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Abstract

We extend Jurado et al. (2015)'s forecast-error-based uncertainty measure to the international context, and construct a new measure of global uncertainty. We examine dynamic causal effects among global uncertainty and other global macroeconomic variables, and provide two important applications of our global uncertainty measure by linking it to the price formation mechanism of oil and international uncertainty spillover effects. We show that the well-documented relation between uncertainty and real activities is not only a regional issue, but also a global phenomenon. Global uncertainty also plays a key role in determining commodity prices, as well as driving business cycle fluctuations in a certain economy.

JEL Classification: C32, E32, F44, O13

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1 Introduction

The Global Financial Crisis of 2007-2009 has brought to the surface the need of understanding macroeconomic uncertainty as an important source of business cycle fluctuations. Since the seminal work of Bloom (2009), the cause and impact of uncertainty draws more and more attention in the economic research and has been studied extensively (e.g. Bachmann et al., 2013; Baker et al., 2016; Caggiano et al., 2014; Carriero et al., 2017; Gilchrist et al., 2014; Jurado et al., 2015; Ludvigson et al., 2016). Most of these studies construct novel uncertainty measures for a certain country, based on a variety of methods. However, there is few research that develops a homogeneous global uncertainty measure, and investigates the macroeconomic impact of uncertainty in the global context.

Understanding the macroeconomic impact of uncertainty in the global context is extremely important. First, consider the commodity market as an example, Kilian (2009) argues that the roots of oil price fluctuations can be decomposed into three components: oil supply, aggregate demand, and oil-specific demand shocks. Leduc and Liu (2016) further points out that the uncertainty shocks are essentially one kind of the aggregate demand shocks. Meanwhile, given the features of a world primary commodity, the price of oil is not likely to be determined by the macroeconomic status of a single country, but rather be set by the overall global economic conditions. Therefore, a global uncertainty measure is needed to understand the price fluctuations of such an important international commodity.

Second, as noted by Mumtaz and Theodoridis (2017), the common global component plays a critical role in driving the time-varying uncertainty across the countries.[1] Macroeconomic uncertainty, even originated within one country, may have impacts beyond that country or even its region. Such kind of spillover effects would not be captured in a satisfactory manner by the existing methodologies unless measuring the uncertainty at the global level. Constructing a global uncertainty measure to identify the spillover effect complements the conventional studies that investigate the impact of country-specific uncertainty on business cycles in a particular economy.[2]

1. The increased globalisation and trade openness are two underlying driving forces behind this increased cross-country macroeconomic uncertainty correlations.

2. Nakamura and Steinsson (2014) and Mumtaz (2018) also point out that, under property conditions, the global uncertainty measure may serve as a underlying instrument for regional and country specific uncertainty index. This is the key in addressing the exogenous problem in the research which investigates the uncertainty impact.

The first objective of this paper is to develop a homogeneous global macroeconomic uncertainty measure. To achieve this goal, we compile a comprehensive dataset that contains 33 world major economies, covering both developed and major developing counties. The dataset includes primary macroeconomic indicators such as GDP, CPI, interest rate, and etc. The time span is 1980 to 2016. We follow the classical econometric framework as in Jurado et al. (2015).[3] This method measures macroeconomic uncertainty as the conditional variance of the unforecastable component common to a set of macroeconomic variables. The methodology, along with the compiled abundant dataset, allows us to construct a homogeneous global macroeconomic uncertainty measure.

After constructing a new measure of global uncertainty, we first analyze the basic property of this measure, and then compare our measure to other popular uncertainty proxies. We also reexamine the relationship among uncertainty and other key macroeconomic variables in the international context. We further provide two meaningful applications of our uncertainty measure. First, we pay a particular attention to tracing out the dynamic responses of oil prices, given the global uncertainty shocks. By introducing the uncertainty in a simple but classical Structural Vector Autoregressions (SVAR) framework (Bloom, 2009), we uncover the dynamic impacts of macroeconomic uncertainty on oil price. Second, we utilize our global uncertainty series to distinguish the global and country-specific uncertainty shocks. The existing literature has overwhelmingly discussed the dynamic impact of country-specific uncertainty shocks on a specific economy (e.g. Bloom, 2009; Carriero et al., 2017; Jurado et al., 2015). By introducing a new global uncertainty proxy, we are also able to identify the spillover effect of global uncertainty shocks on a certain economy.

Our empirical results show that the uncertainty shocks have significant impacts on real economic activities, even in the international context. In particular, the response of GDP and unemployment to global uncertainty indicates a strong relationship. A one-standard-deviation increase in global uncertainty is associated with a reduction in GDP of 0.2 percent and an increase in unemployment of 0.1 percent. Our results are in line with the US-based research, such as Bloom (2009) and Jurado et al. (2015), highlighting that the significant impact of uncertainty shocks on real economic activity is not only a regional issue, but also a global

3. This method starts from the premise that what matters for economic decision making is not whether particular economic indicators have become more or less variable or disperse per se, but rather whether the economy has become more or less predictable; that is, less or more uncertain. See more discussions on the method in Section 2.

phenomenon.

Regarding the world commodity market, a one-standard-deviation increase in global uncertainty triggers 0.15 percent decline in oil prices. Moveover, shocks in uncertainty account for nearly 6 percent of variations in the price of oil, which is one of the most influential factors driving the oil price movements, compared to other global macroeconomic factors. Our findings are also robust when adopting the alternative analysis framework as in Kilian (2009). These results show that global uncertainty plays a critical role in the price formation mechanism of important international commodity such as oil.

Regarding the spillover effect, on the one hand, we show that holding the global uncertainty fixed mitigates the impact of country-specific uncertainty on that economy. This finding provides the evidence that the uncertainty measure generated by a single country's data may reflect the uncertainty shocks in both domestic and foreign economies. On the other hand, we document the strong evidence of uncertainty spillover effect from world to an individual economy. All of these findings point to the importance of distinguishing the global and country-specific components when investigating the macroeconomic impact of uncertainty shocks.

The contribution of this paper is twofold. First, and most importantly, we construct a new measure of global macroeconomic uncertainty. Our global uncertainty measure provides an alternative aspect to capture the aggregate demand shocks as discussed in Kilian (2009), which are generally difficult to measure in the empirical studies. This measure can be unitized by many other studies. Based on this newly constructed global uncertainty measure, we extend the traditional analysis of the impact of uncertainty on macroeconomic activities to the international context, providing the further worldwide empirical evidence of the relationship between macroeconomic uncertainty and real activities. Second, we answer two research questions of particular interest. We investigate the price formation mechanism of world primary commodities, complementing the research investigating the determinants of oil price movements (e.g. Kilian, 2009). We capture the spillover effect of uncertainty shocks and distinguish the global and country-specific uncertainty shocks, complementing the single-country studies such as Bloom (2009) and Jurado et al. (2015).

Our goal to construct a homogeneous global uncertainty measure is related to a few of recent pioneering works. For example, Berger et al. (2015) and Berger et al. (2017) estimate aggregate uncertainty for OECD countries, with a particular focus on the information of the GDP and

CPI. Mumtaz and Theodoridis (2017) investigates the common dynamics of uncertainty across the OECD countries. Cesa-Bianchi et al. (2014) evaluates the global realized volatility based on equity price, exchange rate, long-term government bonds. Based on text reading, Baker et al. (2016) provides a method to construct a global economic policy uncertainty. Ozturk and Sheng (2018) constructs a world uncertainty measure from the Consensus Forecasts over the period of 1989-2014. Our paper complements these research by not only utilizing a dataset with much richer information set to construct a homogeneous global measure with a longer time span and a larger country set, but also provides two meaningful applications to explicitly show how our new measure can shed light on important research questions which are of particular interest in the recent economic studies.[4] Our work explores common macroeconomic uncertainty that encompasses both developed and major developing economies. Provided the increasingly important role of developing countries is playing in the world economy, this setting turns out to be the key in investigating the impact of global uncertainty.

