Revising the Impact of Financial and Non-Financial Global Stock Market Volatility Shocks

Kang, Wensheng and Ratti, Ronald A. and Vespignani, Joaquin L.

Kent State University, University of Missouri, University of Tasmania

2020

Revising the Impact of Financial and Non-Financial Global Stock Market Volatility Shocks

Wensheng Kang[a], Ronald A. Ratti[bd], Joaquin Vespignani[cd]

[a]Kent State University, Department of Economics, U.S.
[b]University of Missouri, Department of Economics, U.S.
[c]University of Tasmania, Tasmanian School of Business and Economics, Australia
[d]Centre for Applied Macroeconomics Analysis, Australian National University, Australia

We decompose global stock market volatility shocks into financial originated shocks and nonfinancial originated shocks. Global stock market volatility shocks arising from financial sources reduce substantially more global outputs and inflation than non-financial sources shocks. Financial stock market volatility shocks forecasts 16.85% and 16.88% of the variation in global growth and inflation, respectively. In contrast, the on-financial stock market volatility shocks forecasts only 8.0% and 2.19% of the variation in global growth and inflation. Beside this markable difference global interest/policy rate responds similarly to both shocks.

Keywords: Global, Stock market volatility Shocks, Monetary Policy, FAVAR

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

Corresponding author: Joaquin Vespignani; University of Tasmania, Tasmanian School of Business and Economics, Australia; Tel. No: +61 3 62262825; E-mail address: Joaquin.Vespignani@utas.edu.au

1. Introduction

In this study, we decompose global stock market volatility shocks into shocks originated from financial and non-financial events. This approach is novel in the sense that we decompose the global stock market volatility proposed by Kang et al (2020) into financial and non-financial events which have significantly affect global stock market volatility. This disaggregation allows us to quantify the impact of financial and non-financial global events shocks to the global economy (e.g. global interest rate, consumer price index (CPI) and industrial production). This study answers the following question: Does the global inflation, output and interest rate response differently to financial and non-financial originated shocks?

This paper contributes to the macroeconomic literature which studies the impact and measurement of global uncertainty by showing that the source of the global stock market volatility (financial or non-financial) shocks are critical to understand the global economic impact. We identified in our sample (1981-2018) the following financial events; the Black Monday (October and November 1987), the Russian Default (September 1998), the WorldCom (July 2002) and the global financial crisis (2008-2009). The non-financial events identified are: the Gulf War II (February 2003) and the 9/11 terrorist attack (September 2001).

Our results suggest that global financial stock market volatility shocks produce larger effects than the non-financial shocks. From 1981 to 2018, global financial stock market volatility forecasts 16.85% and 16.88% of the variation in global growth and inflation, respectively. The non-financial stock market volatility forecasts only 8.0% and 2.19% of the variation in global growth and inflation, respectively. These results are informative for fiscal and monetary policymakers to implement appropriate policy. In addition, this information can be used by forecasters to improve their predictions and understand the duration of uncertainty shocks depending on the underlying sources. The decomposition of stock market volatility shocks would lead to a better understanding of how economic policy might be designed to both, avoiding and mitigating the effects of global stock market volatility shocks.

This paper proceeds as follows. Section 2 provides a brief review of the relevant literature. The data and methodology are explained in Section 3. In Section 4 the empirical results are discussed. Section 5 provides robustness analysis, and Section 6 concludes.

2. Literature review

Uncertainty and stock market volatility are terms very closely related in the macroeconomics literature (domestic and global). Ozturk and Sheng (2018) note that a universal proxy for uncertainty used by economist is implied or realized volatility in the stock market (please see also Bouri and Roubaud (2018) and Bouri et al (2018)). In this review, we describe all measures which has been used as a proxy for global uncertainty. Those measures are sometime referring to global uncertainty, global macroeconomic uncertainty or global financial uncertainty. We use chronological order of publication to present the literature.

Mumtaz and Theodories (2015a) disaggregate uncertainty into domestic and global macroeconomic and financial variables employing a factor model with stochastic volatility for 11 OECD countries. Berger et al (2016) study the impact of global and country-specific output growth uncertainty on macroeconomic performance. They construct a quarterly measure of global uncertainty using real GDP data for OECD countries employing a dynamic factor model. Baker et al (2016) develop a monthly index of global economic policy uncertainty based on the largest 16 countries worldwide. Their novel measure is based on the broad news coverage of policy-related economic uncertainty, number of federal tax code provisions set to expire in the future, and/or the disagreement on the inflation and government spending among economic forecasters.

