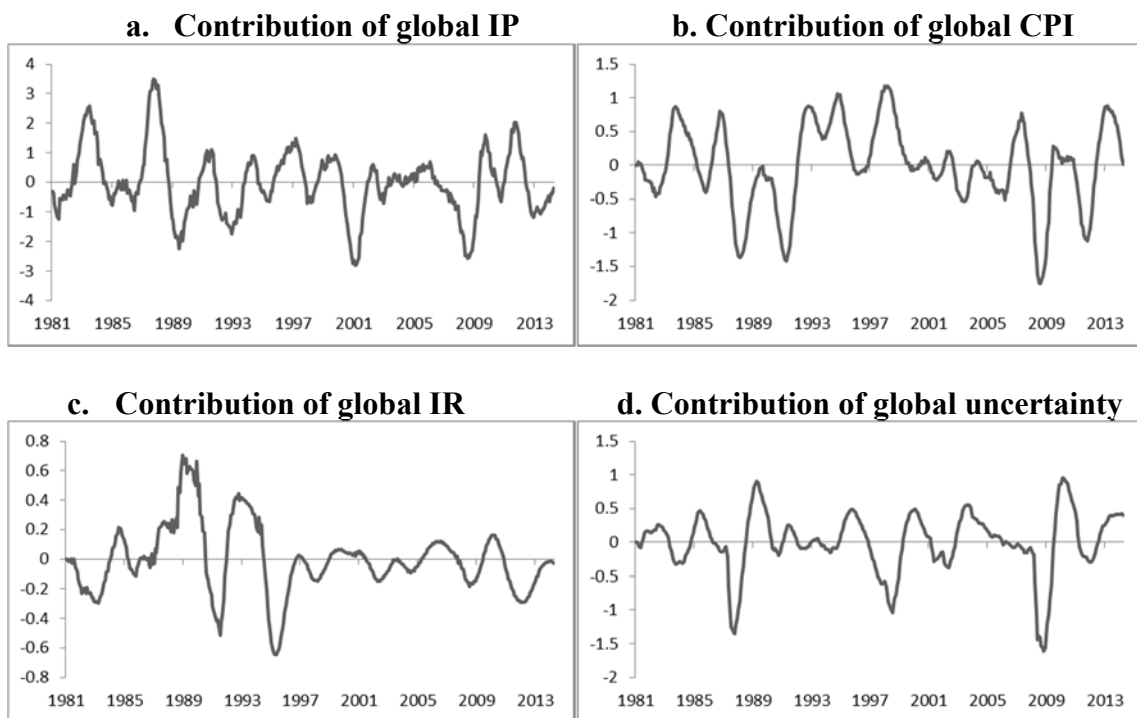
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[14] Note that this robustness analysis was first proposed by Bloom (2009).

Figure C2. BFAVAR model (inverse order in VAR): Response of global Interest rate, global inflation and global output to global uncertainty shocks
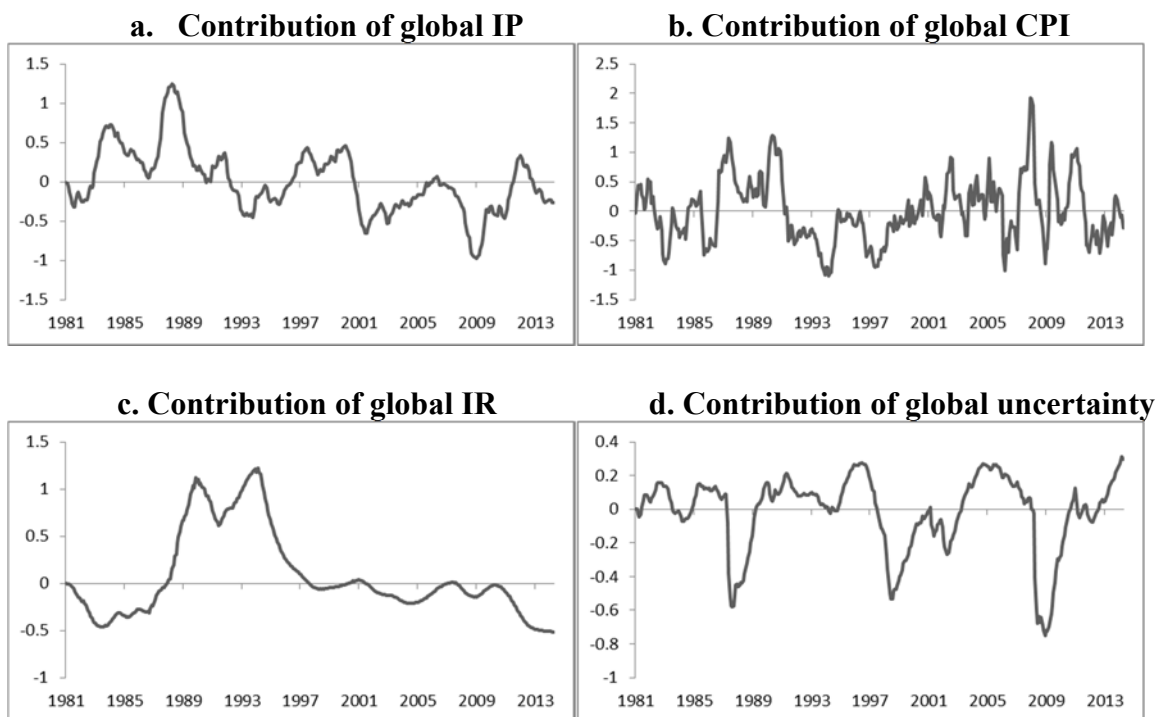

