Financial and Non-Financial Global Stock Market Volatility Shocks

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Abstract

We decompose global stock market volatility shocks into financial originated shocks and non-financial 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 non-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

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1. Introduction

The adverse impact of stock market volatility on economic activity has received renewed interest following the influential study of Bloom (2009). The literature in this area generally focus on the effect of country level stock market volatility on economic variables within a country.[1] The rapid and accelerating process of financial globalization and new technologies prompts the question as to whether it is useful for the stock market volatility to be addressed as a global phenomenon, whose effects are examined for the global economy.

In this study, we focus on decomposing these global shocks into global stock market volatility shocks originated from financial sources and those originated from non-financial sources shocks (such as important global political, wars or terrorist attacks events). This decomposition provides important information for domestic policymakers and supranational organization such as the International Monetary Fund or World Bank to understand and act upon these distinctive shocks and to forecast global variables. A large body of the literature found that high stock market volatility causes firms to postpone investment and hiring and consumers to delay important purchases with unfavourable consequences for economic growth.[2]

Shocks originating from financial sourses may have been amenable to better economic policy design, whereas those due to war, other conflicts or terrorism are less predictable. The decomposition of stock market volatility shocks might lead to a better understanding of how economic policy might be designed to both, avoiding and mitigating the effects of global future shocks.

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[1] See, for example, Bloom (2009), Knotek and Khan (2011), Mumtaz and Theodoridis (2014) and Jurado et al. (2015).

[2] An important thread in the literature is that uncertainty faced by the individual firm is embodied in its own stock price volatility, as discussed in Leahy and Whited (1996) and Bloom (2009) among others.

In this study, we build on the existing literature by constructing a global stock market volatility index using the first principal component of stock market volatility of 15 major developed and developing economies. We also build on Bloom (2009) identification strategy of the major events to decompose the global stock market shock into financial and non-financial originated shocks.

Our decomposition of global stock market volatility shocks shows that global financial stock market volatility shocks produce larger effects than the non-financial shocks. From 1981 to 2014, 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.

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

2. Data and Methodology

2.1. A new index of global stock market volatility

We construct a global stock market volatility index given by the first principal component of stock market volatility of the largest 15 economies. It 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.

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 $t = 1, 2 \ldots, T$. Let

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

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.[3] 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 stock market volatility index (GU_t) is given by the linear combination of all 15 volatility indices $V_{country\ 1,t}$, $V_{country\ 2,t}, ..., V_{country\ 15,t}$,

$$GU_t = a_1 V_{country\ 1,t} + a_2 V_{country\ 2,t} + \cdots + a_{15} V_{country\ 15,t}. \quad (3)$$

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 standardized by the restriction: $a_1^2 + a_2^2 + \cdots + a_{15}^2 = 1$. Data definitions, sources and period availabilities are all reported in Table A1.[4]

2.2 Identifying major global stock market volatility events

In Figure 1 we show the global stock market volatility index developed in Equation (1) to (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.[5] 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

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[3] The countries include Australia, Brazil, Canada, China, Germany, France, India, Italy, Japan, Mexico, Russia, South Korea, South Africa, the United Kingdom (U.K) and the United Sates (U.S). We also 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. An alternative measure of global uncertainty including these countries for a shorter span is discussed in section 8.6.

[4] Data from the stock market are not available for all countries from 1981. The index is constructed with data on the countries for which data are available. A shortcoming of this approach is that for the earlier period, missing data are more apparent for developing countries. Nevertheless, we argue that this is not necessarily a problem, given that in the first part of the sample (1980-1995), the relative weight of developed economies in the global economy is more important than in the more recent period (following China's unprecedented growth starting in mid-1990s). The availability of stock market data for each country is reported in Table A1 in Appendix A.

[5] Note that in the FAVAR analysis below we do not transform the variable to 12-month moving average.

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.

2.3 Other global macroeconomic variables-factors

All data are monthly and extend from January 1981 to December 2014. [6] The global factors include global interest rate (GIR_t), global consumer price index ($GCPI_t$) and global industrial production (GIP_t), which are estimated using data on emerging economies, advanced economies (excluding the U.S.) and the U.S. The data on interest rate, consumer price index (CPI) and industrial production (IP) are taken from database of global Economic indicators (DGEI, Federal Reserve Bank of Dallas), for the G40 countries.[7] In 2015, on a GDP PPP basis, the G40 economies account for 83% of the global GDP. The GIR_t, $GCPI_t$ and GIP_t are the leading principal components derived by

$$GIR_t = [IR_t^{Ad}, IR_t^{US}, IR_t^{Em}], \qquad (6)$$

$$GCPI_t = [CPI_t^{Ad}, CPI_t^{US}, CPI_t^{Em}], \quad (7)$$

$$GIP_t = [IP_t^{Ad}, IP_t^{US}, IP_t^{Em}], \qquad (8)$$

where the superscripts *US*, *Ad* and *Em* represent the United States, advanced economies (excluding the U.S) and emerging economies.[8]

2.4 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 exceeded 1.65 standard deviations: Black Monday, Russian Default,

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[6] Before 1981, data are not available for most variables from many developing countries. Data descriptions, sources and period availabilities are presented in Table A2.