Redl (2017) studies the impact of uncertainty shocks in the U.K. The author develops a global measure of uncertainty based on financial and macroeconomic aggregates of developed economies. Ahir et al (2018) construct an index of world uncertainty using data from Economic Intelligent Unit Country Report (the economist magazine). They find that the world uncertainty tends to be more synchronised amongst developed economies. Mumtaz and Musso (2019) study the evolving impact of global, regional and country-specific uncertainty. They employ a dynamic factor model with time-varying parameters and stochastic volatility using a macroeconomic and financial data for 22 countries. Cesa-Bianchi et al (2018) employ realized stock market volatility as a measure of uncertainty taking a multi-country econometric framework. They identify country-specific and common shocks using a first-order panel vector autoregressive model. An important finding of this paper is that the time-variation of country-specific volatility is explained by global financial factor shocks.

Focusing on global financial uncertainty, Bonciani and Ricci (2018) develop an index of global financial uncertainty by extracting a global factor of around 1000 time series of risky asset returns in the world. Also, Caggiano and Castelnuovo (2019) buid a global financial uncertainty index via a dynamic hierarchical factor model controlling for country-specific and regional-specific uncertainty factors. Ozturk and Sheng (2018) decompose uncertainty into common and idiosyncratic uncertainty using consensus forecast survey data. They develop a monthly measure of uncertainty using data for 45 developing and developed countries. Kang et al (2020) study the impact of U.S and global uncertainty on the global economy. The authors construct an indicator of global uncertainty using the first principal component of the stock market volatility of the 15 largest economies. They find that global uncertainty shocks have more protracted and substantial effects on the global economy than U.S. uncertainty shocks.

A compact literature mapping can be found in Table 1. For a more detailed discussion of the literature please see Castelnuovo (2019).

3. Data and Methodology

3.1 Data

The data is monthly from January 1981 to December 2018. We follow Kang et al (2020) by constructing a global stock market volatility index by implementing a principal component analysis to reduce the dimensionality of the dataset, and subtract the first principal component of the stock market volatility of the largest 15 economies. The stock market indices used are: Standard & Poor's/ASX 200 Index (Australia), BM&F BOVESPA Index (Brazil), Toronto Stock Exchange index (Canada), Shanghai Stock Exchange Composite Index (China), France CAC 40 Stock Market Index (France), Deutsche Boerse AG German Stock Index (Germany), NSE CNX 100 Index (India), FTSE MIB Index (Italy), NIKKEI 225 Stock Market Index (Japan), Mexican Bolsa IPC Index (Mexico), Russia MICEX Stock Market Index (Russia), Korea Stock Exchange KOSPI Index (South Korea), South Africa FTSE/JSE Index (South Africa), Standard & Poor's 500 index (the US) and UK FTSE 100 Stock Market Index (the UK). This index provides a forward-looking indicator that is implicitly weighted in accordance with the impact of different sources of stock market volatility across major countries in the world on equity value.[1]

We also constructed the following global factor-variables: global interest rate (GIR_t), global consumer price index ($GCPI_t$) and global industrial production (GIP_t). We also compressed the three-regional series from the database of global Economic indicators (DGEI) from the Federal Reserve Bank of Dallas. The three-regional indices are reported by DGEI dataset for aggregated emerging economies, aggregated advanced economies (excluding the U.S.) and the U.S. Data descriptions, summary statistics, definition and source of the data are all reported in Table A1.

[1] For more details please see Kang et al (2020).

3.2 Identifying major global stock market volatility events

In Figure 1 we show the global stock market volatility index described in Section 3. Only for clarity of exposition the 12-month moving average of the index is presented. The black line shows this index, and the horizontal broken line shows 1.65 standard deviations.[2] We follow Bloom (2009) and Jurado et al. (2015) in defining stock market volatility shocks as those events which exceed 1.65 standard deviations. The statistically significant events 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 Gulf War II (February 2003) and the Global Financial Crisis (GFC) between 2007-2008.

3.3 Financial vs. non-financial stock market volatility shocks.

In this subsection, we decompose global stock market volatility into financial and non-financial shocks. Our definition of global financial stock market volatility shocks comprises the following events that exceed 1.65 standard deviations: Black Monday, Russian Default, WorldCom and the GFC.[3] The global non-financial stock market volatility shocks that exceed 1.65 standard deviations include the Gulf War II and the 9/11 terrorist attack.

To disaggregate global stock market volatility shocks, we multiply the variable representing global stock market volatility (GU_t) described in Section 3, by two different dummy variables (i.e., $DF_t * GU_t$ and $DNF_t * GU_t$), where the first variable (the global financial stock market volatility shocks) 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.[4] The second variable (the non-financial stock market volatility shocks) is

---

[2] Note that 1.65 standard deviation is around 5% one-tailed significant of the volatility estimated in our sample.

[3] The global financial crisis includes the five main events described; the 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 July 2008, September 2008 and October 2008, respectively.

[4] The dummy variables only take the value of 1 when the identified shock exceeds 1.65 standard deviations following Bloom (2009). Details of the period dummies can be found in Appendix A, Table A3.

constructed by interacting the GU_t index with a dummy variable DNF_t, which takes the value of 1 when a non-financial shock occurs and 0 otherwise.[5] This is an econometric improvement, building on Bloom (2009), who uses only a single dummy variable that 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 effect of stock market volatility shock.