Lags in VAR | Response of GIP to GU | Response of GCPI to GU | Response GIR to GU
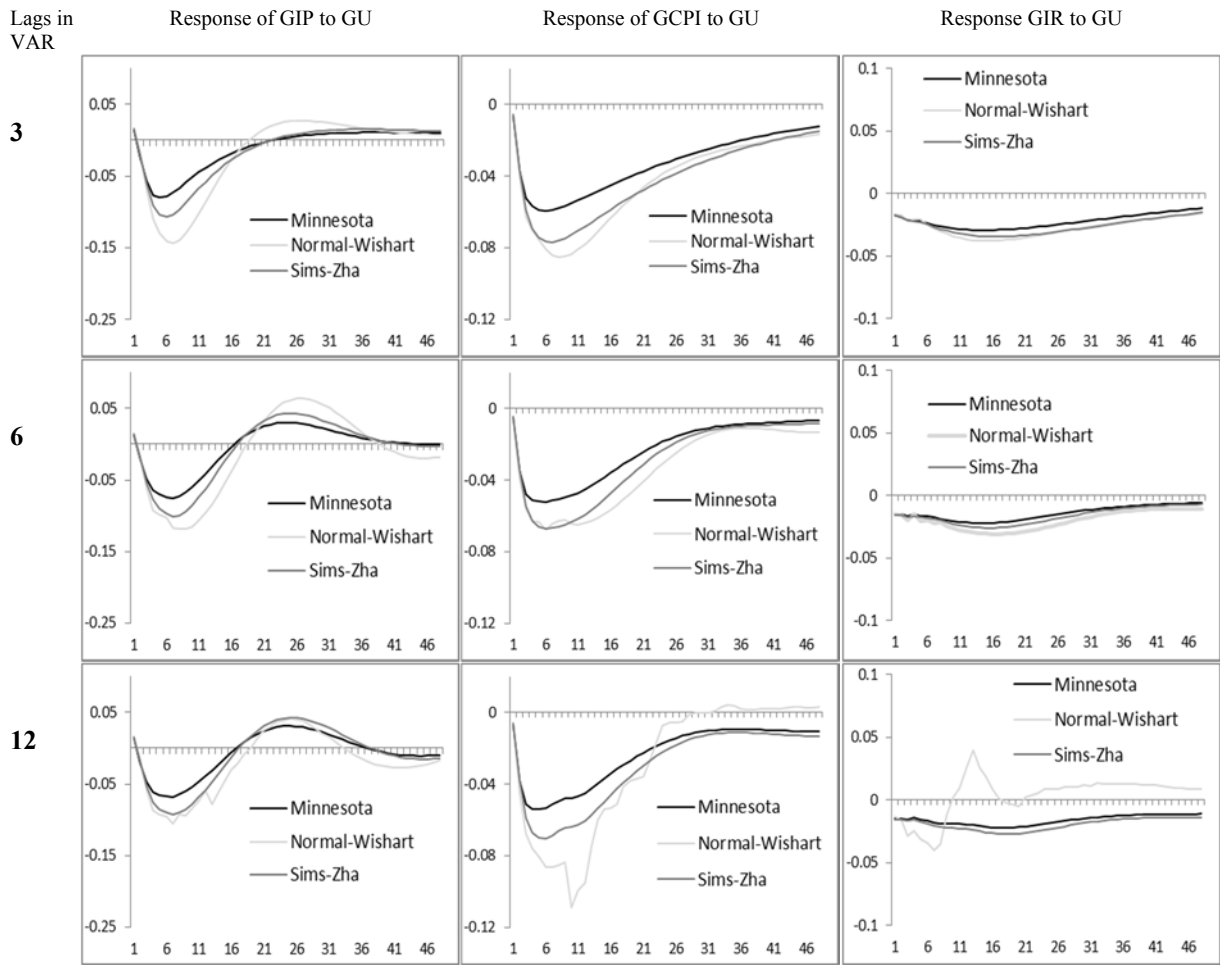
Appendix D. Historical contribution of all global shocks to all global variables

