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Oil prices and global factor macroeconomic variables

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ABSTRACT

This paper investigates the relationship between oil prices, global industrial production, prices, central bank policy interest rate and monetary aggregate with a global factor-augmented error correction model. We confirm the following stylized relationships: i) at global level, money, industrial production and prices are cointegrated; ii) positive innovation in global oil price is connected with global interest rate tightening; iii) positive innovation in global money, price level and industrial production is connected with an increase in oil prices; iv) positive innovations in global interest rate are associated with a decline in oil prices; and v) the U.S., Euro area and China are the main drivers of global macroeconomic factors.

1. Introduction

Since the mid-1990s several important changes have taken place in the global economy and international oil market. With the creation of the ECB in 1999 and the rapid economic growth of China and India, the largest 5 economies (the Euro area, the U.S., China, Japan and India) now account for around 65% of the world economy (measured in purchase power parity), and global demand for oil in recent decades has been driven by brisk growth in major developing economies.[2] Important changes have also occurred in the global economy in terms of central bank actions. With many countries suffering prolonged economic downturns and official/policy interest rates being close to zero, after the global financial crisis in 2008, the U.S., Japan, Euro area and the U.K. central banks have turned to alternative policies to expand monetary aggregates and hence stimulate the economy.

The literature generally analyses the relationship between the U.S. federal funds rate and oil prices. However, in the current context we believe that central bank interest rates at global level and also global monetary aggregates should be considered in interaction with oil prices, particularly given the surge in the Chinese and Indian economies and the new ways that central banks now seek to influence the economy.

The U.S. Energy Information Agency documents that China became the world's largest net importer of oil on an annual basis in 2014. The largest oil consuming countries in 2014 were the U.S., China, Japan and India in that order. India has increased oil consumption by over 50% over 2000–2010. The surge in demand for oil by China and India is forecasted by the IEA to continue well into the future.[3]

While growth in emerging economies has mattered primarily for the latest surge in oil prices, more generally, this is about demand from all countries in the world. Barsky and Kilian (2004) emphasize that oil prices are endogenous with respect to U.S. and global macroeconomic

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[2] Kilian and Hicks (2013) connect real oil price increases to strong growth forecasts in emerging economies (especially in China and India) over 2003–2008 and the decline in real oil prices after mid 2008 with forecasts of decline in global growth. Beirne et al. (2013) estimate the effects of individual countries on oil demand and find that China's GDP growth attaches a premium to the price of oil that is rising over time. Hamilton (2013) notes that the newly industrialized economies have absorbed over two-thirds of the increase in world oil consumption since 1998. Cagliarini and McKibbin (2010) emphasize that growth in emerging economy countries has boosted commodity prices in recent years. Hammoudeh et al. (2014) find that contractionary shocks to China's monetary policy have a negative and persistent impact on commodity prices and Hammoudeh et al. (2015) find that US monetary contractions have a rapid impact on sectoral commodity prices.

[3] The IEA projects that "China, India, and the Middle East will account for 60% of a 30% increase in global energy demand between now and 2035"… "By 2035, almost 90% of Middle Eastern oil flows to Asia" (http://www.worldenergyoutlook.org/pressmedia/quotes/12/).

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conditions.[4] It is also stressed that the behaviour of commodity prices is closely intertwined with global monetary conditions. Barsky and Kilian (2002) show that the global shifts in monetary policy regimes in the 1970s caused shifts in real economic growth and inflation and hence in the real price of oil.[5] Bodenstein et al. (2012) develop a DSGE model and argue that causality runs from the oil market to monetary policy as well as from changes in monetary policy to the supply and demand of oil in global markets. Belke, Bordon and Hendricks (2010) find that causality between global monetary aggregates and oil price runs both ways. The literature is clear that when considering the world price for oil it is necessary to consider the influence of global variables, including those which reflect the stance of monetary policy in the major developing and developed countries.

We believe that this paper contributes to the literature by providing stylized facts on the interaction between oil prices and factor-augmented global macroeconomic variables, including aggregated central bank policy interest rates and liquidity, by estimating a global factors vector error correction model (GFAVEC). A factor-augmented dimension to the GFAVEC model will capture the dynamic of the information provided by many variables to the analysis of short and long run interaction of global oil price, global industrial production, global CPI and global policy interest rate. Global factors are estimated using principal component techniques applied to interest rates, industrial production across countries, and CPI across countries, respectively.[6] The use of factor analysis for crude oil prices is appropriate for analysis of the behaviour of the global economy since West Texas Intermediate (WTI) crude oil price has diverged sharply from Brent and Dubai crude oil prices in recent years.

Some stylized facts that emerge from our empirical analysis are:

i) Global money, global industrial production and global prices are cointegrated.
ii) Granger causality goes from liquidity to oil prices and from oil prices to the global interest rate, global industrial production and global CPI.
iii) Positive innovations in world oil price are connected with statistically significant extended positive effects on global interest rates and global industrial production.
iv) Positive innovation in the global interest rate is linked with a persistent decline in global oil price.
v) Statistically significant persistent increases in global oil price are associated with positive shocks to global M2 and global industrial production.

The methodology and global variables are described in Section 2. Granger causality among the economic variable and global macroeconomic variables is investigated in Section 3. The GFAVEC model is presented in Section 4. The empirical results are presented in Section 5. The robustness of results to alternative definitions of the variables and different model specifications is discussed in Section 6. Section 7 concludes.

2. Data and global factors

2.1. Background

In this paper we estimate a global factor-augmented error correction model. Factor methods have become widely used in the literature to examine the co-movements of aggregate variables since work by Stock and Watson (1998) and Forni et al. (2000). A number of issues have been addressed recently using factor methods. Building on Stock and Watson (2002), Bernanke et al. (2005) propose a factor-augmented VAR (FAVAR) to identify monetary policy shocks. Mumtaz and Surico (2009) extend Bernanke et al. (2005) to consider a FAVAR for an open economy. A factor-augmented approach has been used by Dave et al. (2013) to isolate the bank lending channel in monetary transmission of U.S. monetary policy and by Gilchrist et al. (2009) to assess the impact of credit market shocks on U.S. activity. Le Bihan and Matheron (2012) use principal components to filter out sector-specific shocks to examine the connection between the stickiness of prices and the persistence of inflation. Boivin et al. (2009) assume that the connection between the sticky prices and monetary policy can be captured by five common factors estimated by principal component analysis. Abdallah and Lastrapes (2013) use a FAVAR model to examine house prices across states in the U.S. Beckmann et al. (2014) examine the effect of global shocks on policy making for the US, Euro area, Japan, U.K. and Canada. Juvenal and Petrella (2014) in an examination of the role of speculation in the oil market, construct a factor for speculation based on a large number of macroeconomic and financial variables for the G7.

In line with the dynamic factor models of Bernanke et al. (2005), Stock and Watson (2005), Forni and Gambetti (2010), and others, we construct a global factor-augmented error correction model to examine the relationships between oil prices, global interest rate, global monetary aggregates, global industrial production and global CPI and the weighted trade index of the U.S. dollar. A cointegrating vector for global money, global industrial production and global price level is utilized.

The main advantage of this approach in a global setup is that it is possible to compress data for many countries in single factor without losing degrees of freedom, thereby allowing for the influence of both large developed and developing economies.[7] A single individual variable or factor can capture the dynamic of a large amount of information contained in many variables. Sims (2002) argues that when deciding policy central banks consider a huge amount of data. Koop and Korobilis (2009) provide an overview of factor-augmented VARs and other models.

2.2. The data

The data are monthly from January 1999 to December 2013. The starting period coincides with the creation of the European Central Bank, and data on CPI and interest rate for this block is only available from January 1999. Monthly data is used to overcome the limitation of few observations obtained from quarterly data over a 13-year period. Data are obtained on the central bank discount rate, monetary aggregate M2, consumer price index, and industrial production index for each of the five largest economies consisting of the Euro area, the U.S., Japan, China and India. Oil prices are given by the Brent, Dubai and WTI U.S. dollar international indexes for crude oil prices. The trade weighted index for the U.S. dollar completes the data.[8] Data on each country are from the Federal Reserve of St. Louis (FRED data) and data on oil prices are from the World Bank.

[4] Recent work on global influence on the price of oil include Kilian and Lee (2014) and Kilian and Murphy (2014) investigating the roles of speculation and inventories in influencing the price of oil.

[5] Frankel (1986) in an early paper develops a model linking easier money supply with higher commodity prices. Frankel and Rose (2010) do not find empirical support for such a relationship.

[6] It is emphasized that this is not the same as the stance of global monetary policy since there is no global central bank. In recent years the effect of global liquidity on the prices of commodities has been emphasized by some researchers. Increases in liquidity raise aggregate demand and thereby increase commodity prices.

[7] An alternative approach to the use of factors would be to use weighted averages of the different variables as definitions of the global variables. This approach brings the difficulty of choice of weights, particularly for monthly data. Use of industrial production, for example, raises problems in that the service sectors of the developed economies are so much greater than that of the emerging economies and industrial production is subject to wide swings. The advantage of using principal components is that results depend on an algorithm focusing on the common components in the data and not by the weights selected by the authors.

[8] We use the U.S. TWI to capture exchange rate fluctuation given that the U.S. dollar is the currency most commonly used for trade and saving worldwide. Major currencies index from the Federal Reserve System of the United State includes: the Euro Area, Canada, Japan, United Kingdom, Switzerland, Australia, and Sweden. Weights are discuss in: http://www.federalreserve.gov/pubs/bulletin/2005/winter05_index.pdf.

Information on the interest rate, liquidity (measure by M2 in U.S. dollars), CPI and industrial production for the U.S., Euro area, China, India, and Japan over 1999:01–2013:12 are shown in Fig. 1. The central bank discount rate for each of the five economies has varied over time. Although at widely different levels, the interest rates all show declines following the March–November 2001 recession in the US. With the exception of India, central bank discount rate register increases during the commodity price boom over 2005–2008 and fall during the global financial crises. Liquidity (M2 in U.S. dollar) increases over the fourteen years from 1999:01 to 2013:12 by approximately a factor of 12 in China, 4.8 in India, 2.3 in the U.S., 2.6 in Euro area, and by 2 in Japan.

The consumer price level is up by a factor of 1.34 in China, 2.4 in India, 1.4 in the U.S., 1.35 in Euro area, and down by 4% in Japan. Compared to the U.S., the Euro area and Japan, China and India have grown much faster in recent years. For example, over the fourteen years from 1999:01 to 2013:12 industrial production is up approximately by factors of about 2.9 and 2.3 in China and India respectively, and up by only about 14% and 6% in the U.S. and the Euro area respectively, and down by about 3% in Japan. On the basis of GDP in purchasing power parity in 2013 (in declining order) the U.S., Euro area, China, India, and Japan, are by far and away the largest economies in the world.