The rest of this paper is organized as follows. Section 2 summarizes the methodology and data used for this study. Section 3 outlines the newly constructed uncertainty measure, and provides empirical results. The last section concludes.

2 Methodology and Data

2.1 Econometric Framework

A challenge in empirically investigating the behavior of uncertainty, and its relation to macroeconomic activities is that there is no objective measure of uncertainty.[5] While most existing uncertainty proxies have the advantage of being directly observable, their adequacy relies on how strongly they are correlated with the latent stochastic process of uncertainty. Jurado et al. (2015) proposes a method which measures macroeconomic uncertainty as the conditional variance of the unforecastable component common to a set of macroeconomic variables. This method ensures the econometric estimates of uncertainty as free as possible both from the structure of specific theoretical models, and from dependencies on any single (or small number) of

4. We provides the comparisons of our measures with other popular uncertainty proxies in the empirical section.

5. The empirical literature has relied primarily on uncertainty proxies, such as the implied or realized volatility of stock returns, the cross-sectional dispersion of firm profits, stock returns, or productivity, the cross-sectional dispersion of subjective or survey-based forecasts, or the appearance of certain uncertainty-related words in news publications. Bloom (2014) surveys the relevant works.

observable economic indicators.

To construct the global uncertainty measure, we extend Jurado et al. (2015) to the multi-country framework. Let $X_t = (X_{it}, ..., X_{Nt})'$ generically denote the predictors available for analysis. It is assumed that X_t has an approximate factor structure taking the form

$$X_{it} = \Lambda_i^W F_t^W + \Lambda_i^C F_t^C + e_{it}, \tag{1}$$

where F_t^W (F_t^C) is an $r_{FW} \times 1$ ($r_{FC} \times 1$) vector of latent global (country-specific) common factors, Λ_i^W (Λ_i^C) is a corresponding $r_{FW} \times 1$ ($r_{FC} \times 1$) vector of latent factor loadings, and e_{it} is a vector of idiosyncratic errors. In an approximate dynamic factor structure, the idiosyncratic errors e_{it} are permitted to have a limited amount of cross-sectional correlation.

Let y_{it} genetically denote a series that we wish to compute uncertainty in and whose value in period $h \geq 1$ is estimated from a factor augmented forecasting model with $\hat{F}_t \equiv (\hat{F}_t^C, \hat{F}_t^W)'$

$$y_{jt+1} = \phi_j^y(L) y_{jt} + \gamma_j^F(L)\hat{F}_t + \gamma_j^W(L) W_t + v_{jt+1,}^y \tag{2}$$

where $\phi_j^y(L)$, $\gamma_j^F(L)$, and $\gamma_j^W(L)$ are finite-order polynomials in the lag operator L of orders p_y, p_F and p_W, respectively, the vectors $\hat{F}_t$ are consistent estimates of F_t, and the r_w dimensional vector W_t contains the squares of the original data to capture the potential non-linearities. An important feature of our analysis is that the one-step-ahead prediction error of y_{jt+1}, and of each factor $F_{k,t+1}$ and additional predictor $W_{l,t+1}$, is permitted to have time-varying volatility σ_{jt+1}^y, σ_{kt+1}^F, σ_{lt+1}^W, respectively. This feature generates time-varying uncertainty in the series y_{jt}.

When the factors have autoregressive dynamics, a more compact representation of the systems above is the factor augmented vector autoregression (FAVAR). Let $Z_t \equiv (\hat{F}_t', W_t')'$ be a $r = r_F + r_W$ vector which collects the r_F estimated factors and r_W additional predictors, and define $\mathcal{Z}_t \equiv (Z_t', ..., Z_{t-q+1}')'$. Also let $Y_{jt} = (y_{it}, y_{jt-1}, ..., y_{jt-q-1})'$. Then forecasts for any $h > 1$ can be obtained from FAVAR system, stacked in first-order companion form

$$\begin{pmatrix} \mathcal{Z}_t \\ Y_{jt} \end{pmatrix} = \begin{pmatrix} \Phi^{\mathcal{Z}} & 0 \\ \Lambda_j' & \Phi_j^Y \end{pmatrix} \begin{pmatrix} \mathcal{Z}_{t-1} \\ Y_{jt-1} \end{pmatrix} + \begin{pmatrix} \mathcal{V}_t^{\mathcal{Z}} \\ \mathcal{V}_{jt}^Y \end{pmatrix}, \tag{3}$$

$$\mathcal{Y}_{jt} = \Phi_j^{\mathcal{Y}} \mathcal{Y}_{jt-1} + \mathcal{V}_{jt,}^{\mathcal{Y}}$$

where Λ_j' and Φ_j^Y are functions of the coefficients in the lag polynomials in Eq. (2), Φ_j^Z stacks the autoregressive coefficients of the components of $\mathcal{Z}_t$. By the assumption of stationarity, the largest eigenvalue of $\Phi_j^{\mathcal{Y}}$ is less than one and, under quadratic loss, the optimal $h-$period forecast is the conditional mean

$$E_t \mathcal{Y}_{jt+h} = (\Phi_j^{\mathcal{Y}})^h \mathcal{Y}_{jt.}$$

The forecast error variance at t is

$$\Omega_{jt}^{\mathcal{Y}}(h) \equiv E_t[(\mathcal{Y}_{jt+h} - E_t\mathcal{Y}_{jt+h})(\mathcal{Y}_{jt+h} - E_t\mathcal{Y}_{jt+h})'].$$

Time variation in the mean squared forecast error in general arises from the fact that shocks to both y_{it} and the predictors Z_t may have time-varying variances, defined by

$$\Omega_{jt}^{\mathcal{Y}}(h) \equiv \Phi_j^{\mathcal{Y}} \Omega_{jt}^{\mathcal{Y}}(h-1)(\Phi_j^{\mathcal{Y}})' + E_t(\mathcal{V}_{jt+h}^{\mathcal{Y}}(\mathcal{V}_{jt+h}^{\mathcal{Y}})'). \tag{4}$$

We obtain the individual uncertainty as the expected forecast uncertainty of the scalar series y_{jt+h} given information at time t, denoted $\mathcal{U}_{jt}^{y}(h)$. This is the squared-root of the appropriate entry of the forecast error variance $\Omega_{jt}^{\mathcal{Y}}(h)$. With 1_j being a selection vector,

$$\mathcal{U}_{jt}^{y}(h) = \sqrt{1_j' \Omega_{jt}^{\mathcal{Y}}(h) 1_j}. \tag{5}$$

To estimate macro (world-wide) uncertainty, we form weighted averages of individuals uncertainty estimates for each series:

$$\mathcal{U}_t^G(h) = \sum_{j=1}^{N_y} = w_j \mathcal{U}_{jt}^{y}(h).$$

A simple weighting scheme is to give series of each country the equal weight of their GDP share. If individual uncertainty has a factor structure, the weights can be defined by the eigenvector corresponding to the largest eigenvalue of the $N_y \times N_y$ covariance matrix of individual uncertainty.[6]

6. We experiment both the GDP share and factor structure as weighting schemes to generate the global

In the empirical section below, we adopt eight world factors of F_t^W, and one country-specific factor of F_t^C for each country to estimate the FAVAR framework of Eq. (3). The choice of length in F_t^W is selected by the information criteria proposed in Bai and Ng (2003), and the order of F_t^C is restricted by the number of variables for each country. Note that our empirical results are robust to the reasonable change of order for these factors. We include four lags ($p = 4$) when estimating the model. This selection is supported by the careful inspection of residual autocorrelation. Besides, including more or less lags would not have significant impact on our estimates of global uncertainty. To concenrate our analysis, we only report the first period ahead global uncertainty measures ($h = 1$) , which is also the most commonly discussed and cross-comparable measure in the literature.