3.4 The FAVAR Model

Following Bloom (2009) and Jurado et al. (2015) who have utilized VAR models, we use a FAVAR model to estimate the impact of stock market volatility on key macroeconomics variables. The endogenous variables in the model include the growth of global output $\Delta(GIP_t)$, the growth of global inflation $\Delta(GCPI)_t$, global interest rate (based on central bank official/policy interest rates) GIR_t and the global financial and non-financial stock market volatility interaction variables $(DF_t * GU_t)$ and $(DNF_t * GU_t)$. We follow the macroeconomic literature (see Bloom (2009), Carriero et al (2018), or Kang et al (2020) for examples) in assuming that global stock market volatility affects the key macroeconomic variables: inflation, outputs and interest rate.

The following structural VAR model of order p is utilized:

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

where $y_t = [\Delta(GIP_t), \Delta(GCPI_t), GIR_t, (DF_t * GU_t), (DNF_t * GU_t)]$ is a $(m = 5) \times 1$ vector of endogenous variables, A_0 denotes the 5×5 contemporaneous coefficient matrix, c_0 represents a 5x1 vector of constant terms, A_i refers to the 5×5 autoregressive coefficient matrices and ε_t stands for a 5×1 vector of structural disturbances. We follow Kilian (2009), Bloom (2009), and Jurado et al. (2015) to take the lags $p = 12$ to capture the potentially long-delayed effects of macroeconomic variable shocks on the real economy. Hamilton (2008) and Baumeister and Peersman (2013) argue that the greatest effect on the real economy is generally in about one year. In our sample 12 lags is also consistent with the Akaike Information Criterion (AIC), whereas the Bayesian Information Criterion (BIC) selects only 3 lags (we use the last criteria as a robustness analysis in Figure 3.2). 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 (1) by A_0^{-1}. The reduced-form error term is $e_t = A_0^{-1}\varepsilon_t$, assumed to be Gaussian distributed.

The identifying restrictions on A_0^{-1} is a slightly modified lower-triangle coefficient matrix in the structural VAR model.[6] This setup follows Bekaert et al. (2014) and Jurado et al. (2015) in placing the output variable first, followed by CPI, interest rate and stock market volatility.[7] The ordering of the variables assumes that the macroeconomic aggregates of output and CPI do not respond contemporaneously to shocks to the monetary policy. 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 stock market volatility. The two stock market volatility variables (global financial and non-financial stock market volatility) are ordered last captures the fact that the stock market volatility is a forward-looking indicator and likely responds instantly to monetary policy shocks.

[6] The identifying restrictions on A_0^{-1} as a lower-triangle coefficient matrix in the structural VAR model assumes that the stock market instantaneously respond to each structural shock by using Cholesky decomposition to orthogonalize the residuals in Model (1). Factoring the coefficient matrix (A_0) includes the major approaches of Doolittle, Crout, and Cholesky decompositions. However, the Cholesky decomposition is assumed to be relatively more efficient for the numerical solutions by Monte Carlo simulations. Another strand of literature covers the structural VAR identification via the sign restrictions. Interested readers refer to the recent literature such as Baumeister and Peersman (2013) for alternative identifying restrictions.

[7] Note that stock market volatility is a measure of uncertainty according for example with Bloom (2009).

We estimate the following FAVAR model with the $(m = 5) \times 1$ vector of endogenous variables, $y_t = [\Delta(GIP_t), \Delta(GCPI_t), GIR_t, (FDF_t * GU_t), (DNF_t * GU_t \quad)]$. The slightly modified Cholesky lower triangle contemporaneous matrix is estimated using the following $A_0 y_t$ matrix:

$$\begin{bmatrix} 1 & 0 & 0 & 0 & 0 \\ a_{11} & 1 & 0 & 0 & 0 \\ a_{21} & a_{22} & 1 & 0 & 0 \\ a_{31} & a_{32} & a_{33} & 1 & 0 \\ a_{41} & a_{42} & a_{43} & 0 & 1 \end{bmatrix} \begin{bmatrix} \Delta(GIP_t) \\ \Delta(GCPI_t) \\ GIR_t \\ DF_t * GU_t \\ DNF_t * GU_t \end{bmatrix}. \tag{2}$$

The element of a_{44} is set to be zero, since there is no good reason to impose an order on financial and non-financial stock market volatility. Note that either eliminating the zero restriction on a_{44} and/or changing the order of global financial and non-financial stock market volatility shocks does not alter the main results of our model.