2.3. The global factors

Principal components indexes are constructed for each group of variables for the five economies and are the global interest rate (GIR_t), global CPI ($GCPI_t$) and global industrial production (GIP_t).[9] A global monetary aggregate M2 ($GM2_t$), the sum of M2 monetary aggregates across economies (in U.S. dollars) captures the effect of liquidity. Global oil prices (GOP) is constructed by using a unique principal component index based on information for the Brent, Dubai and WTI U.S. dollar-based international indexes for crude oil prices.

The indicators of global interest rates, global industrial production and of global CPI are the leading principal components for interest rates, industrial production and CPI (in log-level form for industrial production and CPI) of the U.S., Euro area, China, India, and Japan. These are given by

$$GIR_t = \left[IR_t^{Ea}, IR_t^{US}, IR_t^{Ch}, IR_t^{Ja}, IR_t^{In}\right], \tag{1}$$

$$GIP_t = \left[IP_t^{Ea}, IP_t^{US}, IP_t^{Ch}, IP_t^{Ja}, IP_t^{In}\right], \tag{2}$$

$$GCPI_t = \left[CPI_t^{Ea}, CPI_t^{US}, CPI_t^{Ch}, CPI_t^{Ja}, CPI_t^{In}\right], \tag{3}$$

where the superscripts for the variables GIR_t, GIP_t and $GCPI_t$: *Ea*, *US*, *Ch*, *Ja*, and *In*, represent the Euro area, U.S., China, Japan, and India respectively in Eqs. (1), (2) and (3). In Eq. (1), GIR_t is a vector containing the discount rate of the central banks of the Euro area, U.S., China, Japan and India.[10] Eqs. (2) and (3) are vectors containing the industrial production and CPI for the same economies respectively.[11]

The indicator for global oil prices is the leading principal component of the Dubai, Brent and WTI oil prices and is given by

$$GOP_t = \left[OP_t^{Dubai}, OP_t^{WTI}, OP_t^{Brent}\right]. \tag{4}$$

A global factor for oil price better captures movement in oil price relevant for the global economy than the individual prices for Brent, Dubai and WTI oil. U.S. dollar indexes for Brent, Dubai and WTI crude oil prices are shown in Fig. 2. Before the global financial crisis, the WTI and Brent crude oil prices were within a couple of dollars of each other, with WTI usually at a premium relative to Brent. Since 2011, WTI has traded at a significant discount to Brent and on September 21, 2011, the discount achieved $28.49 per barrel. The price gap between Brent and Dubai also fluctuates. Before 2011, Brent crude oil typically traded at a one or two dollar premium relative to Dubai crude oil. The premium for Brent over Dubai surged to $7.60 per barrel in 2011 with the crisis in Libya, before falling to a low of $1.1 per barrel in November 2012, and surging again to almost $6 per barrel in August 2013. Movement in these price gaps reflect changes in the market conditions in various parts of the world driven by economic and political considerations.[12]

We use one factor (the principal component) each for the global interest rate, global industrial production, global CPI, and global oil price to keep the total number of variables in the estimation of the global relationship to a minimum. In an Appendix it is shown that, the first principal component for each variable captures much of the variation in each variable across the five economies (for the interest rate, 44.5%, for industrial production, 60%, and for CPI, 89.6%) and the three oil price indices (99.6%).

In constructing principal components in the basic model we use normalise loadings. With the normalise loading option, more weight is given to variables (country variables in this case) with higher standard deviation. With scores options all the variables are given equal weight (by standardising them). A direct implication of choosing normalise loading is that more weight is given to the variables for developing economies, which generally have higher standard deviation in this sample. This is a desirable feature of the analysis, given the views of Hamilton (2009, 2013), and Kilian and Hicks (2013) that for the period of analysis oil prices are largely influenced by the surge in growth in developing economies.

The first principal component for the global interest rate is drawn in Fig. 3a for normalise loadings, normalise scores, and with equal weighted scores and loadings (information on different loadings is provided in the Appendix). Fig. 3a captures the fall in interest rates at the end of 2008 with the onset of the global financial crisis as well as the fall in interest rates during and following the 2001 recession in the US. The first principal component for the CPI indices in Fig. 3b slopes upward. The slight concavity in the curve over 2000–2006 indicates higher CPI over this period followed by an overall flat rate of inflation in the last half of the sample.

The first principal component for global industrial production is represented in Fig. 3c. Global industrial production has an upward trend until the global financial crisis in 2008. There is a severe correction in GIP_t in 2008–2009, reflecting the global financial crisis, with recovery of global industrial production to early 2008 levels only in 2011. Global industrial production also shows a correction in 2001, coinciding with the March–November 2001 recession in the U.S. The principal component for crude oil prices is shown in Fig. 3d. Oil price rose sharply from January 2007 to June 2008. Concurrent with the global financial crisis and the weak global economy, the oil price fell steeply until

[9] Note that the first and second principal components of these series are less than 100% representative of the original variables.

[10] Structural factors in VAR models to better identify the effects of monetary policy have appeared in a number of contributions (for example, by Belviso and Milani (2006); Laganà (2009) and Kim and Taylor (2012), among others), but less so in work on commodity prices. An exception is by Lombardi et al. (2012) examining global commodity cycles in a FAVAR model in which factors represent common trends in metals and food prices.

[11] The first principal component for country CPIs to indicate global inflation is similar to Ciccarelli and Mojon (2009) method of identifying global inflation based on price indices for 22 OECD countries and a factor model with fixed coefficients. Within the factor analysis framework, a different approach is taken by Mumtaz and Surico (2012) who derive factors representing global inflation from a panel of 164 inflation indicators for the G7 and three other countries.

[12] WTI represents the price oil producers receive in the U.S. and Brent and Dubai represents the prices received internationally. The WTI and Brent crude oils share a similar quality and Dubai has higher sulphur. The recent negative premium for WTI relative to Brent is usually explained in terms of oil production in the US exceeding cheap transportation capacity by pipeline to refiners on the US Gulf Coast. Fluctuation in the premium for Brent over Dubai is usually tied to political events in North Africa and the Middle East.

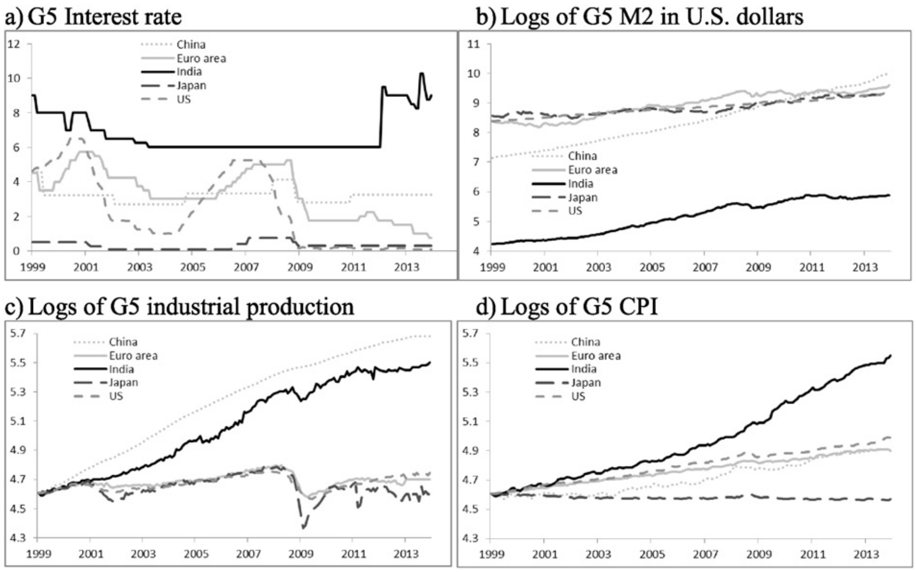

Fig. 1. Macroeconomic economy-level variables. Notes: Central bank discount rates, M2 monetary aggregates, consumer price indices, and industrial production indices are for each of the five largest economies (the G5). The G5 consists of the U.S., the Euro area, Japan, China and India. Interest rates are in per cent. Log of M2 data in U.S. dollars is shown. Logs of industrial production and the CPI are also shown. Data are monthly.

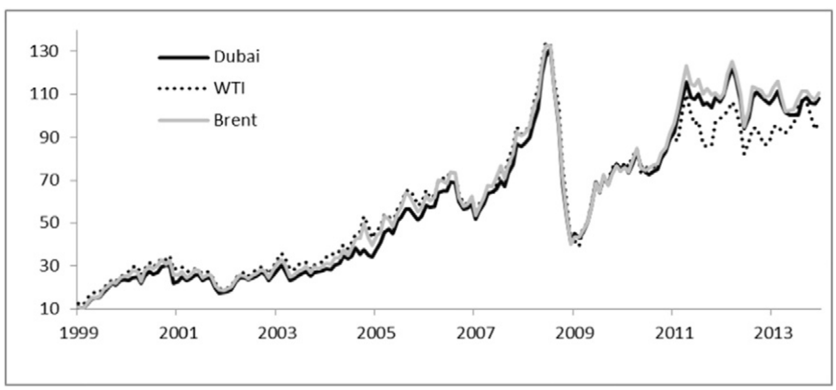

Fig. 2. U.S. dollar indexes for Brent, Dubai and WTI crude oil prices. Notes: Brent, Dubai and WTI crude oil prices are U.S. dollar indices. Data are monthly.

January 2009 before substantially rebounding over the next few years. The log of the trade weighted index of the U.S. dollar is shown in Fig. 3e. The trade weighted U.S. dollar peaks in early 2002 and then shows a gradual downward movement with a levelling off in recent years. The log of global M2 is shown in Fig. 3f and shows an upward trend.

Information on the correlations between country-specific and the corresponding global variable for M2, short-term interest rate, industrial production and CPI are reported in the columns in Table 1. The global interest rate correlation with country interest rates is high for the Euro area, China and Japan (over 75% for each), 54% for the U.S. and only 29% for India. The global industrial production correlation with country-level industrial production is high for the U.S. and India (88% each), and 71%, 65% and 63% for Japan, Euro area and China, respectively, in terms of log levels. The correlations of log first-differences of the data on output are smaller for the U.S., China and India, but slightly larger for the Euro area and Japan. The global CPI connection with that of each country-level CPI is high with correlations at 82% and above. The correlations of log first-differences of the data on prices for each country with global CPI inflation are quite different than the correlations of log levels of the data on prices. The global M2 is highly correlated with M2 in each of the five economies in terms of log levels. The correlations of log first-differences of the data on M2 are much smaller, especially for the U.S., China and India. In analysis in the Appendix, the log differences of the variables are stationary.