2.2 Data

To construct the global uncertainty index, we need a comprehensive dataset that covers the major economies in the world. The choice of the starting date reflects our desire to maximize the sample size in the time dimension, meanwhile, including as many countries as possible. Where necessary, the variables are log differenced to induce stationarity. Finally, we standardize all series used in this study.

Our dataset to construct the global uncertainty index covers the information from 33 world major economies, over the time span from 1980Q1 to 2013Q3. We first adopt the latest version of the Global VAR (GVAR) dataset.[7] The construction of GVAR dataset is based on data from Haver Analytics, the International Monetary Fund's International Financial Statistics (IFS) database, and Bloomberg. It contains the primary macroeconomic indicators for each economy, including real GDP, inflation, equity price, exchange rate, and short- and long-term interest rates. Table 1 displays the set of countries included in our study.

uncertainty. These two methods generate very similar results. In the following empirical sections, we report the results based on the GDP share.

7. The latest GVAR dataset, available from the GVAR Toolbox webpage, is prepared by Rodrigo Mariscal, Ambrogio Cesa Bianchi and Alessandro Rebucci at the Inter-American Development Bank, Washington DC, US.

TABLE 1
Countries in the Baseline Case

Asia and Pacific	North America	Europe
Australia	Canada	Austria
China	Mexico	Belgium
India	United States	Finland
Indonesia		France
Japan	**South America**	Germany
Korea	Argentina	Italy
Malaysia	Brazil	Netherlands
New Zealand	Chile	Norway
Philippines	Peru	Spain
Singapore		Sweden
Thailand	**Middle East and Africa**	Switzerland
	Saudi Arabia	Turkey
	South Africa	United Kingdom

Notes: Countries in our sample cover 90% of world total output.

We also enrich the GVAR dataset with the abundant dataset compiled in Mumtaz and Theodoridis (2017), which provides comprehensive quarterly data on eleven OECD countries. This dataset considers data for the United States, the United Kingdom, Canada, Germany, France, Spain, Italy, the Netherlands, Sweden, Japan and Australia. For each country, the data runs from 1960Q1 to 2013Q3. The dataset attempts to maintain a similar composition of macroeconomic and financial series. For each country, the dataset includes real activity variables (e.g., exports, imports, consumption, investment, production, GDP), measures of inflation and earnings, interest rates and term spreads, corporate bond spreads, exchange rates, stock prices, and etc.[8] In sum, we combine the abundant information from GVAR and Mumtaz and Theodoridis (2017) dataset to construct a new measure of global uncertainty, which reflects the comprehensive economic conditions covering both the developed and major developing counties.

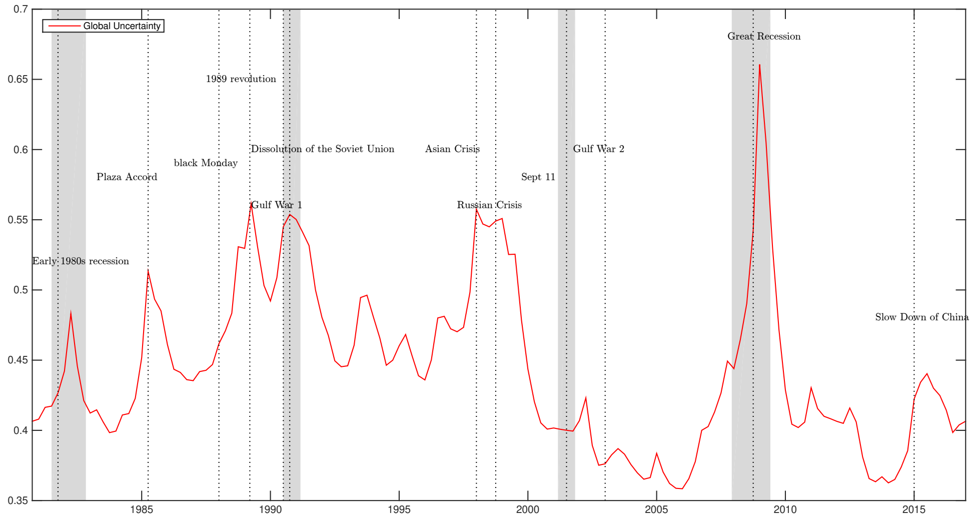
3 Empirical Results

3.1 Estimates of Global Macroeconomic Uncertainty

We present estimates of our global macroeconomic uncertainty measure in Figure 1, along with the NBER US recession dates. In general, Figure 1 shows that global macroeconomic uncertainty exhibits a countercyclical pattern to the US business cycle. For example, global macroeconomic

8. The appendix in Mumtaz and Theodoridis (2017) reports a full list of the series included and the data sources.

FIGURE 1 Global Macroeconomic Uncertainty Measure



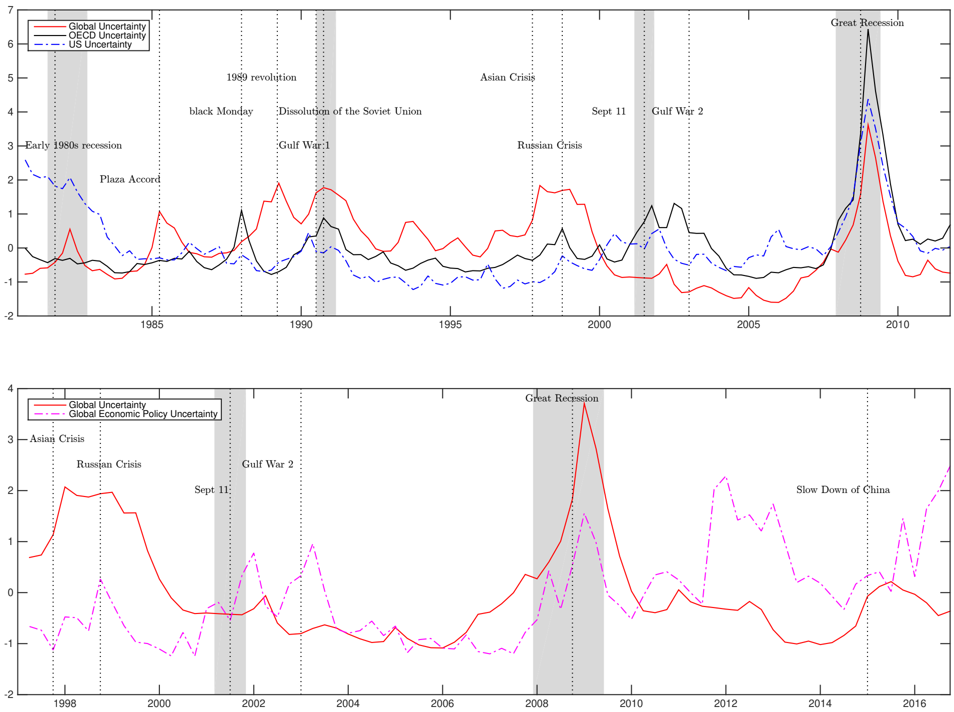
Notes: We construct the global macroeconomic uncertainty measure by estimating the FAVAR model in Eq. (3) with the data from 33 world major economies.

uncertainty shows spikes around the 1981-1982 recessions, the 1990-1991 recessions, and the Great Recession of 2007-2009. However, we also document the distinctions between our global uncertainty measure and the US business cycle patterns. For example, as expected, we document a surge of global uncertainty during the 1997 Asian financial crisis period. These results provide the first evidence to highlight the heterogeneity between the country-specific and aggregate uncertainty, stressing the importance of constructing a global measure for uncertainty.