Figure D1. Contribution to global industrial production

a. Contribution of global IP	b. Contribution of global CPI

c. Contribution of global IR	d. Contribution of global uncertainty

Figure D2. Contribution to global CPI

a. Contribution of global IP	b. Contribution of global CPI

c. Contribution of global IR	d. Contribution of global uncertainty

Figure D3. Contribution to global interest rate

a. Contribution of global IP	b. Contribution of global CPI

c. Contribution of global IR	d. Contribution of global uncertainty
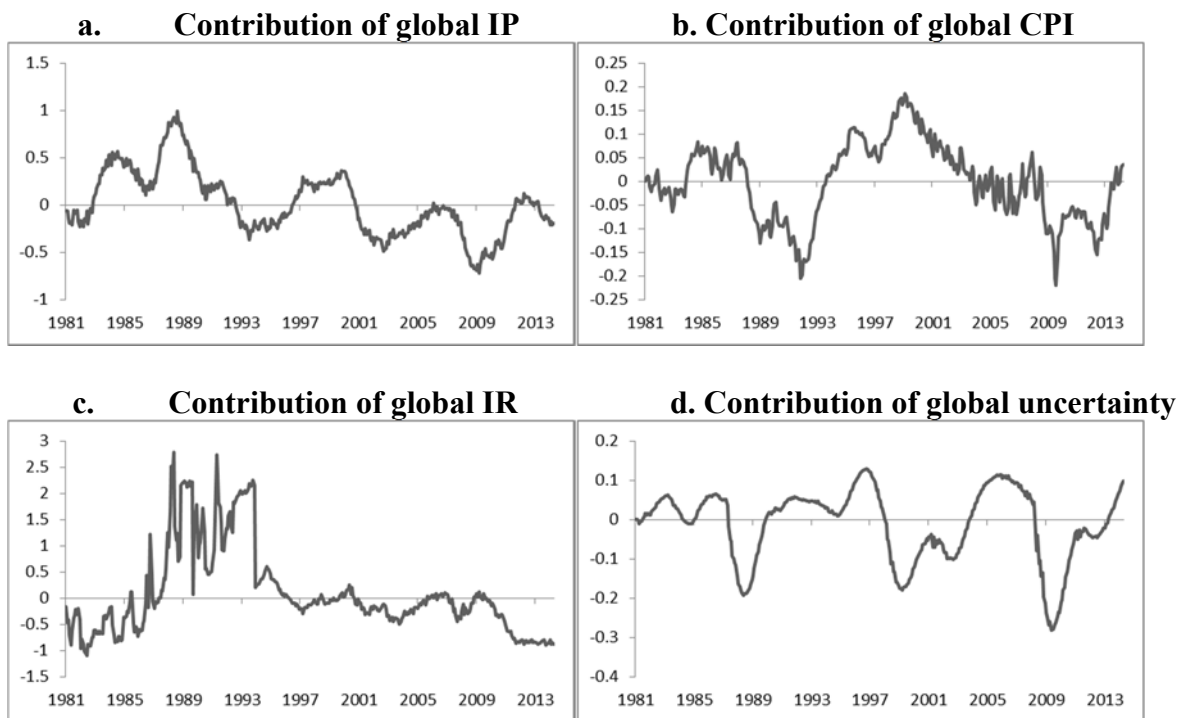
Appendix E. Dummy variables description of section 6

Table E1. Chronology of the global financial crisis events

Time	Event
September 13, 2007	Northern Rock has sought emergency funding from the Bank of England in its capacity as "lender of last resort"
February 17, 2008	The UK government announces that struggling Northern Rock is to be nationalised for a temporary period.
July 14, 2008	Financial authorities in U.S. step in to assist America's two largest lenders, Fannie Mae and Freddie Mac, owners or guarantors of 5 trillion worth of home loans.
September 15, 2008	Wall Street bank Lehman Brothers (U.S.) files for Chapter 11 bankruptcy protection and another US bank, Merrill Lynch, is taken over by the Bank of America.
October 20, 2008	The U.S. government took control of AIG. The U.S. The federal government to take control of the company and guarantee to loan it up to $85 billion.

Table E2. Dummy variables for financial and non-financial shocks

Global financial shocks above 1.65 SD		Global non-financial shocks above 1.65 SD	
Shock	Monthly dummy	Shock	Monthly dummy
Black Monday	February to July 1987	September 11 terrorist attack	September to November 2001
Russian sovereign debt crisis	May and June 1997	Gulf War II	May to August 2002
Global financial crisis	September 2007 to November 2008		

The dummy variables only take the value of 1 when the identified shock exceeds 1.65 standard deviations following Bloom (2009).

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[i] Note that Australia is excluded as CPI index is only reported in quarterly frequency by the Australian Bureau of Statistics.

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