3. Causality test

We now examine the direction of causality between the variables at global level and also the causality between the developed and developing large economies and the variables at global level. The issue of causality between global variables and global oil price is not usually addressed in the literature, but is clearly of interest given the increased interconnectedness of the world economy. Work on the impact of a large economy on other economies has naturally focused on the role of the U.S. in the international transmission of shocks.[13] China and India are now large economies and their impact on global variables needs to be examined along with that of the U.S., Euro area and Japan.

3.1. Directional influence among global variables

In Table 2, the Granger causality direction results for the global interest rate, global M2, global industrial production and global CPI with global oil price are presented. The balance of the evidence is that global oil price Granger causes global interest rate, global industrial production

[13] With regard to monetary policy, Kim (2001) and Canova (2005) find that monetary expansion in the U.S. causes economic expansion in the non-US G-6 and in Latin America by lowering interest rates across these economies.

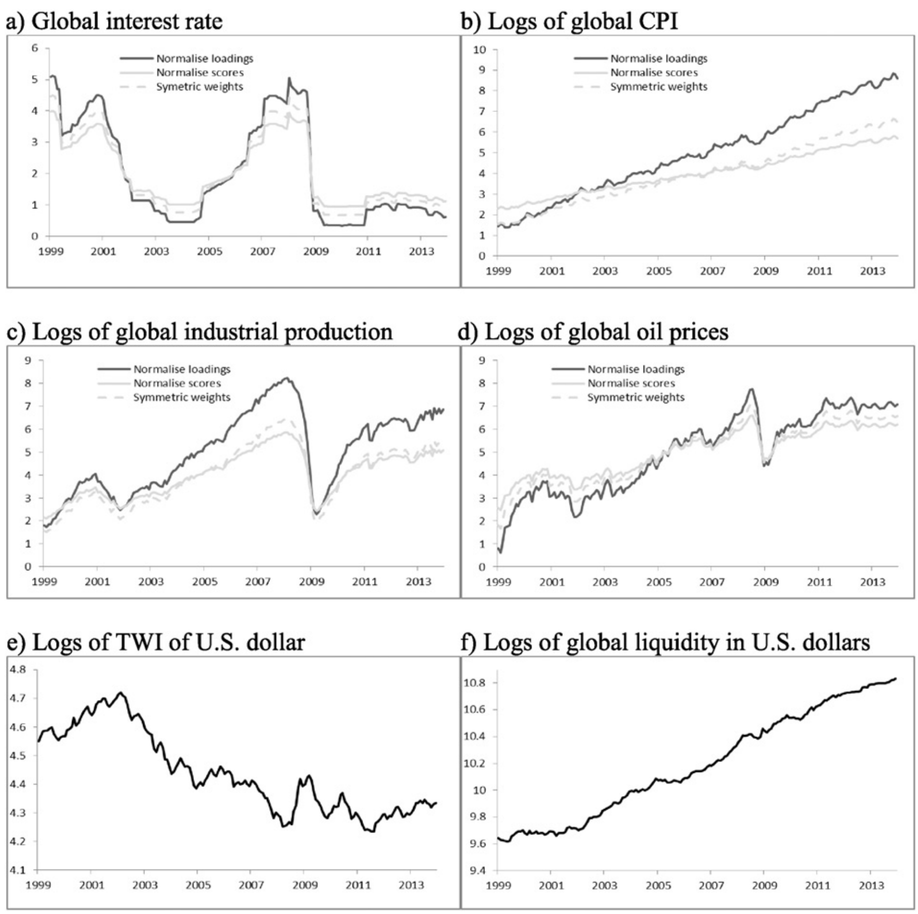

Fig. 3. Global variables (principal components). Notes: The leading principal components for global interest rates, global industrial production and global CPI (in log-level form for industrial production and CPI) are each obtained from data on central bank interest rate, industrial production and CPI for the U.S., Euro area, China, India, and Japan. The leading principal component for oil price is obtained from data on the Dubai, Brent and WTI oil prices. Alternative principal components are shown for normalise loadings, normalise scores and with equal weighted scores and loadings. TWI U.S. dollar is the log of the trade weighted index of the U.S. dollar. Global liquidity is the log of global M2 which is the sum in U.S. dollars of M2 for the U.S., Euro area, China, India, and Japan.

and global CPI, and not the reverse of these outcomes. These results supplement the large literature assigning oil price shock a major role in influencing real activity in individual economies by suggesting that even global variables are influenced by oil prices. Hamilton's (1983) influential paper on the effect of oil prices on the U.S. economy over the post-World War II period treated oil price changes as exogenous. This supposition was maintained by Lee et al. (1995), Hamilton (1996) and Bernanke et al. (1997), among many others, who documented a negative connection between oil price increases and real activity in the US.[14] Hamilton (2009) also distinguishes oil price shocks due to demand and supply side influences.

It is found in Table 2 that global oil price does not Granger cause global M2, but global M2 does Granger cause global oil price. This latter result is in line with the literature documenting a positive effect of global liquidity on commodity prices. Belke, Orth and Setzer (2010) find that global liquidity has a significant impact on commodity prices, and Ratti and Vespignani (2013) show that increases in global real M2 have led to statistically significant increases in real oil prices in recent years. Overall, we conclude that Granger causality goes from liquidity to oil prices and from oil prices to the global interest rate, global industrial production and global CPI.

3.2. Which economies drive global variables?

With the upward surge of large developing economies such as China and India, and the creation of the Euro area in January 1999, a natural question arises: which economies drive the global economy? In Table 3a, results for Granger causality test between global interest rate and country-specific interest rates are shown. Similarly, in Tables 3b, 3c and 3d results are presented for the Granger causality test between global M2, global industrial production and global CPI and corresponding country-specific variables.

In Table 3a it is found that the interest rate in China Granger causes the global interest rate and vice versa at all lag lengths. This result is consistent with the view that China has become a major force in the world economy. There is also evidence that interest rates in the U.S., Euro area and Japan Granger cause the global interest rate and vice versa, depending on lag length. The interest rate in India and the global interest rate do not influence each other.

Table 1
Correlations of country and global data on each variable.

Country	Global M2	Global interest rate	Global output	Global CPI
Euro area	0.96 (0.83)	0.76	0.65 (0.73)	0.96 (−0.11)
U.S.	0.99 (0.11)	0.54	0.88 (0.56)	0.95 (−0.003)
China	0.99 (0.24)	0.76	0.63 (0.25)	0.86 (0.19)
Japan	0.93 (0.69)	0.77	0.71 (0.73)	0.82 (−0.68)
India	0.97 (0.21)	0.29	0.88 (0.16)	0.89 (−0.13)

Notes: Correlations are of logs (and in brackets of log first-differences) of country and global values for M2, output and consumer price index. The interest rate is in percent.

[14] A significant negative association between oil price shocks and economic activity has been found for most countries in their samples by Cologni and Manera (2008) for the G-7, Jimenez-Rodriguez and Sanchez (2005) for G-7 and Norway, and Cunado and Perez de Garcia (2005) for Asian countries.

Table 2
Granger causality tests for global oil price and global variables: 1999:1–2013:12 (log-level).

Granger test/lags	1	3	6	12	24
GOP does not Granger cause GIR	2.78***	2.17*	3.57***	2.51***	1.79**
GIR does not Granger cause GOP	0.70	0.87	0.69	1.34	1.56*
GOP does not Granger cause GM2	0.01	0.39	1.85*	1.22	0.79
GM2 does not Granger GOP	6.83***	3.46***	2.18**	1.82*	0.94
GOP does not Granger cause GIP	1.51	8.33***	5.99***	3.20***	2.13***
GIP does not Granger cause GOP	0.23	1.98	1.06	1.50	0.81
GOP does not Granger cause GCPI	1.99	2.14*	1.40	2.45***	1.85**
GCPI does not Granger cause GOP	0.66	2.13*	1.32	1.53	1.12

Notes: Variables are global oil price (GOP), global interest rate (GIR), global M2 (GM2), global industrial production (GIP), and global price level (GCPI). ***, **, and * indicate rejection of the null hypothesis at 1, 5 and 10% levels of significance, respectively.

Table 3a
Granger causality tests for global interest rate and country-specific interest rates: 1999:1–2013:12 (log-level).

Granger test/lags	1	3	6	12	24
USIR does not Granger cause GIR	12.7***	7.78***	5.54***	2.91***	1.42
GIR does not Granger cause USIR	33.02***	4.82***	2.55***	1.21	0.97
EAIR does not Granger cause GIR	4.27***	5.69***	2.79***	1.10	0.97
GIR does not Granger cause EAIR	6.00***	2.39*	4.47	1.37	1.81***
CHIR does not Granger cause GIR	14.23***	9.24***	3.80***	3.24***	2.26***
GIR does not Granger cause CHIR	7.17***	4.81***	3.12***	3.24***	1.79***
INIR does not Granger cause GIR	0.39	0.44	0.52	0.35	0.48
GIR does not Granger cause INIR	0.15	0.33	0.18	0.30	0.36
JIR does not Granger cause GIR	0.84	0.57	0.89	2.36***	1.57*
GIR does not Granger cause JIR	1.99	3.13***	1.56	1.49	1.25

Notes: Variables are global interest rate (GIR), U.S. interest rate (USIR), Euro Area interest rate (EAIR), China interest rate (CHIR), India interest rate (INIR), and Japan interest rate (JIR). ***, **, and * indicate rejection of the null hypothesis at 1, 5 and 10% levels of significance, respectively.

In Table 3b it is found that global M2 is Granger caused by M2 in China, Japan and the US. Only Japan's M2 Granger causes global M2. Global industrial production is driven by industrial production in all five economies (with the U.S. and Euro area having stronger results). Global industrial production Granger causes industrial production in the U.S., Euro area, China and Japan. Global inflation is driven by inflation in the U.S., Euro area, China and India, but not by inflation in Japan. Inflation in China and the Euro area is Granger caused by global inflation.

In summary, the results indicate that the U.S. and China have most breadth of influence across the global variables for interest rate, liquidity, and industrial production and consumer prices. It is found that in terms of Granger causality the U.S. and China influence the global interest rate, global M2, global industrial production and global CPI. The Euro area influences the global interest rate, global industrial production and global CPI (but not global M2). Japan influences global M2 and global industrial production (but not the global interest rate and global CPI). India influences global industrial production and global CPI (but not global interest rate and global M2), suggesting that India is most divorced from the global economy at least in terms of the financial variables (GIR and GM2). All five economies influence global industrial production. The results indicate a degree of interdependence between China and the global economy that is similar to levels of interdependence between the global economy and either the U.S., Euro area, or Japan.