[7] 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).

[8] We deal with missing data in early observations for some series by building the factors with series only available at this time to maximise the number of observations.

WorldCom and the GFC.[9] 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 GU_t 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 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. [10] The second variable (the non-financial stock market volatility shocks) is 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.[11]

2.5 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 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 the global financial and non-financial stock market volatility interaction variables $(DF_t * GU_t)$ and $(DNF_t * GU_t)$.

The following structural VAR model of order p is utilized:

$$A_0 y_t = c_0 + \sum_{i=1}^{p} A_i y_{t-i} + \varepsilon_t, (9)$$

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

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[9] The global financial crisis includes the five main events described in Table A3 (Appendix A), including 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.

[10] 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 A4.

[11] Note that this is an econometric innovation, 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.

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.[12] 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 (9) by A_0^{-1}. The reduced-form error term is $e_t = A_0^{-1}\varepsilon_t$ and is assumed to be Gaussian distributed.

The identifying restrictions on A_0^{-1} is a lower-triangle coefficient matrix in the structural VAR model. 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.[13] 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 stock market volatility variables ordered last captures the fact that the stock market volatility is a forward-looking indicator and likely responds instantly to monetary policy shocks.

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

$$\begin{bmatrix} 1 & 0 & 0 & 0 & 0 \\ a_{11} & 1 & 0 & 0 & 0 \\ a_{21} & a_{22} & 1 & 0 & 0 \\ a_{31} & a_{32} & a_{33} & 1 & 0 \\ a_{41} & a_{42} & a_{43} & 0 & 1 \end{bmatrix} \begin{bmatrix} \Delta(GIP_t) \\ \Delta(GCPI_t) \\ GIR_t \\ DF_t * GU_t \\ DNF_t * GU_t \end{bmatrix}. (10)$$

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

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[12] We follow Bloom (2009) and Jurado et al. (2015) in setting p=12, which allows for a potentially long-delay of effects of uncertainty shocks on the economy and for a sufficient number of lags to remove serial correlation.
[13] Note that stock market volatility is a measure of uncertainty according for example with Bloom (2009).

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. 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 are almost twice as large as the non-financial shocks on global IP (up to -0.19 and -0.10, respectively). Also, the impact of financial shocks on global IP is faster.[14] 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.

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

Table 1 report 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

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[14] 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.

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.

4. Robustness analysis

The benchmark model estimated in Equation (9) and (10), reports results when 12 lags are specified in the FAVAR system in line with the literature. 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.[15] We also estimate the model with an alternative measure of global stock market volatility. Rather than use the factor-variable described in Equation (1) to (3), we construct an index applying a GDP-weighted index of country specific volatility (also for the largest 15 economies).[16] 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 Equations (1) to (3).[17] All results or alternative estimations support our main results shown in Figure 2 and Table 1 in terms of sign and size of the effect, and are available upon request from the authors.

5. 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

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[15] Note that the Bayesian Information Criterion indicates that the optimal lag is 3, while the Akaike Information Criterion indicates 4 lags as the optimal lag structure in the FAVAR system.

[16] Note that for this alternative measure, 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.

[17] 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 uncertainty from 1990.

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 2014, 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.

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**Table 1. 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
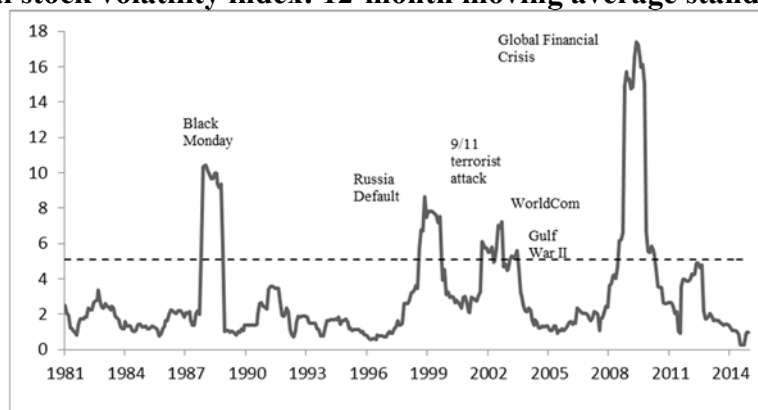
Figure 2. Responses of global variables to financial and non-financial global stock market volatility shocks