3.5 Alternative identification restrictions

In this section, we evaluate alternative contemporaneous identification restrictions. In Equation (3), we follow the robustness's analysis performed by Bloom (2009) by inverse the order of the variables in the VAR system. In this exercise, we keep the assumption that both global financial and non-financial stock market volatility variables cannot influence each other contemporaneously as there is no literature or theoretical reason to assume contemporaneous impact. In Equation (2), we follow the country-specific literature (see for example (Dedola and Lippi (2005) or Ratti and Vespignani (2016)) in ordering output ahead of inflation in the VAR system. However, this assumption is not so clear at the global level as data must be aggregated from multinational sources. Consequently, we switch the order of these two variables in Equation (4) to check this restriction.

$$\begin{bmatrix} 1 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 \\ a_{21} & a_{22} & 1 & 0 & 0 \\ a_{31} & a_{32} & a_{33} & 1 & 0 \\ a_{41} & a_{42} & a_{43} & a_{44} & 1 \end{bmatrix} \begin{bmatrix} DNF_t * GU \\ DF_t * GU \\ GIR_t \\ \Delta(GCPI_t) \\ \Delta(GIP_t)\ _t \end{bmatrix}, \tag{3}$$

$$\begin{bmatrix} 1 & 0 & 0 & 0 & 0 \\ a_{11} & 1 & 0 & 0 & 0 \\ a_{21} & a_{22} & 1 & 0 & 0 \\ a_{31} & a_{32} & a_{33} & 1 & 0 \\ a_{41} & a_{42} & a_{43} & 0 & 1 \end{bmatrix} \begin{bmatrix} \Delta(GCPI_t) \\ \Delta(GIP_t) \\ GIR_t \\ DF_t * GU_t \\ DNF_t * GU_t \end{bmatrix} . \qquad (4)$$

In Table 2, the log-likelihood ratio test for overidentified restrictions is presented, this test supports the restrictions imposed in Equation (2) with highest p-value from the Chi-square distribution. Comparing restrictions imposed in Equations (2), (3) and (4), the null hypothesis of restrictions is valid cannot be rejected at 10% level for restrictions imposed in Equation (2). However, restrictions imposed in Equations (3) and (4) can be rejected at 1% and 5% significant levels (respectively).

4. Empirical results

Figure 2 compares the impacts of financial and non-financial stock market volatility shocks on key global macroeconomic variables. In the first and second rows, we show the impact of financial and non-financial stock market volatility shocks (respectively) on global IP (first column), CPI (second column) and interest rate (third column).

Results in the first column suggests that the impact of financial stock market volatility shocks is almost twice as large as the non-financial shocks on global IP (up to -0.19 and -0.10, respectively). Also, the impact of global financial stock market volatility shocks on global IP is faster than global non-financial stock market volatility shocks. The greatest impact of financial shocks on global IP is observed between 6 to 10 months later compared to 11 to 16 months later for non-financial shocks. The differences between the responses of global CPI to those shocks are remarkable. Financial stock market volatility shocks have a clear negative effect on global CPI, which is statistically significant at conventional levels. By contrast, non-financial shocks do not have a statistically significant effect on global CPI. Interestingly, the third column of Figure 2 shows that although only financial stock market shocks are deflationary, global interest rates response in both cases by similar magnitude.

Using monthly data from 1962 to 2008, Bloom (2009) shows that the negative response of US industrial production to stock volatility shocks is around -1% within 4 months in general, with a subsequent recovery in 7 months. Kang et al. (2020) present that global uncertainty shocks cause a significant drop in the global industrial production that reaches around -1.5% in 6 months, using monthly data from 1981 to 2014. Our results using monthly data from 1981 to 2018 confirm the negative effects and further highlight the importance of distinguishing between the significant and persistent effects of financial shocks and the temporary effects of non-financial innovations.

4.1 Variance decomposition of global macroeconomic variables to financial and non-financial stock market volatility shocks

Table 1 reports the fractions of forecast error variance decomposition for the global IP, CPI and interest rate. To conserve space, we report only the contribution of the variables of interest (financial and non-financial stock market volatility shocks). The contribution of global financial stock market volatility explains 16.85%, 16.88%, 2.28% of the variation in global growth, inflation and interest rate after 24 months. The first two contributions are statistically significant at 1% level. The contribution of global non-financial stock market volatility explains only 8.0%, 2.19%, 1.92% of the variation in global growth, inflation and interest rate after 24 months and the results are statistically insignificant.

5. Robustness analysis

The benchmark model estimated in Equations (1) and (2) reports results when 12 lags are specified in the FAVAR system in line with the literature and with AIC selection criterion. However, we also estimate this equation with shorter lag structures. Precisely, we re-estimate the model with 3, 4, 6 and 9 lags obtaining similar results which support our main findings.