Table 3b
Granger causality tests for global M2 and country-specific M2: 1999:1–2013:12 (log-level).

Granger test/lags	1	3	6	12	24
USM2 does not Granger cause GM2	7.98***	3.58***	2.32**	2.25**	1.92**
GM2 does not Granger cause USM2	0.06	1.31	0.63	0.62	0.85
EAM2 does not Granger cause GM2	0.34	1.11	1.23	0.90	0.95
GM2 does not Granger cause EAM2	0.00	1.47	1.13	1.20	1.30
CHM2 does not Granger cause GM2	7.41***	2.42*	1.17	1.17	1.44
GM2 does not Granger cause CHM2	0.97	0.49	0.82	0.81	1.10
INM2 does not Granger cause GM2	3.46*	1.10	1.63	1.30	0.81
GM2 does not Granger cause INM2	0.75	1.83	1.07	1.36	1.17
JM2 does not Granger cause GM2	5.73***	5.20***	2.94***	2.07**	1.10
GM2 does not Granger cause JM2	5.17***	4.59***	2.15*	1.63*	1.48*

Notes: Variables are global M2 (GM2), U.S. M2 (USM2), Euro Area M2 (EAM2), China M2 (CHM2), India M2 (INM2), and Japan M2 (JM2). ***, **, and * indicate rejection of the null hypothesis at 1, 5 and 10% levels of significance, respectively.

Table 3c
Granger causality tests for global industrial production and country-specific industrial production: 1999:1–2013:12 (log-level).

Granger test/lags	1	3	6	12	24
USIP does not Granger cause GIP	0.29	2.02	5.39***	3.55***	2.27***
GIP does not Granger cause USIP	0.84	6.34***	3.07***	2.17**	1.51*
EAIP does not Granger cause GIP	1.87	2.88**	5.40***	3.57***	2.28***
GIP does not Granger cause EAIP	1.58	4.05***	1.34	2.07**	1.44
CHIP does not Granger cause GIP	0.01	4.66***	1.95*	1.28	1.40
GIP does not Granger cause CHIP	21.66***	1.37	0.99	1.51	1.57*
INIP does not Granger cause GIP	0.02	4.32***	2.21*	1.48	1.26
GIP does not Granger cause INIP	0.18	2.47*	1.68	1.11	1.32
JIP does not Granger cause GIP	2.29	3.24***	1.14	0.96	0.70
GIP does not Granger cause JIP	0.21	2.95***	2.52**	1.97**	1.62*

Notes: Variables are global industrial production (GIP), U.S. industrial production (USIP), Euro Area industrial production (EAIP), China industrial production (CHY), India industrial production (INIP), and Japan industrial production (JIP). ***, **, and * indicate rejection of the null hypothesis at 1, 5 and 10% levels of significance, respectively.

Table 3d
Granger causality tests for global price level and country-specific price level: 1999:1–2013:12 (log-level).

Granger test/lags	1	3	6	12	24
USCPI does not Granger cause GCPI	3.06**	1.37	1.97	2.21**	1.00
GCPI does not Granger cause USCPI	1.74	1.70	0.68	1.26	1.20
EACPI does not Granger cause GCPI	2.94*	1.89	4.09***	2.25***	1.39*
GCPI does not Granger cause EACPI	3.33*	1.04	1.79	2.28***	2.24
CHCPI does not Granger cause GCPI	1.24	1.00	5.29***	6.75***	1.95**
GCPI does not Granger cause CHCPI	4.43**	12.60***	13.46***	4.28***	1.83**
INCPI does not Granger cause GCPI	3.56*	1.23	5.23***	4.13***	1.23
GCPI does not Granger cause INCPI	0.13	1.37	0.86	1.45	0.24
JCPI does not Granger cause GCPI	1.42	0.60	1.22	0.91	1.07
GCPI does not Granger cause JCPI	2.37	2.46*	1.65	1.80*	1.35

Notes: Variables are global price level (GCPI), U.S. price level (USCPI), Euro Area price level (EACPI), China price level (CHCPI), India price level (INCPI), and Japan price level (JCPI). ***, **, and * indicate rejection of the null hypothesis at 1, 5 and 10% levels of significance, respectively.

4. The model

The GFAVEC model can expressed as:

$$B_0 X_t = \beta + \sum_{i=1}^{j} B_i X_{t-i} + \varsigma Break_t + \varphi ECT1_{t-1} + \varepsilon_t \quad (5)$$

where j is an optimal lag length, determined by the Schwarz criterion (three lags in this case), X_t is an $n \times 1$ vector of endogenous variables, ECT_t is an $n \times 1$ vector of error correction terms (explained below), and $Break_t$ is an $n \times 1$ vector of dummy variables taking the value of 1 from 2008:M9 to 2008:12 and zero otherwise (as explained in the following section). B_0 is an $n \times n$ matrix of identifying restrictions, B_i, $i = 1, \ldots, j$, are $n \times n$ matrices of coefficients, ς is an $n \times 1$ vector of coefficients capturing change over the global financial crisis, φ is an $n \times 1$ vector of coefficients indicating speed of adjustment to long-run equilibrium, and ε_t is a random variable assumed to be independent of the variables on the right hand side of Eq. (5).[15]

[15] Pesaran et al. (2004) develop an error-correcting global VAR (GVAR) framework for global macroeconomic modelling. The GVAR combines models for each economy with foreign variables external to a domestic economy constructed on a trade-weighted basis.

The vector X_t is expressed as:

$$X_t = [GIR_t, \Delta\log(GM2_t),\ \log(GCPI_t), \Delta\log(GIP_t), \Delta\log(GOP_t), \Delta\log(USTWI_t)\ ]. \quad (6)$$

The endogenous variables in Eq. (6) are the global interest rate, global monetary aggregate, global consumer price level, global industrial production, oil price, and trade weighted U.S. dollar. For these global variables there is not a strong prior belief on variable order and concurrent restrictions. Country-specific analyses by Leeper and Zha (2003), Sims and Zha (2006a, 2006b), Sousa (2010, 2014) and others, identify a monetary policy rule equation within SVAR models founded on theory or the expected time of the central bank reaction to information being available. For example, a country-specific central bank is assumed to perceive inflation when inflation indicators are released and to react accordingly. Whether the global interest rate, capturing developed and developing country official interest rates, responds to global variables in the same way is not clear.

Our baseline analysis of the model in Eqs. (1)–(6) uses generalized cumulative impulse responses (GIRFs) on the grounds that contemporaneous restrictions for global variables are not established in the literature. Garratt et al. (2006) and Dees et al. (2007), in analysis of global systems, argue that generalized impulse response functions (GIRFs) can provide useful information on the dynamics of the transmission of shocks in vector autoregressive systems. Generalized impulse response analysis, developed by Koop et al. (1996) and Pesaran and Shin (1998), is invariant to the ordering of the variables and coincides with a Cholesky decomposition when the variable shocked is ordered first and does not react contemporaneously to any other variable in the system. In extensive robustness analysis of the GIRF results, we obtain and report outcomes from a structural model for the global economy that mimics country-specific models.

4.1. The long run relationship among money, prices and industrial production at global level

We investigate whether a long run relationship applies to the global variables of industrial production, consumer prices and money.[16] Our empirical analysis shows that an equilibrium relationship holds between these variables and that global money has a role to play in influencing global industrial production and prices. A cointegration relationship among global money, global industrial production and global prices is found to exist.[17] The error correction term in Eq. (1) is given by:

$$ECT_t = \log(GCPI_t) - \alpha - \theta\log(GIP_t) - \delta\log(GM2_t) \sim I(0). \quad (7)$$

Results for test of cointegration among global money, global industrial production and global prices are presented in Table 4. Table 4a reports that the Johansen cointegration test points to a unique cointegration vector when no trend and intercept is used and when trend and intercept is used. Following the literature, we specified the error correction term using intercept and trend. In Table 4b, the trace cointegration test reveals that the null hypothesis of the number of cointegration vectors is less or equal to r is rejected when r = 0 at 1% level, while either the hypothesis of r ≤ 1 and r ≤ 2 cannot be rejected even at 20% level. In the maximum eigenvalue test in Table 4c, the null hypothesis that the number of the cointegrating vector is r can only be rejected when r = 0, while the hypotheses of either r = 1 and r = 2 cannot be rejected even at 15% level.

4.2. Structural break and the global financial crisis

Fig. 3 shows a large drop in global interest rates from 2008:M9, during the period of the global financial crisis. Consequently, several dummy variables are introduced into the model to capture a possible structural break and are tested in this section. In Table 5, results from the log likelihood ratio test (LR) are presented, evaluating the model in Eqs. (5)–(7) with different dummy variables. We test dummy variables for 3 periods. First, a dummy variable to capture change in relationships between variables during the most intense period of the global financial crisis, dummy variable from 2008:09 to 2008:12, is introduced. Second, to test for the effect of change in the relationships between variables connected to possible systematic change in monetary policy during and after the global financial crises, a dummy variable is introduced from 2009:01 to the end of the sample. Thirdly, to capture the effects of both the first two dummy variables, a dummy variable is introduced from 2008:09 to the end of the sample. This dummy variable captures systematic change that started immediately with the initial shock of the global financial crisis and continues beyond the crisis through to the present.

Results in Table 5, shows that LR test rejects the null hypothesis of no structural break at 1% significant level for the dummy variable from the period 2008:09 to 2008:12 (the chi-square value is 39.66). The null hypothesis of no structural break for the dummy variables from the periods 2008:09 to 2013:12 and from 2009:01 to 2013:12 cannot be rejected. In line with these results, we include a dummy variable, value 1 over 2008:09 to 2008:12 and 0 otherwise, in the model in Eqs. (5) to (7).

5. Empirical results

The generalized cumulative impulse responses of variables in the GFAVEC model (in Eqs. (5), (6) and (7)) to one-standard deviation structural innovations are shown in Fig. 4. The dashed lines represent a one standard error confidence band around the estimates of the coefficients of the impulse response functions.[18] The first row in Fig. 4 shows the response of the global interest rate to structural innovations in the global interest rate, global M2, global CPI, global industrial production, oil price, and the trade weighted U.S. dollar exchange rate, in turn. Similarly, the second, third, fourth, fifth and sixth rows show the response of global M2, global CPI, global industrial production, oil price, and the trade weighted US dollar exchange rate, respectively, to structural innovations in GIR_t, $\Delta\log(GM2_t)$, $\Delta\log(GCPI_t)$, in $\Delta\log(GIP_t)$, $\Delta\log(GOP_t)$, and $\Delta\log(USTWI_t)$ in turn.

5.1. Response of global interest rate to structural shocks

It is not clear from the literature what the effects on global interest rates should be from structural shocks to the global variables. The countries in the G5 have different exchange rate regimes, capital controls and monetary policies. There is no global central bank and the global interest represents the first principal component of the data on the discount rates of the G5.