The dotted vertical lines in Figure 1 further indicate that the uptrends in global uncertainty have coincided with important global events. For example, looking across all uncertainty measures overtime, the 2007-2009 recession clearly represents the most striking episode of heightened uncertainty since 1980. The 1997 Asian financial crisis is a close second. The early 1980s recessions are severe global economic contractions, which are also associated with a surge of global uncertainty. Along with the major economic crisis, the major events such as the signing of the Plaza Accord and the revolution of 1989 also relate to an increase in global uncertainty. More recently, the slow down of economic growth in China has also triggered a rise in uncertainty in the international level.

It is also of interest to compare our measure to other existing uncertainty proxies. These uncertainty proxies have been discussed in detail in the studies such as Jurado et al. (2015),

FIGURE 2 Comparison of Uncertainty Measures



Notes: The global economic policy measure in Baker et al. (2016) has a relative short time span.

Mumtaz and Theodoridis (2017) and Baker et al. (2016). Figure 2 plots the standardized series of these proxies, together with the our global uncertainty measure.[9] Figure 2 shows that these measures share strong commonalities in their long-run movements. For example, all of these measures are clearly countercyclical. However, further analysis of these plots also indicates a considerable cross-measure difference. For example, as discussed above, besides the recent Great Recession, our global measure highlights the spikes of uncertainty that correspond to the Asian financial crisis. In contrast, other measures mainly reports the dynamics of uncertainty in developed countries, which fails to capture the uncertainty shocks in the developed countries.

To translate the graphical pattern into a statistical representation, we report the correlations of uncertainty measures in Table 2. As expected, our global measure is more correlated with the regional uncertainty measure of OECD uncertainty. Also note that, the economic policy uncertainty measure differs the most from our measure. The reason for this may lie in how these two measures are constructed.[10]

9. Note that the global economic policy measure in Baker et al. (2016) has a relatively short time span.

10. The global economic policy uncertainty measure is based on text reading, which calculates the appearance of certain uncertainty-related key words in news publications.

Table 3 further reports the summary statistics of our uncertainty measure, as well as other indices. Table 3 also displays the first-order auto-correlation coefficient, and estimates of the half-life of uncertainty innovations from a univariate auto-regression for each measure. The half-life coefficient reflects the time required for a shock to reduce to half of its initial value, which measures the persistence of the series. Overall, several statistical facts about the estimate of global uncertainty stand out in Table 3. First, the global uncertainty measure is right skewed and fat-tailed, which is line with other uncertainty measures. Second, global uncertainty shocks are fairly persistent. The half-life of global uncertainty is nearly 8 quarters, which is less persistent to the US but more persistent to OECD and economic policy uncertainty measure.

TABLE 2 Cross-correlation of Different Uncertainty Measures

	Our Measure	OECD Measure	US Macroeconomic Measure	Economic Policy Measure
Our Measure	1.00	0.61	0.44	0.23
OECD Measure		1.00	0.87	0.59
US Macroeconomic Measure			1.00	0.44
Economic Policy Measure				1.00

TABLE 3 Summary Statistics

	Our Measure	OECD Measure	US Macroeconomic Measure
Min	-1.60	-0.89	-1.22
Max	3.62	6.44	4.38
Skewness	0.71	3.61	1.81
Kurtosis	3.35	19.82	6.77
Ar(1)	0.92	0.87	0.94
Half Life	7.89	5.11	10.96

	Our Measure	Economic Policy Measure
Min	-1.09	-1.25
Max	3.71	3.28
Skewness	1.46	1.03
Kurtosis	4.83	3.63
Ar(1)	0.92	0.81
Half Life	8.39	3.27

Notes: Economic Policy Measure starts from 1997, which is relatively shorter compared with other uncertainty measures.

3.2 Global Uncertainty and Macroeconomic Dynamics

Existing empirical studies on uncertainty has often found important relationships between the real activity and uncertainty proxies. In particular, these proxies are countercyclical and VAR estimates suggest that they have substantial impacts on output and employment given an innovation in these uncertainty measures.[11] In this section, we extend these existing literature to the global context. To achieve that, we first construct global macroeconomic factors. The construction of global macroeconomic factors follows the strands of the literature that investigates the world business cycle (e.g. Kose et al., 2012, 2003, 2008). Second, we relate these macroeconomic variables to global uncertainty, and investigate the dynamic responses of these global macroeconomic factors.

We first plot the dynamics of the global factor series for each macroeconomic variable, as shown in Figure 3. These global factors are generated by the simple principle component method. We show that the patterns of each series capture the major global events. For example, the trough of the stock series matches the major stock market crashes over the world. The global CPI and interest rate has declined in the recent years, which corresponds to the great moderation. The downtrend movements of global GDP series match the periods of economic recessions.[12]

We now use a standard VAR model to investigate the dynamic responses of these key macroeconomic variables to innovations in global uncertainty. To do so, we estimate impulse-response functions (IRFs) from a seven-variable model similar to Bloom (2009) and —henceforth, VAR-7:[13]

$$\begin{bmatrix} Stock\ Price \\ Uncertainty \\ Interest\ Rate \\ CPI \\ Hours \\ Unemployment \\ GDP \end{bmatrix}.$$

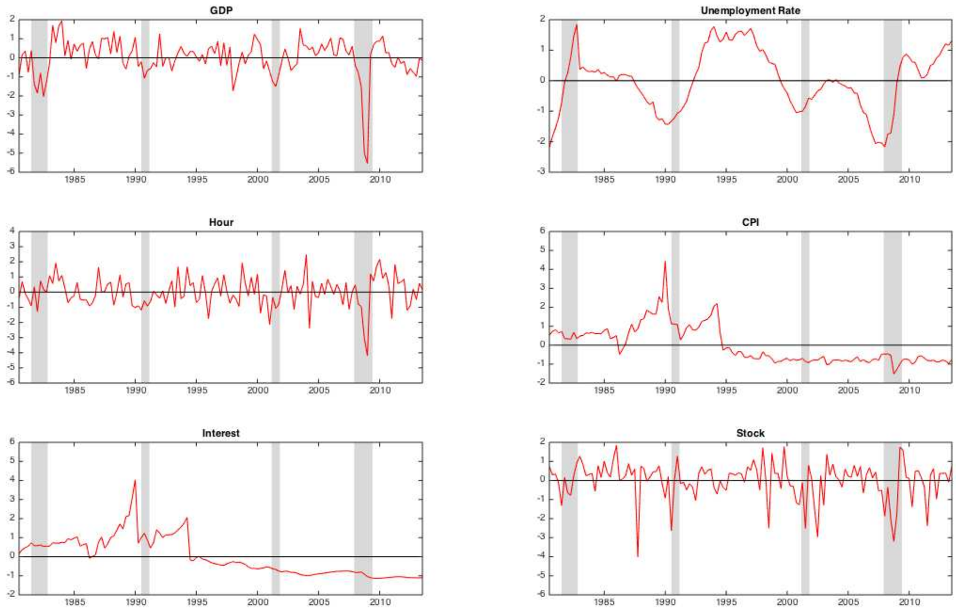
Following Bloom (2009), we adopt the standard recursive method to achieve the identifi-

11. For example, in Bloom (2009), a key result is that a rise in some proxies (notably stock market volatility) at first depresses real activity and then increases it, leading to an over-shoot of its long run level, consistent with the predictions of some theoretical models on uncertainty as a driving force of macroeconomic fluctuations.

12. We also discuss the global factors which are generated only by the OECD data to avoid the outliers and extreme movements for some developing countries. Overall, our results are robust to the alternative datasets. For more discussions on this issue, see Section 3.4.