The BIC indicates that the optimal lag is 3 as the optimal lag structure in the FAVAR system. We also estimate the model with an alternative measure of global stock market volatility. Rather than use the factor-variable described in Section 3. Concretely, we construct an index applying a GDP-weighted index of country specific volatility (also for the largest 15 economies. We weight each country of the 15 largest economies using GDP Purchase Power Parity (PPP) in U.S. dollars as reported by the World Bank. A second alternative measure of global stock market volatility considered is for the largest 20 economies (rather than 15 economies) using the factor described in Section 3.[8] All results or alternative estimations support our main results shown in Figure 2 and Table 3 in terms of sign and size of the effect, and are available upon request from the authors.[9]

In Figure 3.1 and 3.2 we show results for two alternative specifications. To conserve space only two robust specifications are shown. In Figure 3.1, we estimate the benchmark model from Equation (2) using Cholesky decomposition. Concretely, we do not restrict zero to the parameter a_{44}. Results are comparable to those obtained in Figure 2, although it is observed that standard errors are larger in both estimations (financial and non-financial global stock market volatility shocks). In Figure 3.2, we estimate the benchmark model from Equation (2), using only 3 lags in the VAR system selected by the BIC (3 lags). Comparing this result to our benchmark model, it is observed that non-financial global stock market volatility shocks are quantitatively smaller on global industrial production, global inflation and global interest rate. However, the financial global stock market volatility shocks are almost unchanged. These results further support our view that global financial originated stock market volatility shocks

[8] The additional countries included in this measure are Indonesia, Iran, Thailand, Nigeria and Poland. Note that the stock market data for these countries is only available for a shorter span (therefore not included in the original index). Consequently, the inclusion of these five countries only change the benchmark measure of global stock market volatility only from 1990.
[9] The topic for future research would conduct time-varying analysis on the impact of global uncertainty on the real economy related with international evidence across countries.

have larger and longer-lasting effects on the global economy than global non-financial stock market volatility shocks.

6. Conclusions

In this paper, we present a methodology to decompose global stock market volatility shocks into financial and non-financial shocks. For this purpose, we developed a novel index of global stock market volatility using principal component analysis of the stock market volatility indexes for the largest 15 economies. Global financial stock market volatility shocks show a much larger effect on the global economy compare to non-financial stock market volatility shocks. From 1981 to 2018, global financial stock market volatility forecasts 16.85% and 16.88% of the variation in global growth and global inflation, respectively, while non-financial stock market volatility shocks forecast only 8.0% and 2.19% of the variation in global growth and global inflation, respectively. Beside this markable difference global interest/policy rate respond similarly to both shocks. As policymakers are typically interested in responding to major uncertainty shocks, our results highlight the importance of distinguishing between the significant/persistent effects of financial shocks and the temporary effects of non-financial innovations. Investors should respond more cautiously to the global financial stock market volatility shocks.

References

Ahir, H., Bloom, N. and Furceri, D., 2018. The world uncertainty index. *Available at SSRN 3275033*.

Baker, S.R., Bloom, N. and Davis, S.J., 2016. Measuring economic policy uncertainty. *The Quarterly Journal of Economics*, *131*(4), pp.1593-1636.

Baumeister, C. and Peersman, G., 2013. Time-varying effects of oil supply shocks on the US economy. *American Economic Journal: Macroeconomics*, 5(4), pp. 1-28.

Bekaert, G., Hoerova, M. and Duca, M.L., 2013. Risk, uncertainty and monetary policy. *Journal of Monetary Economics*, *60*(7), pp.771-788.

Berger, T., Grabert, S. and Kempa, B., 2016. Global and country-specific output growth uncertainty and macroeconomic performance. *Oxford Bulletin of Economics and Statistics*, *78*(5), pp.694-716

Bloom, N., 2009. The impact of uncertainty shocks. *econometrica*, *77*(3), pp.623-685.

Bonciani, D. and Ricci, M., 2018. The global effects of global risk and uncertainty.

Bouri, E. and Roubaud, D., 2018. Dynamic network of implied volatility transmission among US equities, strategic commodities, and BRICS equities. *International Review of Financial Analysis*, *57*, pp.1-12.

Bouri, E., Gupta, R., Hosseini, S. and Lau, C.K.M., 2018. Does global fear predict fear in BRICS stock markets? Evidence from a Bayesian Graphical Structural VAR model. *Emerging Markets Review*, *34*, pp.124-142.

Bouri, E., Lucey, B., and Roubaud, D. 2020. Dynamics and determinants of spillovers across the option-implied volatilities of US equities. *The Quarterly Review of Economics and Finance*, *75*, 257-264.

Caggianao, G., and Catelnuovo, E., 2019. Global Uncertainty. Monash University and University of Melbourne, available at https;//sites.google.com/site/efremcastenuovo/

Carriero, A., Clark, T.E. and Marcellino, M., 2018. Measuring uncertainty and its impact on the economy. *Review of Economics and Statistics*, *100*(5), pp.799-815.

Cesa-Bianchi, A., Pesaran, M.H. and Rebucci, A., 2018. Uncertainty and economic activity: A multicountry perspective. *The Review of Financial Studies*.