In the first row of Fig. 4, a positive shock to global M2 is associated with a rising global interest rate over time. This result is consistent with Thornton's (2014) observation that a liquidity effect is not observed at country level. Also in the first row of Fig. 4, positive shocks to global CPI, to global industrial production, and to oil price lead to statistically significant and persistent increases in the global interest rate (in the third through fifth diagrams in row 1).[19] The results indicate

[16] Examples of investigations of cointegration (based on work by Engle and Granger (1987)) between price level, monetary aggregate and industrial production for the US are provided by Swanson (1998); Bachmeier and Swanson (2005); Garratt et al. (2009); Browne and Cronin (2010), and others.

[17] Note that the coefficients for the estimated ECT for the G5 and G8 economies are: $\log(GCPI_t) = -48.19 + 0.051\log(GIP_t) + 5.19\log(GM2_t)$ and $\log(GCPI_t) = -1.85 + 0.388\log(GIP_t) + 0.016\log(GM2_t)$, respectively. Note that all coefficients are statistically significant at least at 5% and signs are consistent with economic theory.

[18] 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.

[19] Consistent with this finding, Mallick and Sousa (2013) report that commodity price shocks can result in an aggressive response from BRIC central banks concerned with inflation stabilisation.

Table 4
Cointegration test: logs of global CPI (GCPI), global money (GM2) and global industrial production (GIP).

a) Cointegration test with different specifications

Endogenous variables: log(global CPI_t), log(global $M2_t$), log(global industrial production)

Test type	None trend and intercept	Linear trend and intercept
Trace	1	1
Max-Eig	1	1

Notes: *Critical values based on MacKinnon-Haug-Michelis (1999). **Selected (0.05 level*) number of cointegrating relations by model.

b) Unrestricted cointegration rank test (trace)

Null hypothesis: the number of cointegrating vectors is less than or equal to r
Alternative hypothesis: there are more than r cointegrating vectors

Hypothesized		Eigenvalue	Trace statistic	0.05 Critical value	Prob.**
Null	Alternative				
r = 0	r ≥ 1	0.19	45.5	29.79	0.00
r ≤ 1	r ≥ 2	0.05	9.94	15.49	0.28
r ≤ 2	r ≥ 3	0.00	0.24	3.94	0.62

**MacKinnon-Haug-Michelis (1999) p-values

c) Unrestricted cointegration rank test (maximum eigenvalue)

Null hypothesis: the number of cointegrating vectors is r

Alternative hypothesis: there are (r + 1) cointegrating vectors

Hypothesized		Eigenvalue	Max-eigenvalue stat.	0.05 Critical value	Prob.**
Null	Alternative				
r = 0	r = 1	0.22	60.83	42.9	0.00
r = 1	r = 2	0.07	20.9	25.88	0.18
r = 2	r = 3	0.04	7.94	12.52	0.25

**MacKinnon-Haug-Michelis (1999) p-values

that there is a general tightening of monetary policy on a global level, as indicated by a rise in the global interest rate, when global level liquidity is increasing, the economy is heating up in terms of rising industrial production and prices, and oil prices are rising.

A positive shock to the trade weighted value of the U.S. dollar results in a significant decline in the global interest rate (in the sixth diagram in row 1 of Fig. 4). This result is in harmony with Shin's (2014) reasoning that a stronger U.S. dollar constitutes a tightening of global financial conditions that central banks might offset. The burden of dollar-denominated debt repayment results in a tightening of global financial conditions when the U.S. dollar rises.

5.2. Response of global variables to structural shock to global interest rate

In the first column of Fig. 4, a positive shock to global interest rates leads to a statistically significant and persistent decline in global M2. Monetary tightening at global level is connected with reduced CPI and nominal oil price, and after a positive bump to reduced global industrial production. This is consistent with the finding by Hammoudeh et al. (2015) within a structural VAR framework that increases in the federal funds rate are associated with declines in energy prices. In the second column of Fig. 4, a positive shock to global M2 is linked with increases in CPI and nominal oil price, and after four months with increased global industrial production.

Table 5
LR test.

Null hypothesis for LR test: no structural change

Alternative hypothesis for LR test: structural change

	Degree of freedom	χ^2 critical value with at 95%	χ^2 value
Dummy variable: 2008:M9 to data end	6	12.59	5.95
Dummy variable: 2008:M9 to 2008:M12	6	12.59	39.66***
Dummy variable: 2009:M1 to data end	6	12.59	2.14

Notes: The LR test is $LR = (T-m)(\ln|\Sigma_r| - \ln|\Sigma_{ur}|) \sim \chi^2(q)$, where: T is the number of observations, m is the number of parameters in each equation of the unrestricted system plus contains, Σ is the determinant of the residual covariance matrix, and q is the number of dummy variables times number of equations.
*** denoting significance at the 1%.

5.3. Liquidity and structural shocks

The second column in Fig. 4 reports the effects on the global variables of a positive structural shock to liquidity. Global liquidity significantly impacts global CPI 3 and 4 months later. The impact on oil price is statistically significant after 3 months and remains so over the 20-month horizon. A positive innovation in global liquidity significantly impacts industrial production over a 5 to 13-month horizon. In line with results in the literature, increases in global liquidity are associated with global expansion and rising oil and global consumer prices.

5.4. The oil price and structural shocks

The impulse responses of oil price to global variables are presented in the fifth row of Fig. 4. A negative shock to global interest rates and positive shocks to global M2, to global CPI, and to global industrial production, lead to statistically significant and persistent increases in global oil price (in the first through fourth diagrams). A positive innovation in M2 supports a higher level of spending with positive effects on nominal oil price. A positive shock in the global CPI, reflects a negative shock to the real price of oil and an increase in oil price. A positive innovation in global industrial production indicates a higher level of global real activity with concomitant increases in the demand for crude oil and an increase in the global oil price.

In the fifth column of Fig. 4, a positive innovation in oil price is associated with a statistically significant positive effect on the global interest

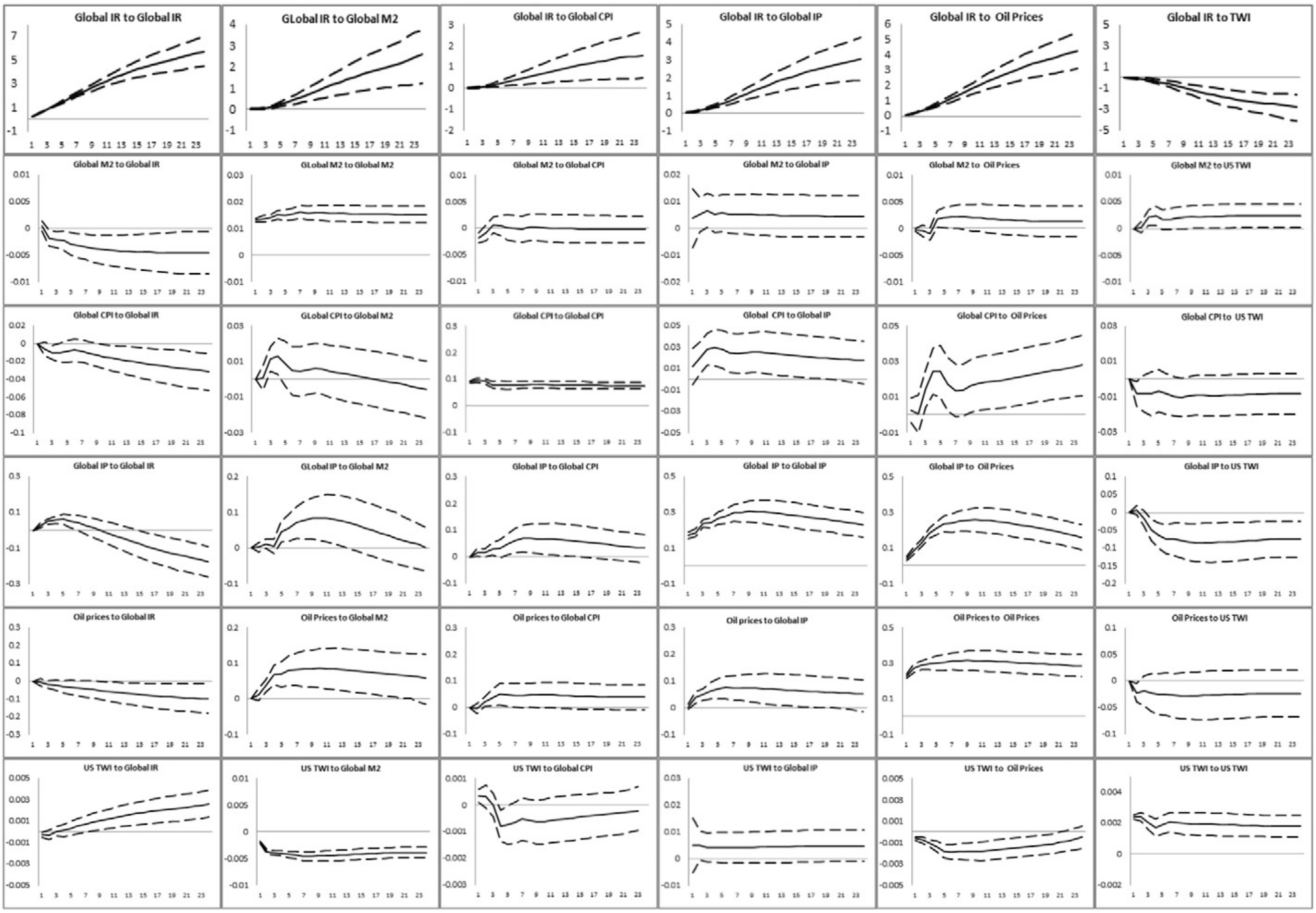

Fig. 4. Cumulative impulse response function 1999:01 to 2013:12. Notes: Each row shows the cumulative impulse response of a variable to one-standard deviation generalized innovations in the global interest rate, global M2, global CPI, global industrial production, oil price, and the trade weighted U.S. dollar exchange rate, respectively. The variables being impacted in the first through sixth row are in descending order global interest rate, global M2, global CPI, global industrial production, oil price, and the trade weighted U.S. dollar exchange rate. The impulse responses are obtained from the GFAVEC model in Eqs. (5), (6) and (7). The dashed lines represent a one standard error confidence band around the estimates of the coefficients of the impulse response functions.

rate and on global industrial production. The finding of a positive association between oil price and global output may seem surprising. However, at the global level a rise in oil price has a distribution effect between consumers and producers of oil as well as a positive effect on the production of oil. The effect of a rise in oil price on global industrial production depends on the overall effects on global consumption and investment in reaction to a rise in the real price of oil.