Global stock market volatility shocks	Response of GIP	Response of GCPI	Response GIR
Financial			
Non-Financial			
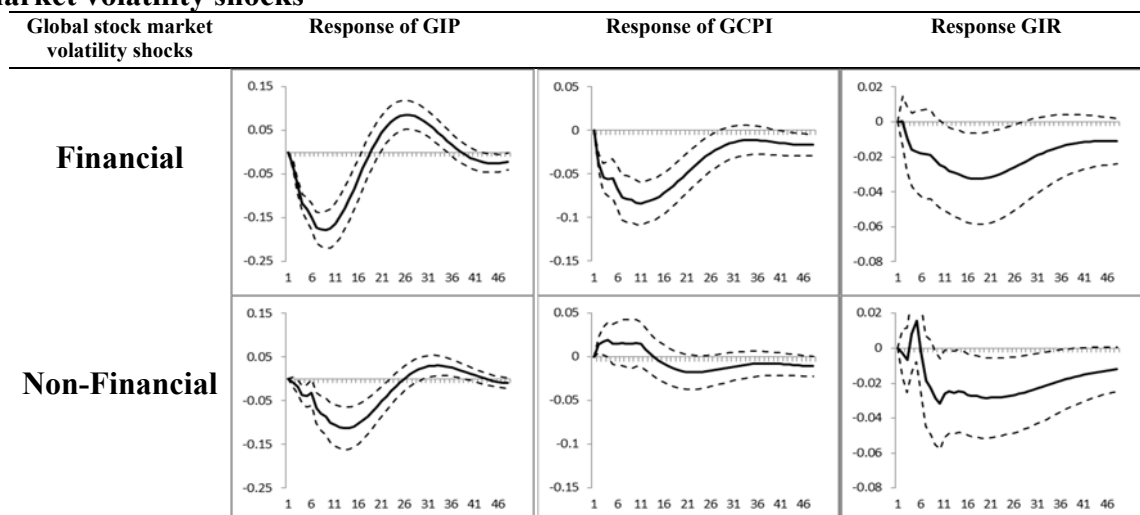
Appendix A: Data Appendix

Table A1. Global stock market data from Datastream 5.1.

Main stock market indicators by country	Period
Australia: Standard & Poor's/ASX 200 Index.	Jan 1981- Dec 2014
Brazil: BM&F BOVESPA Index	Jan 1991- Dec 2014
Canada: Toronto Stock Exchange index	Jan 1981- Dec 2014
China: Shanghai Stock Exchange Composite Index	Dec 1990- Dec 2014
France: France CAC 40 Stock Market Index	Jan 1987- Dec 2014
Germany: Deutsche Boerse AG German Stock Index	Jan 1993- Dec 2014
India: NSE CNX 100 Index	Jan 2003- Dec 2014
Italy: FTSE MIB Index	Mar 2003- Dec 2014
Japan: NIKKEI 225 Stock Market Index	Jul 1988- Dec 2014
Mexico: Mexican Bolsa IPC Index	Dec 1991-Dec 2014
Russia: Russia MICEX Stock Market Index	Jan 1994- Dec 2014
South Korea: Korea Stock Exchange KOSPI Index	Jan 1990- Dec 2014
South Africa: South Africa FTSE/JSE Index	Jan 2001- Dec 2014
U.S: Standard & Poor's 500 index.	Jan 1981- Dec 2014
U.K: UK FTSE 100 Stock Market Index	Jan 1981- Dec 2014

Table A2. Global variables from Database of Global Economic Indicators, FRBD.

Name and description	Period
IP for the U.S: is the total industrial production excluding construction for the U.S economy, index 2005=100.	Jan 1981- Dec 2014
IP for advanced economies (ex. U.S): is the total industrial production excluding construction for the largest 31 advanced economies excluding the U.S, index 2005=100.	Jan 1981- Dec 2014
IP for emerging economies: is the total industrial production excluding construction for the largest 26 emerging economies, index 2005=100.	Jan 1987- Dec 2014
CPI for the U.S: is the headline consumer price index for the U.S, index 2005=100.	Jan 1981- Dec 2014
CPI for advanced economies (ex. U.S): is the headline consumer price index for the largest 31 advanced economies excluding the U.S, index 2005=100.	Jan 1981- Dec 2014
CPI for emerging economies: is the headline consumer price index for the largest emerging economies excluding the U.S, index 2005=100.	Feb 1984- Dec 2014
Interest rate for the U.S: Federal funds target rate	Jan 1981- Dec 2014
Interest rate for advanced economies (ex. the U.S: Short term official policy rate (maturity 3 months or less) for the largest 31 advanced economies excluding the U.S.	July 1985- Dec 2014
Interest rate for emerging economies (ex. the U.S): Short term official policy rate (maturity 3 months or less) for the largest 26 emerging economies excluding the U.S.	Jan 1981- Dec 2014

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 A4. Dummy variables for financial and non-financial shocks for Equation 9

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).