Caggiano, G., Castelnuovo, E. and Figueres, J.M., 2020. Economic policy uncertainty spillovers in booms and busts. *Oxford Bulletin of Economics and Statistics*, *82*(1), pp.125-155.

Grossman, V., Mack, A. and Martinez-Garcia, E., 2014. A new database of global economic indicators. *Journal of Economic and Social Measurement*, *39*(3), pp.163-197.

Dedola, Luca & Lippi, Francesco, 2005. The monetary transmission mechanism: Evidence from the industries of five OECD countries, European Economic Review, 49, pp 1543-1569.

Hamilton, J.D., 2008. Oil and the macroeconomy. The New Palgrave Dictionary of Economics, 2nd ed., edited by Steven N. Durlauf and Lawrence Blume. Palgrave Macmillan. Doi: 10.1057/9780230226203.1215.

Jurado, K., Ludvigson, S.C. and Ng, S., 2015. Measuring uncertainty. *American Economic Review*, *105*(3), pp.1177-1216.

Kang, W., Ratti, R.A. and Vespignani, J., 2020. Impact of global uncertainty on the global economy and large developed and developing economies. *Applied Economics*, *52*(22), pp.2392-2407.

Kilian, L., 2009. Not all oil price shocks are alike: Disentangling demand and supply shocks in the crude oil market. *American Economic Review*, *99*(3), pp.1053-69.

Knotek, E.S. and Khan, S., 2011. How do households respond to uncertainty shocks?. *Kansas City Federal Reserve Board Economic Revivew*.

Mumtaz, H. and Theodoridis, K., 2015. The international transmission of volatility shocks: An empirical analysis. *Journal of the European Economic Association*, *13*(3), pp.512-533.

Mumtaz, H. and Musso, A., 2019. The evolving impact of global, region-specific, and country-specific uncertainty. *Journal of Business & Economic Statistics*, pp.1-16.

Vespignani, J.L., and Ratti, R.A., 2016. Not all international monetary shocks are alike for the Japanese economy, Economic Modelling, 52, pp 822-837.

Redl, C., 2017. The impact of uncertainty shocks in the United Kingdom.

Ozturk, E.O. and Sheng, X.S., 2018. Measuring global and country-specific uncertainty. *Journal of international money and finance*, *88*, pp.276-295.

Table 1: Summary of measures of global uncertainty

Authors and year of publication	Name/Measure	Description/methodology	Number of countries	Data Frequency	Period
Mumtaz and Theodories (2015a)	Global uncertainty	Factor model with stochastic volatility with financial and macroeconomics variables	11 OECD countries	Quarterly	1960Q1-2013Q3
Berger, Grabert, and Kempa (2016)	Global uncertainty	Dynamic factor model with stochastic volatility	20 OECD countries	Quarterly	1971Q1-2013Q4
Baker, Bloom and Davis (2016)	Global economic policy uncertainty	Frequency of own-country newspaper articles that contain a trio of terms pertaining to the economy, policy and uncertainty	16 countries	Monthly	1997M1-2016M8
Redl (2017)	Global macroeconomics uncertainty	Text-based model based using Macro and financial aggregates of industrialized countries	Mixed of country-specific and global series	Monthly	1991M1-2016M7
Ahir et al (2018)	World uncertainty index	Text-based collecting the word uncertainty from the Economist Intelligent Unit country report	143 countries	Quarterly	1970Q1-2020Q1
Mumtaz and Musso (2019)	Global uncertainty	Dynamic factor model with time-varying parameter and stochastic volatility	22 OECD countries	Quarterly	1960Q1-2016Q4
Bonciani and Ricci (2018)	Global financial uncertainty	Factor from 1000 risky assets	36 advanced and emerging economies open economies	Monthly	1990M1-201512
Ozturk and Sheng (2018)	Global uncertainty	Common factor of country individual survey data from the consensus forecast	45 countries	Quarterly	1989Q1-2014Q4
Cesa-Bianchi, Pesaran and Rebucci (2018)	Global real and financial uncertainty	Common factors of country-specific volatility	32 advanced and emerging economies	Quarterly	1979-2011
Caggiano and Castelnuovo (2019)	Global financial uncertainty	Principal component analysis considering of 3 financial measures of volatility of financial returns.	39 countries	Monthly	1992M7-2018M4
Kang, Ratti and Vespignani (2020)	Global Macroeconomics Uncertainty	Principal component analysis of largest 15 stock market volatility indices	15 Countries	Monthly	1981M1-2014M12

Table 2. Log likelihood ratio test for over-identified restrictions (chi-square distribution)

Null hypothesis; restrictions are valid			
Model restriction/Equations	(2)	(3)	(4)
P-value	0.112	0.003	0.021

Notes: The log likelihood ratio test for over-identification Chi-square values are reported for each of the three models shown in Equations (2), (3) and (4). The test is for non-recursive identification restrictions in the contemporaneous matrix restrictions in Equations (2), (3) and (4). The highest value for over-identification test restriction is for the model of choice in Equation (2), indicating that the restriction cannot be rejected at higher significant level than for the other models.