13. Bloom (2009) and Jurado et al. (2015) estimate a VAR-8 model for the US. We exclude wage from their VAR-8 model due to a lack of consistent wage data across the countries. Note that when we experiment the wage data of representative economy, such as the US, our baseline results won't change both quantitatively and qualitatively.

FIGURE 3 Global Macroeconomic Factors

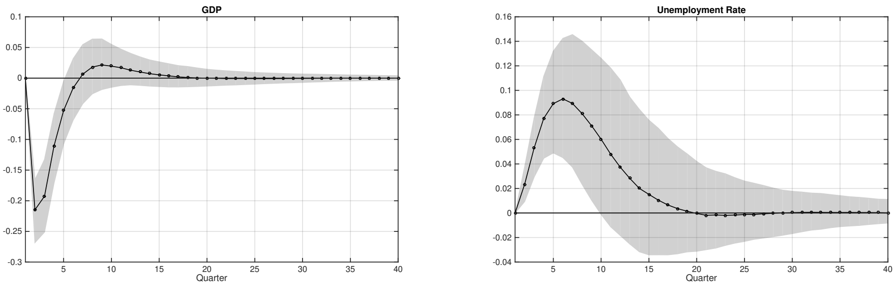


Notes: We adopt a simple principle component method to generate these global factors.

cation. Figure 4 shows the dynamic responses of major global factors. As expected, at the global level, a surge in uncertainty triggers a significant decline in GDP. Meanwhile, there is a rise in unemployment associated with the uncertainty shocks. These results are in line with the empirical findings and theory on the uncertainty impact on a particular country, showing the significant macroeconomic effect of uncertainty shocks. Figure 5 also plots the responses of major financial variable, stock price, given the uncertainty shocks. We show that a one-standard-deviation of uncertainty shocks triggers a 0.1 percent decline in the stock price. Our finding supports the theory that the increase of uncertainty in general leads to a panic sentiment in the financial market, which boosts the selling of the stock shares and thereafter decreases the stock prices.

Table 4 plots the variance decomposition results. We show that global uncertainty can explain around 10 percent variation of GDP fluctuations, and 8 percent of unemployment. These results provide further evidence on the substantial role of uncertainty in determining the world business cycle. Besides, Table 4 also shows that uncertainty shocks can explain a significant fraction of variations for other global factors of interest such as working hours, CPI, and interest rates.

FIGURE 4 IRFs of Global Macroeconomic Activities



Notes: The solid dotted line represents the IRFs given the global uncertainty shocks. Shaded areas represent 68% confidence bands over 10,000 bootstrap repetitions.

FIGURE 5 IRFs of Global Stock Market

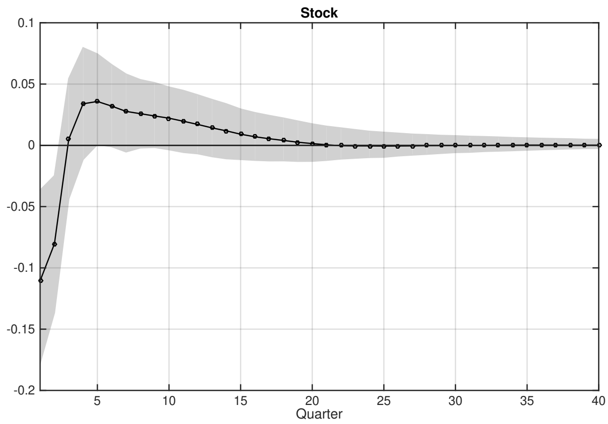


TABLE 4 Variance Decomposition: Uncertainty

	GDP	Unemployment	Hours	CPI	Interest Rate	Uncertianty	Stock Price
Explained by:				Uncertianty			
K=3	8.940%	1.585%	3.210%	0.272%	0.324%	86.429%	2.809%
K=12	10.846%	6.628%	4.623%	1.750%	2.177%	64.566%	3.940%
K=40	10.919%	7.819%	5.006%	3.160%	3.636%	55.397%	4.466%

Notes: The symbol of 'K' denotes forecasting periods in variance decomposition.

3.3 Global Uncertainty Measure: Two Applications

3.3.1 Global Uncertainty and Oil Price

The relationship between the price of oil and the level of economic activity is a fundamental issue in macroeconomics. At least since the first oil crisis in 1973, the macroeconomic effects of oil prices have been studied extensively (e.g. Barsky and Kilian, 2004; Hamilton, 1983, 2003). Although findings in the literature show significant variations, it is generally documented that oil price has a significant relationship with real activity in the US and other countries.[14]

In the 2000s, along with the emerging literature on the impact of uncertainty on real activity, strong oil price volatility triggers intensive debates in the literature on the possible drivers of oil price (e.g. Kilian, 2008, 2009; Singleton, 2013). Although it is well documented that both conventional supply and demand factors contribute to oil price movements, these factors themselves have difficulty in fully explaining the dramatic volatility pattern of oil price (Kilian, 2009; Lippi and Nobili, 2012; Peersman and Van Robays, 2009). This challenge stimulates the assessment of the role of non-fundamental drivers, such as speculation and uncertainty, in the literature, and uncertainty becomes a popular topic (Hamilton, 2009; Kilian and Murphy, 2013; Singleton, 2013).

Among the literature investigating the price formation mechanism of primary global commodity, the seminal work of Kilian (2009) argues that the roots of oil price fluctuations can be decomposed into three components: oil supply, aggregate demand and oil-specific demand shocks.[15] The aggregate demand shocks are usually difficult to measure in empirical studies. To overcome this issue, Kilian (2009) adopts dry cargo single voyage ocean freight rates as a proxy of the aggregate demand shocks. Leduc and Liu (2016) provides both empirical results and a theoretical framework to show that uncertainty shocks are essentially one kind of aggregate demand shocks. As a result, a question of particular interest is how the commodity price will respond to one particular component of aggregate demand shocks—macroeconomic uncertainty shocks.[16]

14. Policy makers are also interested in oil price movements because they have wide impacts on macroeconomic aggregates such as economic growth, relative prices, inflation, income distribution, investment, production and financial markets (Herrera and Pesavento, 2009; Montoro, 2012; Shi and Sun, 2017).

15. According to Kilian (2009), the last shock is designed to capture shifts in the price of oil driven by higher precautionary demand associated with market concerns about the availability of future oil supplies.

16. Several mechanisms through which macro uncertainty affects oil price have been documented in the literature. One widely documented channel is that uncertainty changes the decision making behaviour of economic agents (Bernanke, 1983; Bloom et al., 2007; Litzenberger and Rabinowitz, 1995; Pindyck, 1991), such as delay in the production or consumption decision in the case of oil firms (Elder and Serletis, 2010; Favero et al., 2018; Kellogg, 2014). There are a large literature providing both theoretical and empirical evidence on how uncertainty affects the decision to invest and consume (Van Robays, 2016). For example, the option value to wait theory proposed by Bernanke (1983) suggests that in the case of making irreversible decisions, investors might forego current returns in order to wait and gain from more information that will become available in the future. Economic policy uncertainty (EPU) is recognized as a key factor to affect real activity (Bloom, 2014), which further affect oil price movement. Van Robays (2016) argued that uncertainty lowers the price elasticity of oil demand and supply and thus higher macroeconomic uncertainty significantly increases the sensitivity of oil prices to shocks in oil demand and supply. A less documented channel is that uncertainty increases the use of oil futures markets, such as hedging instruments, resulting in less sensitive demand and supply to oil price changes (Baumeister and

In this section, we provide an important application of the global uncertainty measure, and revisit the debates of key determinants of the real price of oil by using our measure of macroeconomic uncertainty. We contribute to the debate on whether periods of steep volatility are driven by oil supply and demand fundamentals, and estimating how much of oil price variations is determined by uncertainty shocks. We first estimate the impact of uncertainty on oil price in a typical macroeconomic economic model that includes GDP growth, inflation, and etc. Then, following Kilian (2009), we also estimate an alternative structural model with the consideration of world oil production, real price of crude oil, and global economic activity.[17]