Positive shocks to oil price have significant effects on global M2 and global CPI at impact only.[20] A negative shock in oil price leads to a statistically significant increase in the trade weighted value of the U.S. dollar. A rise in the price of oil is associated with the depreciation of the dollar because the U.S. trade deficit widens. This latter result is consistent with the finding by Aloui et al. (2013) that a rise in the price of oil is associated with the depreciation of the U.S. dollar.

6. Robustness of results to alternative specifications

In this section, the robustness of results to changing the definition of the global variables, to alternative identification restrictions, and to different definitions of the principal components is examined.

6.1. G8 economies

We expand the analysis from the five largest economies to the eight largest economies on GDP based on purchase power parity (PPP). This means in constructing principal components for the interest rate, industrial production and inflation we add data on these variables for Russia, Brazil and the U.K. to those for the U.S., Euro area, Japan, China and India. Our first preference is to use data from the five largest economies because these economies are much closer in size than the sixth, seventh and eights economies (Russia, Brazil and the U.K.). Boivin and Ng (2006) caution that expansion of the underlying data could result in factors that are less helpful for forecasting when a useful factor in a small dataset becomes dominated in a larger dataset.[21] However, the major developing economies (taken to be the BRIC countries, Brazil, the Russian Federation, India and China) have had dramatic increases in real income in recent years and their inclusion along with the largest developed economies in an analysis of global effects of oil prices is a reasonable robustness analysis. The G8 economies account for around 70% of world GDP measure by real PPP in U.S. dollars. The global measure of M2 will now be the sum of M2 in the largest eight economies in U.S. dollars.

It is found that global prices, global industrial production and global monetary aggregate remain cointegrated with expansion to consideration of the G8 economies. The LR test with data for the G8 economies

[20] Valadkhani (2014) suggests that the relationship between oil price and the consumer price index has changed over time (for Canada and the U.S.).

[21] Note that the risk of including economies of different sizes may lead to the overrepresentation (weights) of small economies when principal components are estimated.

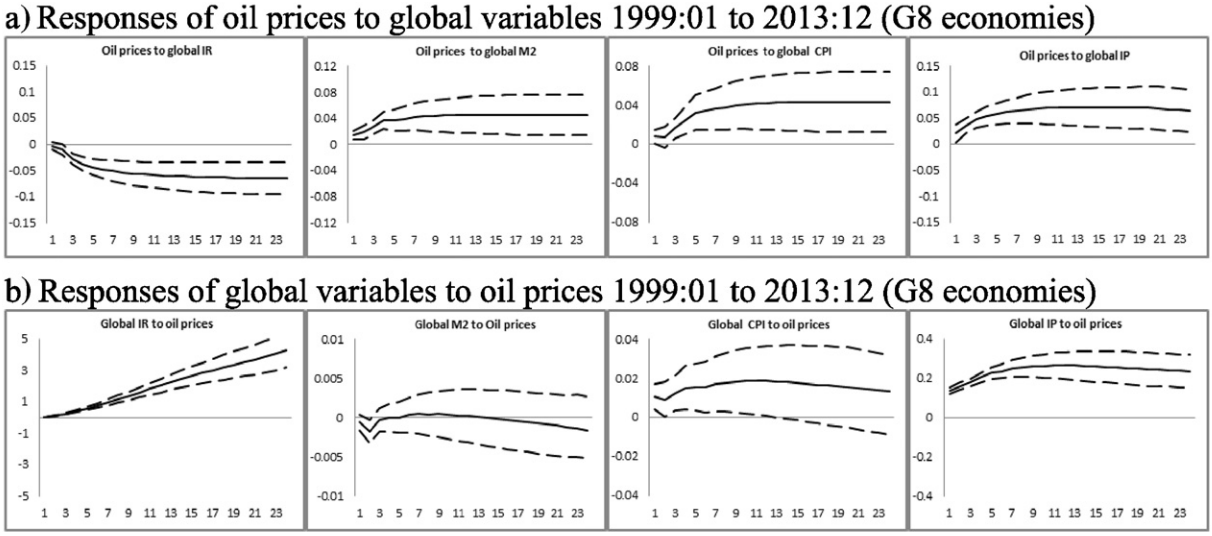

Fig. 5. a. Responses of oil prices to global variables 1999:01 to 2013:12 (G8 economies). b. Responses of global variables to oil prices 1999:01 to 2013:12 (G8 economies). Notes: The first row in this figure shows the response of the oil prices to one-standard deviation generalized innovations in the global interest rate, global M2, global CPI, global industrial production, oil price, and the trade weighted U.S. dollar exchange rate using data for the G8 economies. The second row in this figure shows the response the macro variables to one-standard deviation generalized innovations in oil prices. The dashed lines represent a one standard error confidence band around the estimates of the coefficients of the impulse response functions.

shows that the null hypothesis of no structural break is rejected at 1% (chi-square value of 38.26) with a dummy variable from the period 2008:09 to 2008:12 to capture the global financial crisis.

The GIRFs of oil price to global variables based on the eight largest economies are presented in Fig. 5a. Key results are unchanged from those obtained based on analysis of the five largest economies. Monetary easing on a global scale is linked to rising oil prices. Positive innovations in global M2, in global CPI, and in global industrial production, are associated with statistically significant and persistent increases in global oil price. The effect of global CPI on oil price is positive and statistically significant. The GIRFs of global variables to positive shocks to oil price appear in Fig. 5b. The main result is similar for the model for the eight largest economies to that obtained from the model for the five largest economies, with a positive innovation in oil price being associated with statistically significant positive effects on the global official interest rate.

6.2. Structural identification restrictions and estimates

In this section we obtain impulse response function (IRF) results from a model with identifying restrictions for the global economy that parallel identifying restrictions made by Kim and Roubini (2000) for individual advanced economies. We also compare the IRF results with the GIRF results. Similar restrictions are also used by Gordon and Leeper (1994), Sims and Zha (2006b), Christiano et al. (1999) and Kim (2001). Dedola and Lippi (2005) introduce a commodity price index rather than oil price into the VAR model. The contemporaneous impact of monetary policy shocks on industrial production and consumer prices is zero. Forni and Gambetti (2010) refer to this as a standard identification scheme.

In the Kim and Roubini (2000) model, the monetary policy feedback rule does not allow monetary policy to respond within the month to price level and industrial production events, but allows a contemporaneous response to both monetary aggregates and oil prices. Monetary aggregate responds contemporaneously to the domestic interest rate, CPI and industrial production, assuming that the real demand for money depends contemporaneously on the interest rate and real income. The CPI is influenced contemporaneously by both industrial production and oil prices, while industrial production is assumed to be influenced by oil prices. Oil prices are assumed to be contemporaneously exogenous to all variables in the model on the ground of information delay. Given the forward looking nature of the exchange rate on asset prices and this variable's information daily availability, the exchange rate is assumed to respond contemporaneously to all variables in the model.

In line with this discussion of identifying restrictions based on Kim and Roubini (2000), the matrix B_0X_t in Eq. (5) is given by:

$$B_0X_t = \begin{bmatrix} 1 & -b_{01} & 0 & 0 & -b_{04} & -b_{05} \\ -b_{10} & 1 & -b_{12} & -b_{13} & 0 & 0 \\ 0 & 0 & 1 & -b_{23} & -b_{24} & 0 \\ 0 & 0 & 0 & 1 & -b_{34} & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 \\ -b_{50} & -b_{51} & -b_{52} & -b_{53} & -b_{54} & 1 \end{bmatrix} \begin{bmatrix} \Delta\log(GIR_t) \\ \Delta\log(GM2_t) \\ \Delta\log(GCPI_t) \\ \Delta\log(GIP_t) \\ \Delta\log(GOP_t) \\ \Delta\log(USTWI_t) \end{bmatrix}. \tag{8}$$

Fig. 6 shows the responses of variables in the GFAVEC using the identifying restrictions in Eq. (8) to one-standard deviation structural innovations. The dashed lines represent a one standard error confidence band around the estimates of the coefficients of the (structural) IRFs.[22] The estimates are for the G8 economies (results are virtually the same for the G5 economies).[23] In comparing cumulative impulse response results from the structural model in Eq. (8) with the generalized cumulative impulse response functions in Fig. 4, we find very few differences. The main findings are unchanged. Positive innovations in global oil price are linked to statistically significant global interest rate tightening. Positive innovations in global money and industrial production are connected with statistically significant increases in oil prices. Positive innovations in global interest rate are associated with statistically significant declines in oil prices, and positive shocks to the trade weighted U.S. dollar are linked with statistically significant reductions in oil price.

6.3. Different weights in principal components

Our baseline model uses principal components with normalise loadings. In this section we use principal components with normalise scores. Results with principal components with normalise scores are very similar to those for principal components with normalise loadings. The

[22] 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.

[23] Note that contemporaneous coefficients are generally statistically significant at 10% in both the systems in Eq. (5) and in Eq. (8).