Table 3. Variance decomposition of global macroeconomic variables

Contribution from/months	Global IP		Global CPI		Global IR	
Stock market volatility shocks	Financial	Non-financial	Financial	Non-financial	Financial	Non-financial
1	0.00	0.00	0.00	0.00	0.00	0.00
6	12.25***	0.88	5.44*	1.53	0.34	0.14
12	18.95***	4.66	13.02**	2.63	0.94	0.99
18	17.26***	7.78	16.64**	2.17	1.72	1.46
24	16.85***	8.00	16.88**	2.19	2.28	1.92

Notes: ***, **, * indicates rejection of the null hypothesis at 1%, 5% and 10%, levels of significance respectively.

Figure 1. Global stock volatility index: 12-month moving average standard deviation

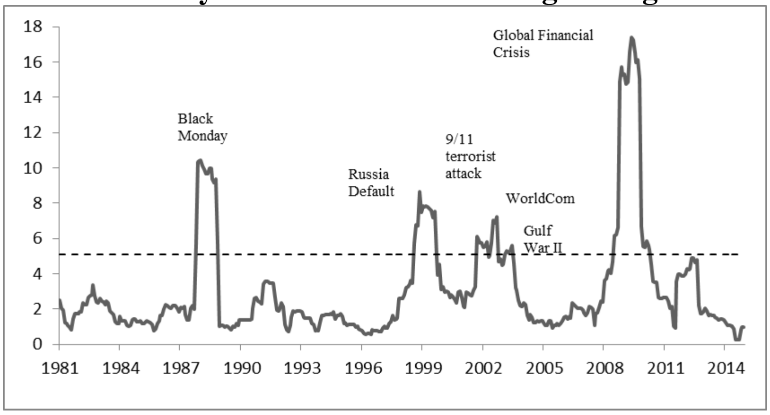


Figure 2. Responses of global variables to financial and non-financial global stock market volatility shocks

Global stock market volatility shocks	Response of GIP	Response of GCPI	Response GIR
Financial			
Non-Financial			

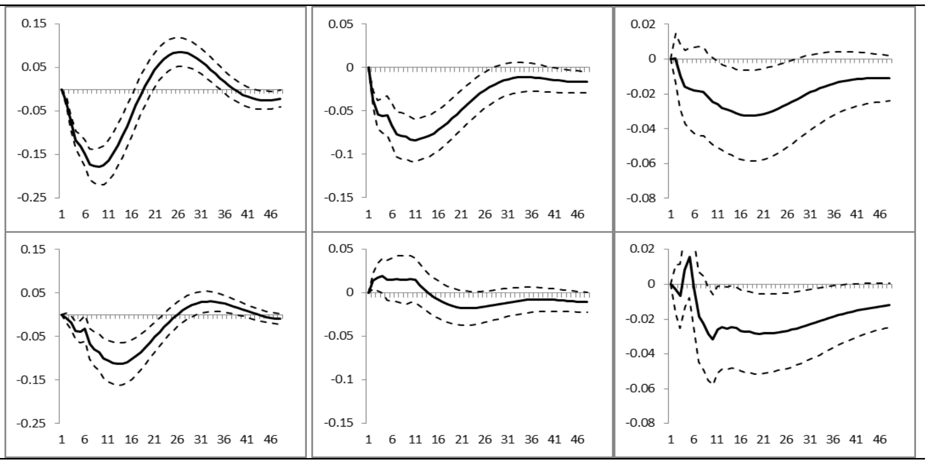


Figure 3.1 Robustness's Analysis: The Benchmark model with Cholesky decomposition

Global stock market volatility shocks	Response of GIP	Response of GCPI	Response GIR
Financial			
Non-Financial			