We first augment the previous VAR-7 framework to analyze the impacts of macro uncertainty on the oil price. We place the oil price as the last component, and adopt the recursive method to achieve identification. This identification scheme is realistic since the oil price shocks are not likely to affect the world real economic activities contemporaneously.[18]

The left panel of Figure 6 reports the dynamic responses of oil price given the global uncertainty shocks. As expected, we document that macroeconomic uncertainty shocks have significant impact on the oil price. In particular, the oil price experiences an instant decline of 0.15 percent, which dies out quickly in the following 4 periods. These results confirm that the uncertainty shocks are essentially aggregate demand shocks, and market participants may reshape their beliefs when facing of an increasing uncertainty.[19]

The right panel of Figure 6 and Table 5 also present the variance decomposition results. We show that uncertainty can explain nearly 6 percent variance of oil price movements in the long run. Moreover, among all the macroeconomic factors, the uncertainty plays the third most important role in driving the oil price fluctuations, only after the GDP and interest rate. All of these findings point out the importance of macroeconomic uncertainty in oil price formation mechanism, cautioning the future study to take uncertainty into account when investigating oil price movements.

Peersman, 2012).

17. We also experiment the impact of uncertainty shocks on other important international commodities such as raw material and metal. In general, the results are similar for these commodities. We report the corresponding discussions in Section 3.4.

18. Our estimation results are robust to the reasonable changes of identification scheme. For more discussions on this issue, see Section 3.4.

19. The negative correlation between uncertainty and commodity prices is also documented in some existing literature. For example, Aloui et al. (2016) find a negative dependence between the equity and economic policy uncertainty indices and the crude-oil return in their entire sample period.

FIGURE 6 IRFs and Variance Decomposition of Oil Price

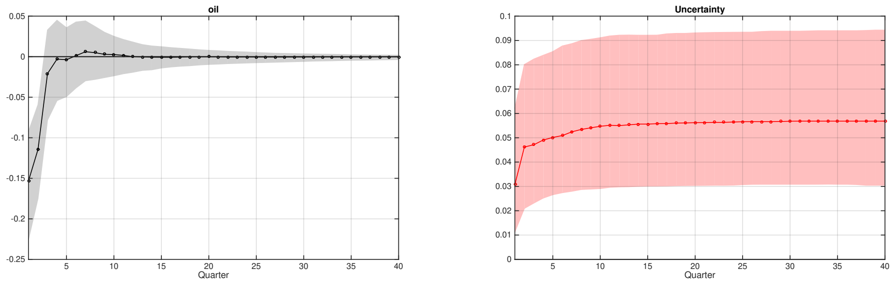


TABLE 5 Variance Decomposition: Uncertainty

	Oil Price							
Explained by:	GDP	Unemployment	Hours	CPI	Interest Rate	Uncertianty	Stock Price	Oil Price
K=3	7.145%	1.280%	1.394%	2.216%	4.923%	4.714%	1.810%	73.401%
K=12	7.302%	2.333%	1.582%	3.336%	5.717%	5.500%	1.942%	69.197%
K=40	7.297%	2.626%	1.596%	3.735%	5.862%	5.683%	1.948%	67.869%

Following Kilian (2009), we also estimate a four-variable SVAR model as follows:

$$A_0 z_t = \alpha + \sum_{i=1}^{4} A_i z_{t-j} + \varepsilon_t, \tag{6}$$

where ε_t denotes the vector of serially and mutually uncorrelated structural innovations, and the SVAR is based on the quarterly data for $z_t = (\Delta prod_t, rea_t, uncer_t, rpo_t)'$. $\Delta prod_t$ is the percent change in global crude oil production, Δrea_t denotes the index of real economic activity constructed in Kilian (2009), $uncer_t$ refers to the global uncertainty measure, and Δrpo_t is the real price of oil. Figure 7 plots the historical rates of these series. Following the Kilian (2009), we postulate that A_0^{-1} has a recursive structure such that the reduced-form errors ε_t can be decomposed according to $e_t = A_0^{-1}\varepsilon_t$:

$$e_t \equiv \begin{pmatrix} e_t^{\Delta prod} \\ e_t^{rea} \\ e_t^{uncer} \\ e_t^{rpo} \end{pmatrix} = \begin{bmatrix} a_{11} & 0 & 0 & 0 \\ a_{21} & a_{22} & 0 & 0 \\ a_{31} & a_{32} & a_{33} & 0 \\ a_{41} & a_{42} & a_{43} & a_{44} \end{bmatrix} \begin{pmatrix} \varepsilon_t^{oil\ supply\ shock} \\ \varepsilon_t^{aggregate\ demand\ shock} \\ \varepsilon_t^{uncertainty\ shock} \\ \varepsilon_t^{oil-specific\ demand\ shock} \end{pmatrix}.[20] \tag{7}$$

Figures 8 and 9 report the results when adopting the Kilian (2009)'s framework. Our findings confirm that the global uncertainty shocks, which is one typical of conventional aggregate

20. For more discussions on the validity of this identification scheme, see Kilian (2009). Our estimation results are also robust to the reasonable changes of this ordering scheme. We report the corresponding results in Section 3.4.