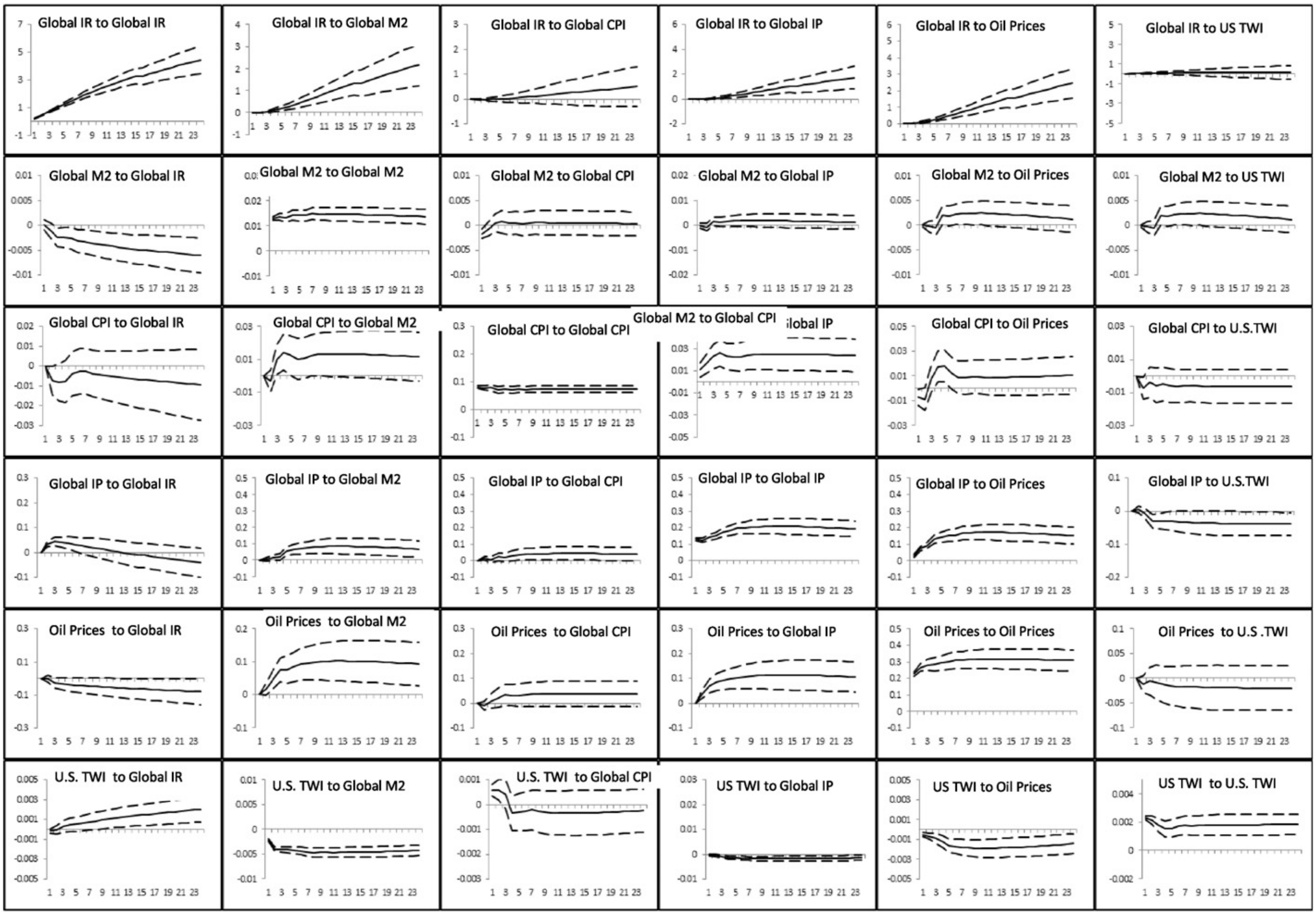

Fig. 6. Cumulative impulse response functions for G8 variables 1999:01 to 2013:12. Notes: The cumulative impulse responses are obtained from the GFAVEC model in Eq. (8) based on data for the G8. Each row shows the cumulative impulse response of a variable to one-standard deviation structural innovations in the global interest rate, global M2, global CPI, global industrial production, oil price, and the trade weighted U.S. dollar exchange rate, respectively. The variables being impacted in the first through sixth row are in descending order global interest rate, global M2, global CPI, global industrial production, oil price, and the trade weighted U.S. dollar exchange rate. The cumulative impulse responses are obtained from the GFAVEC model with identifying restrictions in Eq. (8). The dashed lines represent a one standard error confidence band around the estimates of the coefficients of the impulse response functions.

GIRFs of oil price (global variables) to global variables (oil price) with principal components with normalise scores are shown in Fig. 7a, b.

6.4. Statistical properties of the GFAVEC model

To test for autocorrelation, the residual serial correlation LM test is estimated. Since the data utilized in this study are monthly, we use twelve lags in the serial correlation LM test in the event that seasonality effects are present. The results for this test for models specified in Sections 4, 6.1, 6.2 and 6.3 suggest the absence of serial correlation. In particular, the null hypothesis of no serial correlation cannot be rejected in the first lag (at the 5% level).

Residual heteroskedasticity LM tests for all models are also estimated. It is found that the null hypothesis of no heteroskedasticity of the joint combinations of all error term products cannot be rejected at the 5% level for all models. (For the residual serial correlation and the residual heteroskedasticity LM tests see Enders (2004; Chapter 5)).

An important condition to be satisfied in the VAR/VEC model is that the lag structure included be stationary. This condition is investigated by the inverse roots of AR characteristic test. For all models specified in Sections 4, 6.1, 6.2 and 6.3, the AR characteristic test shows that no root lies outside the unit circle, suggesting that our models have stable roots. (For the AR characteristic test see Enders (2004); p. 266)). All results in this section are available upon request from the authors.

7. Conclusion

This paper proposes the use of a global factors augmented error correction model (GFAVEC) to examine the dynamic interaction of global interest rates, global industrial production, and global CPI, and the trade weighted value of the U.S. dollar with world oil prices. This novel approach is used to identify shocks to these variables using GIRF or structural shocks. Structural factors are constructed to capture information provided by many variables (countries). Global factors are estimated using principal component techniques applied to policy interest rates, industrial production and CPI across countries. The collective stance of monetary policy actions by major central banks is caught by the level of global interest rates. A global factor is also estimated for the global price of oil from the various leading oil price indices.

Global money, global industrial production and global prices are cointegrated. Granger causality goes from global liquidity to oil prices and from oil prices to the global interest rate, global industrial production and global CPI. Monetary tightening indicated by positive innovation in central bank discount rates results in significant and sustained decreases in oil prices. Positive shocks to global M2, to global CPI, and to global industrial production, lead to statistically significant and persistent increases in global oil price. A negative innovation in the trade weighted value of the U.S. dollar rate leads to statistically significant and persistent increase in global oil price in U.S. dollars. A rise in oil price results in significant increases in global interest rates. A positive

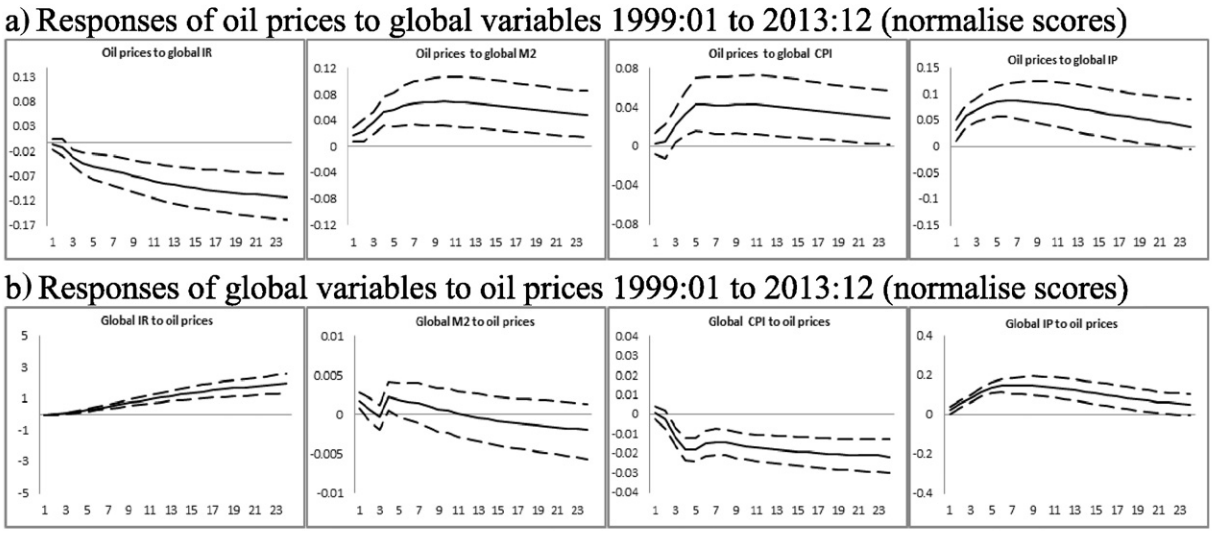

Fig. 7. a. Responses of oil prices to global variables 1999:01 to 2013:12 (normalise scores). b. Responses of global variables to oil prices 1999:01 to 2013:12 (normalise scores). Notes: The first row in this figure shows the generalized impulse responses of the oil price (to one-standard deviation innovations) using data with principal components constructed with normalise scores for the G5 economies. The second row in this figure shows and the response the macro variables to one-standard deviation generalized innovations in oil prices. The dashed lines represent a one standard error confidence band around the estimates of the coefficients of the impulse response functions.

innovation in (U.S. dollar) oil price leads to a decline in the trade weighted value of the U.S. dollar rate.

Granger causality tests from economy-level to global-level variables show that, for the period 1999–2013, the U.S. and China variables Granger cause the global variables, global interest rate, global M2, global industrial production and global CPI. The Euro area variables Granger cause 3 out of 4 global variables (global interest rate, global industrial production and global CPI), and India and Japan Granger cause 2 out of 4 global variables (Japan's variables influence global M2 and global industrial production while India's variables influence global industrial production and global CPI). The results indicate a degree of interdependence and influence between China and the global economy that is somewhat similar to levels of interdependence between the global economy and either the U.S. or Euro area.

We emphasize that the paper examines the linear effects of an oil price shock on global macroeconomic variables. A number of papers in the literature note that the interconnections between oil prices and economic activity are more complicated. It is documented that oil shocks may have an asymmetric impact on macroeconomic variables and that nonlinearities in the connections may be important. Previous empirical analyses have found that changes in oil price volatility significantly affect macroeconomic variables (Ferderer, 1997; Lee et al., 1995). Unexpected oil price movements can be associated with increased uncertainty about future oil prices (Bernanke, 1983; Pindyck, 1991), leading firms to delay investments decisions. As a result, not only oil price increases but also high oil price volatility is detrimental to economic growth with complications for monetary policy. Future work should address the implications of asymmetric, nonlinearities, and uncertainty in the relationships between oil price shocks and global macroeconomic variables.

The global official/policy interest rate set by central banks has been shown to play a major role the dynamic interconnections between world oil price shocks and global macroeconomic variables. Positive innovations in global oil price are associated with increases in the global official/policy interest rate and positive innovations in the latter are associated with decreases in global oil price. When making decisions to shape the global economy, decision makers at central banks should recognise that these links exist even in the absence of formal policy coordination.

Appendix A

A.1. Statistics on the principal components

Fig. A.1. contains a plot of the variance of the principal components using normalise loadings for the interest rate, industrial production, CPI and oil price. Each plot shows the variance accounted for by the first component and then for the second, third, etc., components for each variable. In Tables A1 and A2, we report the percentage of total variance explained by the first, second and third principal components, for the five largest and for the eight largest economies, respectively. For the global CPI and global oil price, in particular, the first principal components capture nearly all of the information in the five economy-level consumer price indices (88%) and the three oil price indices (99%). The first principal component for industrial productions (interest rate) captures 60% (46%) of the news in the five economy-level interest rates (industrial production). It is shown that for both groups of economies the percentage of total variance explained by the first, second and third principal components are very similar.

Alternative principal components can also be derived from the Eqs. (1) through (4). These alternatives are: normalise loadings (where the variance is equal to the estimated eigenvalues; normalise scores (with unit variances with symmetric weights); and with equal weighted scores and loadings. The representation for equal weighted scores and loadings falls in between those for normalise loadings and normalise scores. In the basic model constructing principal components we use normalise loadings.