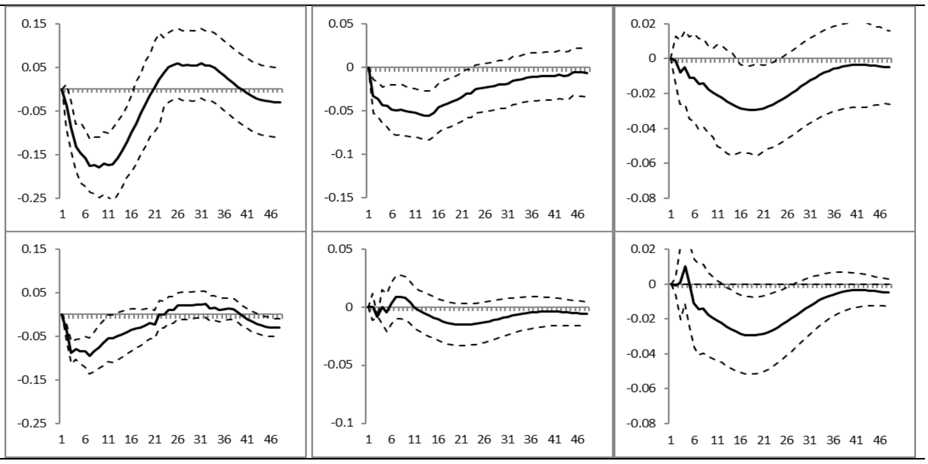
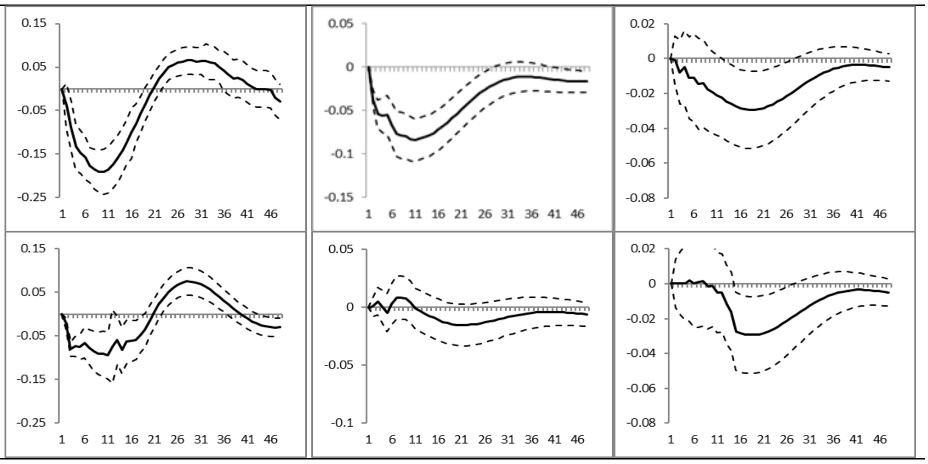


Figure 3.2 Robustness's Analysis: The Benchmark model with 3 lags (Selected by BIC)

Global stock market volatility shocks	Response of GIP	Response of GCPI	Response GIR
Financial			
Non-Financial			



Appendix A: Data Appendix

Table A1. Global variables from Database of Global Economic Indicators, FRBD.

Name and description	Period
<u>*IP for the U.S*</u>: is the total industrial production excluding construction for the U.S economy, index 2005=100.	Jan 1981- Dec 2018
<u>*IP for advanced economies (ex. U.S):*</u> is the total industrial production excluding construction for the largest 31 advanced economies excluding the U.S, index 2005=100.	Jan 1981- Dec 2018
<u>*IP for emerging economies:*</u> is the total industrial production excluding construction for the largest 26 emerging economies, index 2005=100.	Jan 1987- Dec 2018
<u>*CPI for the U.S*</u>: is the headline consumer price index for the U.S, index 2005=100.	Jan 1981- Dec 2018
<u>*CPI for advanced economies (ex. U.S):*</u> is the headline consumer price index for the largest 31 advanced economies excluding the U.S, index 2005=100.	Jan 1981- Dec 2018
<u>*CPI for emerging economies*</u>: is the headline consumer price index for the largest emerging economies excluding the U.S, index 2005=100.	Feb 1984- Dec 2018
<u>*Interest rate for the U.S*</u>: Federal funds target rate	Jan 1981- Dec 2018
<u>Interest rate for advanced economies (ex. the U.S</u>: Short term official policy rate (maturity 3 months or less) for the largest 31 advanced economies excluding the U.S.	July 1985- Dec 2018
<u>*Interest rate for emerging economies (ex. the U.S)*</u>: Short term official policy rate (maturity 3 months or less) for the largest 26 emerging economies excluding the U.S.	Jan 1981- Dec 2018

Notes: Global indicators for advanced and emerging are aggregated using U.S trade weights [for more detail see: Grossman, Mack and Martinez-Garcia(2004)].

Table A2. Summary statistics

Variable	Mean	Maximum	Minimum	Standard deviation
$\Delta(GIP_t)$	-0.0008	3.0487	-5.8244	1.3555
$\Delta(GCPI_t)$	0.0040	5.9697	-3.2722	1.3816
GIR_t	-0.0499	3.3240	-1.4292	1.1187
$DF_t * GU_t$	0.7417	109.1899	0.0000	5.9827
$DNF_t * GU_t$	0.1839	18.5802	0.0000	1.4247

Table A3. 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	Feb. to July 1987	Sept. 11 terrorist attack	Sept. to Nov. 2001
Russian sovereign debt crisis	May and June 1997	Gulf War II	May to Aug.2002
Global financial crisis	Sept. 2007 to Nov. 2008		

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