FIGURE 7 Historical Rates of Oil Market Variables

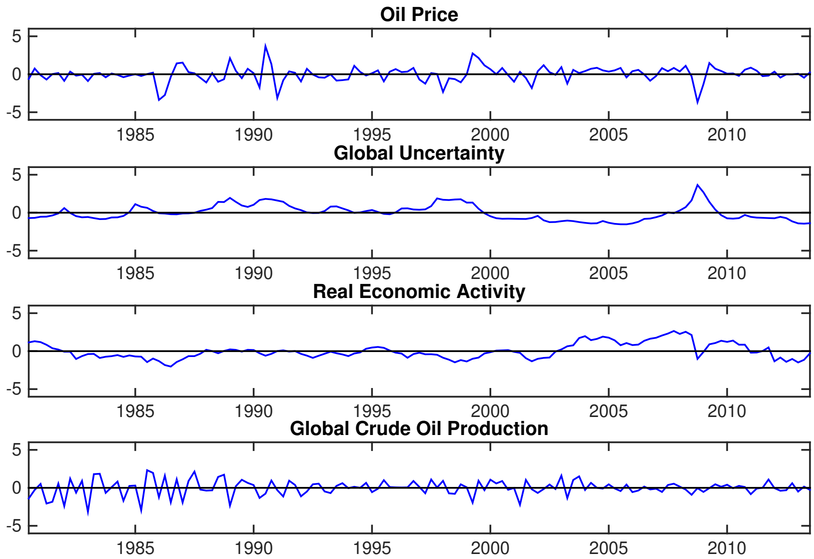


FIGURE 8 Responses of Oil Market Variables:
under Kilian's Framework

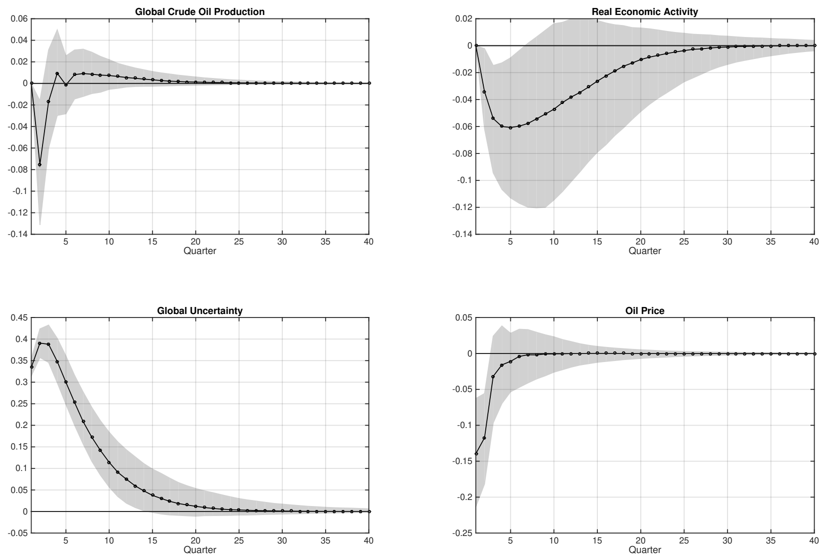
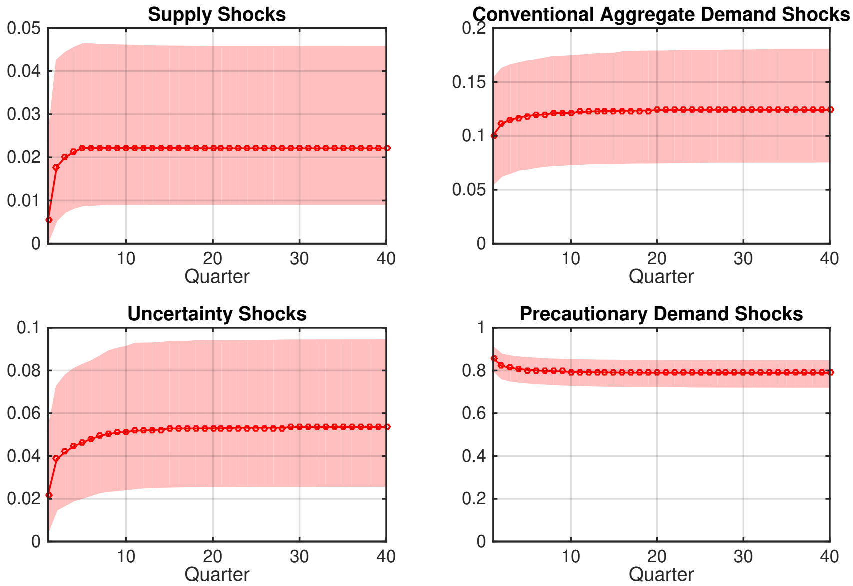


FIGURE 9 Variance Decomposition of Oil Price: under Kilian's Framework



demand shock, plays a critical role in determining the oil price movements. In particular, after accounting for the supply and conventional aggregate demand factors, a one-standard-deviation increase in global uncertainty leads to a 0.15 percent significant decline in oil price. Meanwhile, the uncertainty shocks can again explain nearly 6 percent of oil price variances in the long run. Moveover, the impact of uncertainty shocks is comparable to the conventional aggregate demand shock, and is much stronger compared to the supply-side factors. All of these results highlight importance of the second moment shocks, together with the traditional level shocks, in the price formation mechanism in oil market.

3.3.2 Global Uncertainty Versus Country-specific Uncertainty

Recent literature has overwhelmingly discussed the impact of uncertainty shocks on a certain economy (e.g. Bloom, 2009; Carriero et al., 2017; Jurado et al., 2015). However, another strand of literature also documents that the globalization spurs the rising production, trade and financial integration across countries and has triggered a common business cycle at global and country group levels (Kose et al., 2012, 2003, 2008; Stock and Watson, 2005). The world economies highly interact with each other, and therefore, the uncertainty shocks may transmit across countries through these cross-country linkages. In this regard, Mumtaz and Theodoridis (2017) provides the detailed empirical evidence of the commonly dynamics of uncertainty across the countries, and constructs a two country DSGE model to capture the uncertainty spillover from one country to another.[21] However, most of uncertainty measure used in the existing literature, which although is constructed based on the domestic data, fails to disentangle the country-specific and global components in uncertainty shocks.

In this section, we explicitly examine the cross-country spillover effect of uncertainty shocks, and utilize the newly constructed global uncertainty series to distinguish the global and country-specific uncertainty shocks. To examine this question, we first construct the macroeconomic uncertainty measure for the UK, and then investigate the interactions between the UK uncertainty and global uncertainty. We pay a particular attention to the UK for two reasons. First, the UK is a typical "small" open economy, which ensures that the macroeconomic uncertainty shocks initialed in the UK are unlikely to affect the global uncertainty. This assumption is adopted by many other studies (e.g. Canova, 2005; Mumtaz and Surico, 2009), and plays a key role in our identification in the VAR model. Second, as a developed country, the UK provides abundant macroeconomic data with relatively better quality across a longer time span.

FIGURE 10 Macroeconomic Uncertainty in the UK

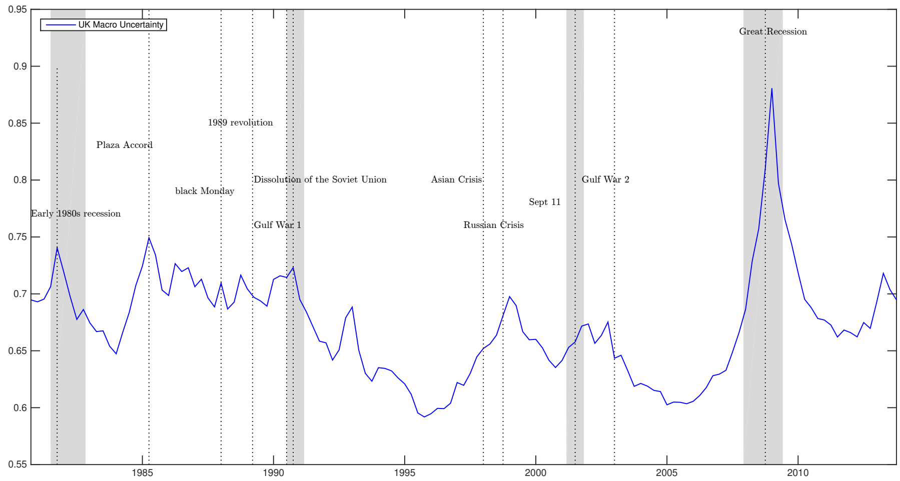
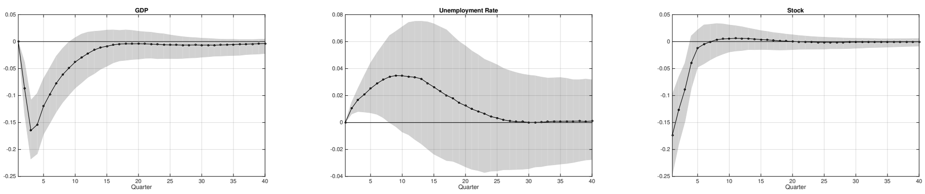


Figure 10 plots the estimated macroeconomic uncertainty for the UK based on the same method of Jurado et al. (2015) as before. In general, this UK macroeconomic uncertainty series can capture the major economic events of the UK, and is in line with the corresponding results

21. Some other literature also discuss this spillover effect. For example, using a SVAR model, Huang et al. (2018) investigates the transmission of macroeconomic uncertainty between the worlds largest two economies and find a unidirectional spillover of macroeconomic uncertainty from the US to China. Such spillover effects can be explained by the intensive multilateral trade and the contagious monetary policies from the US.