A.2. Stationary properties of the data

In Tables A3 and A4 the stationary properties of the data are reported for the country-specific variables and the global variables, respectively. Augmented Dickey–Fuller (ADF) test and the Kwiatkowski–Phillips–Schmidt–Shin (KPSS) are estimated for all variables. The null hypothesis for the ADF test is that the variable has a unit root and the null hypothesis for the KPSS test is that the variable is stationary. Test results for the interest rate are omitted in line with procedure in the literature (e.g. Kim (2001); Kim and Roubini (2000) and Sims and Zha, 2006a, 2006b). The interest rate is generally used in levels since it is bounded by zero and expressed as an annual percentage change.

Under the ADF and the KPSS tests, the country-level data for the monetary aggregate, consumer price index and industrial production are for most cases only first difference stationary. For China M2 the ADF test does not reject the null hypothesis of a unit root (indicating that the variable is second-different stationary) and the KPSS test does reject the null hypothesis that this variable is only first difference stationary (at conventional levels of confidence). For China industrial production, the ADF test indicates that this variable is first different stationary while the KPSS test cannot confirm this result. To be consistent with our estimations across countries we decided to work with these variables in first differences.

In testing the stationary properties of oil prices (the last 3 rows in Table A3), results indicate that Dubai and Brent oil prices are only first difference stationary. For WTI oil prices results are less clear with the ADF test indicating first difference stationary and the KPSS test indicating only second difference stationary (results available upon request). Following the literature and for comparison reasons, we decided to use these variables in first difference.

In Table A4, the ADF and KPSS tests indicate that the logs of global M2, global consumer price index, global oil price, and trade weighted U.S. dollar are first difference stationary. The results for global industrial production are ambiguous, with the KPSS test being consistent with first difference stationary, and the ADF test rejecting the null hypothesis of unit root at 10% level of confidence. For consistency with country-level studies, we treat global industrial production as a first difference stationary variable.

A.3. Global principal components estimation: G5 vs. G8 largest economies

In Fig. A2 the global variables created with principal components for both the group of five largest economies and the group of eight largest economies are plotted. For conciseness the group of five largest economies is termed G5 and the group of eight largest economies is termed G8. The global interest rate (first principal component) based on the G5 is slightly higher (lower) in the first (second) half of the sample than that based on the G8. However, the movements in both G5 and G8 based global interest rates closely track one another.

The global CPI based on data for the G8 has a steeper slope the global CPI based on data for the G5. This is probably due to Brazil and Russia both having had substantial increases in price levels (compared with the other economies) over 1999–2013. Global industrial production, given by the principal component for industrial production in the G8 has fewer steep recessions following 2001 (the recession in the U.S.) and that following the global financial crisis than indicated by the principal component for industrial production in the G5. M2 for the G8 shows similar pattern to that for the G5.

Table A1
Variation explained by the first, second and third principal components for each variable for the five largest economies and for oil prices.

	Interest rate	Output	CPI	Oil prices
1st principal component	44.5%	60.0%	89.6%	99.6%
2nd principal component	21.7%	33.7%	9.0%	0.31%
3st principal component	17.1%	4.2%	0.1%	0.01%

Notes: The five largest economies are the U.S., Euro area, China, Japan and India.

Table A2
Variation explained by first, second and third principal components for each variable for the eight largest economies.

	Interest rate	Output	CPI
1st principal component	46.1%	62.1%	90.1%
2nd principal component	19.0%	33.1%	7.3%
3st principal component	15.8%	2.4%	1.5%

Notes: The eight largest economies are the U.S., Euro area, China, Japan, India, the U.K., Russia and Brazil.

Table A3
Test for unit roots 1999:1–2013:12: Domestic variables.

Null hypothesis for ADF test: the variable has a unit root.
Alternative hypothesis for ADF test: the variable has not a unit root.
Null hypothesis for KPSS test: variable is stationary.
Alternative hypothesis for KPSS test: variable is not stationary.

Level	ADF	KPSS	First difference	ADF	KPSS
log ($USM2_t$)	0.21	1.62***	Δlog ($USM2_t$)	−10.08***	0.094
log ($EAM2_t$)	−0.49	1.54***	Δlog ($EAM2_t$)	−12.37***	0.16
log ($CHM2_t$)	0.37	1.62***	Δlog ($CHM2_t$)	−1.95	0.74
log ($JM2_t$)	−0.12	1.40***	Δlog ($JM2_t$)	−12.66***	0.12
log ($INM2_t$)	−0.98	1.61***	Δlog ($INM2_t$)	−11.29***	0.2
log ($USCPI_t$)	−1.08	1.63***	Δlog ($USCPI_t$)	−8.90***	0.13
log ($EACPI_t$)	−0.41	1.63***	Δlog ($EACPI_t$)	−3.32**	0.24
log ($CHCPI_t$)	−0.17	1.55***	Δlog ($CHCPI_t$)	−2.58*	0.3
log ($JCPI_t$)	−2.25	0.94***	Δlog ($JCPI_t$)	−2.75*	0.1
log ($INCPI_t$)	4.63	1.57***	Δlog ($INCPI_t$)	−2.58*	0.72*
log ($USIP_t$)	−2.42	0.40*	Δlog ($USIP_t$)	−3.09**	0.07
log ($EAIP_t$)	−2.3	0.34*	Δlog ($EAIP_t$)	−3.95***	0.11
log ($CHIP_t$)	−2.52	1.61***	Δlog ($CHIP_t$)	−2.62*	1.11***
log (JIP_t)	−2.53	0.35*	Δlog (JIP_t)	−10.35***	0.06
log ($INIP_t$)	−0.75	1.62***	Δlog ($INIP_t$)	−18.03***	0.15
log (OPD_t)	−2.19	1.54***	Δlog (OPD_t)	−9.52***	0.08
log (OPW_t)	−2.43	1.48	Δlog (OPW_t)	−9.81***	0.1
log (OPB_t)	−2.29	1.52***	Δlog (OPB_t)	−9.35***	0.09

Notes: U.S., EA, J, CH and IN indicate the U.S., Euro area, China, Japan and India, respectively. M2, CPI and IP indicate M2, consumer price index and industrial production, respectively. OPD, OPW and OPB indicate Dubai, WTI and Brent oil price, respectively. The first difference of the series is indicated by Δ. The lag selection criteria for the ADF are based on Schwarz information Criteria (SIC) and for the KPSS is the Newey–West Bandwidth. ***, **, and * indicate rejection of the null hypothesis at 1, 5 and 10% levels of significance, respectively.

Table A4
Test for unit roots 1999:1–2013:12: Global variables.

Null hypothesis for ADF test: the variable has a unit root.
Alternative hypothesis for ADF test: the variable has not a unit root.
Null hypothesis for KPSS test: variable is stationary.
Alternative hypothesis for KPSS test: variable is not stationary.

Level	ADF	KPSS	First difference	ADF	KPSS
log ($GM2_t$)	0.92	1.61***	Δlog ($G3M2_t$)	−12.90***	0.24
log ($GCPI_t$)	−1.92	1.52***	Δlog ($GCPI_t$)	1.00***	0.73
log (GIP_t)	−2.94*	0.77***	Δlog (GIP_t)	−4.56***	0.09
log (GOP_t)	−2.51	1.51***	Δlog (GOP_t)	−10.01***	0.11
log ($USTWI_t$)	−0.99	1.41***	Δlog ($USTWI_t$)	−9.22***	0.09

Notes: Variables are global M2 (GM2), global price level (GCPI), global industrial production (GIP), global oil price (GOP), and global interest rate (GIR), and trade weighted index of the U.S. dollar (USTWI). The first difference of a series is indicated by Δ. The lag selection criteria for the ADF is based on Schwarz information Criteria (SIC) and for the KPSS is the Newey–West Bandwidth. ***, **, and * indicate rejection of the null hypothesis at 1, 5 and 10% levels of significance, respectively.

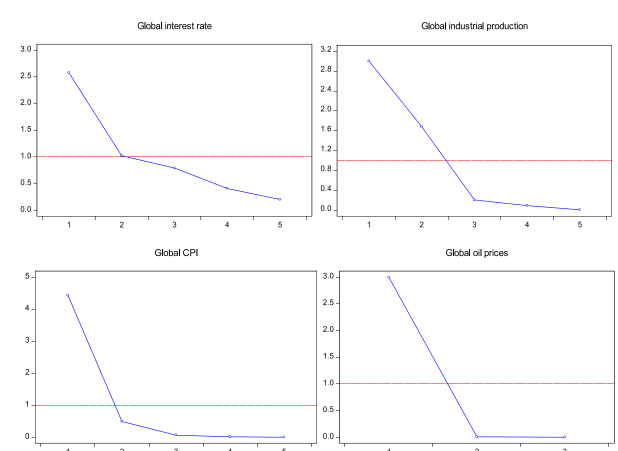

Fig. A1. Scree plot (ordered eigenvalues) for global principal components.

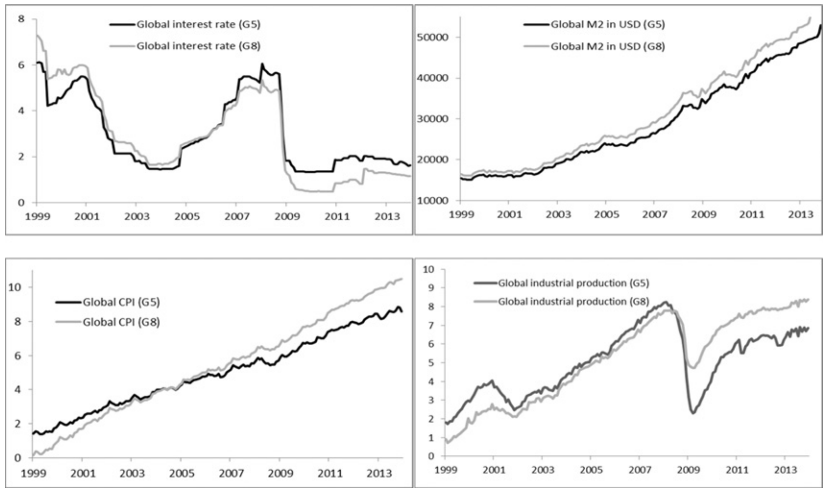

Fig. A2. Global principal components estimation: G5 vs. G8 largest economies. Notes: The G5 consists of the U.S., Euro area, China, India, and Japan. The G8 consists of the G5 plus Brazil, Russia and the U.K.

Appendix B. Supplementary data

Supplementary data to this article can be found online at http://dx.doi.org/10.1016/j.eneco.2016.06.002.

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