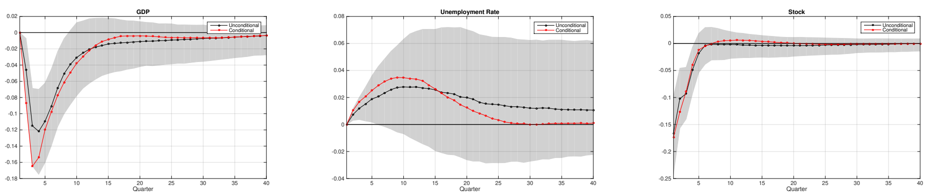
generated by Mumtaz and Theodoridis (2017). However, since we do not rule out the regional or global factors at this stage, this UK macroeconomic uncertainty measure depicts the dynamics of both OECD and country-specific uncertainty series in the UK, which are reported in Mumtaz and Theodoridis (2017). This finding provides the first evidence that although the uncertainty measure are generated by domestic data of a certain country, this uncertainty measure may still reflect uncertainty shocks originated from both domestic and foreign economy.

FIGURE 11 IRFs of uncertainty shock on the UK



In Figure 11, we experiment the empirical results employing our newly constructed UK uncertainty measure. This kind of single country analysis is the typical exercise which is commonly adopted in the literature. Figure 11 plots the responses of major UK macroeconomic indicators such as GDP, unemployment rates and stock returns given the uncertainty shocks. As expected, we find that the responses of real economic activities are substantial. Meanwhile, regarding the financial variables such as stock returns, we also document significant impacts of the UK uncertainty shocks.

FIGURE 12 IRFs of country-specific uncertainty on the UK,
holding the global uncertainty fixed



Notes: The blue line represents the IRFs when holding the global uncertainty fixed. We also report the results in Figure 11 as the red line for the comparison purpose.

We now distinguish the global and country-specific uncertainty shocks. As a comparison to Figure 11, we plot the responses of major UK macroeconomic indicators when holding the global uncertainty fixed in Figure 12. This figure shows that after controlling the global uncertainty, the effect of country-specific uncertainty shocks is in general mitigated, especially in the short run. For example, we document a 0.16 percent decline of GDP given one standard deviation uncertainty shock, compared to a 0.12 percent decline when holding the global uncertainty level fixed. However, regarding the financial variable, we document the similar responses of stock returns with and without holding the global uncertainty fixed. Overall, our results highlight the importance of identifying the global components when investigating conventional country-specific uncertainty impact.

FIGURE 13 IRFs of global uncertainty on the UK

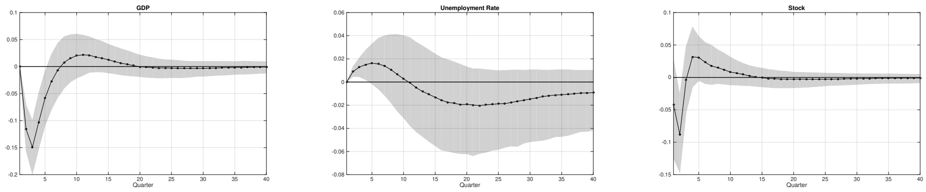


Figure 13 further plots responses of the UK macroeconomic variables given the global uncertainty shocks. This figure investigates the underlying spillover effect. Apart from the country-specific uncertainty, Figure 13 shows that the global uncertainty shock also has strong domestic effects on both the real and financial variable for the UK. As a result, the documented overall significant impact in Figure 11 can be regarded as a combination impact of both country-specific and global uncertainty shocks.

3.4 Further Discussions

3.4.1 Alternative Country Set

One possible concern on our baseline results is that the global factors used in the Section 3.2 and 3.3 are generated by including both developed and developing countries, which may be driven by the abnormal movements in the macroeconomic indicators of developing countries. For example, the surge of the global interest rate in the 1990s may be triggered by the dramatic increase of interest rate in Argentina in the corresponding periods.

To deal with this issue, we re-estimate the macroeconomic factors shown in Figure 3 based on only the data of OECD countries. In other worlds, we are estimating the impact of global uncertainty on OECD common factors. Figures A1 and A2 in Appendix present the main results. As expected, the baseline results are robust when we adopt only the OECD factors.

3.4.2 Alternative Identification Scheme

In the Section 3.3.1, we place the global uncertainty before the oil price, and assume that the uncertainty shocks have an instant impact on oil price. However, one may argue that, as the most important international commodity, the oil price movement itself may trigger a change in global uncertainty contemporaneously. To address this concern, we experiment the results by restricting the global uncertainty shocks can only have impact on all the macroeconomic variables of interest after one quarter. Based on this setting, we are actually estimating the lower bound of the impacts of global uncertainty shocks.

Figure A3 reports the results in the VAR-7 framework, and Figure A4 and A5 reports the results under Kilian (2009)'s framework. We show that the global uncertainty shocks still have significant impacts on oil price in this alternative identification scheme. Even under this identification scheme, the uncertainty shocks can explain 2 to 3 percent variations of oil price movements.

3.4.3 Comparison with Economic Policy Uncertainty

Another question of interest is the comparison between the macroeconomic effects of our measure and other global measures. We adopt the global economic policy uncertainty, which is the most popular global measure used to make the comparisons.

Figures A6 and A7 in the Appendix show that our results are in general in line with the results generated by the economic policy uncertainty. However, we should note that the heterogeneity also exhibits. For example, the economic policy uncertainty is in general more related to the financial variables. This is related to the way of constructing the economic policy uncertainty measure. The text reading method can easily capture market sentiments during the financial contagion period. In sum, all of these results show that our global uncertainty measure can provides an alternative when we need to utilize the uncertainty proxy in the international context.

3.4.4 Global Uncertainty and Other Commodities

We also analyze the impacts of macro uncertainty on two other key international commodities: agricultural raw material and metal.[22] We choose the composite index of agricultural raw materials and metals as commodity price measures, which contains the major exported and imported goods such as rubber, cotton, iron, copper, and etc.

The left panel of Figure A8 shows the dynamic responses of the raw material price given the global uncertainty shocks. We document a significant decline of raw material price immediately after the uncertainty shocks, followed by a small overshoot and then a stabilization in the following fifteenth quarters. The right panel of Figure A8 presents the variance decomposition results. We show that uncertainty can explain approximately 9 percent variance of raw material price movements in the long run. In Figure A9, we generate simulation results for the metal price. Similarly, we document a significant decline of the metal price given the uncertainty shocks. Figure A9 also shows uncertainty shocks can explain nearly 10 percent of the long-run variance of metal price fluctuations. In sum, the results related to agricultural raw material and the metal market are similar to those of the oil market. All of these results show that the uncertainty shocks play an essential role in the price formation mechanism of world primary commodities.

4 Concluding Remarks

Uncertainty is an extremely important economic concept and attracts more and more research on this topic in recent years. By adopting a comprehensive dataset covering both developed and major developing countries, we extend Jurado et al. (2015) forecast-error-based uncertainty measure to the international context, and construct a homogeneous global uncertainty measure. We compare this newly developed global uncertainty measure with other existing macroeconomic uncertainty proxies. The global uncertainty measure developed in this paper can be utilized in many other studies, serving as an alternative when one needs to identify the uncertainty shocks at the aggregate global level.

Based on the newly constructed global uncertainty measure, we reexamine the relationship among uncertainty and macroeconomic activities in the international context. The empirical

22. The agricultural raw material and metals price indices were both taken from the IMF's Primary Commodity Prices monthly data and subsequently aggregated to the quarterly frequency.

results show that the uncertainty shocks have significant impacts on economic activities, even in the international context. Our findings highlight that uncertainty shocks as a source of business cycle fluctuations found in the literature is not only a regional issue, but also a global phenomenon.

We also provide two meaningful contexts to illustrate how to apply our global uncertainty measures. First, our global uncertainty measure provides an alternative aspect to capture the aggregate demand shocks as discussed in Kilian (2009), which are generally difficult to measure in the empirical studies. We show that macroeconomic uncertainty, together with the aggregate demand shocks in level, are important in determining the oil price movements. Second, our global uncertainty measure helps to capture the spillover effect of uncertainty shocks and distinguish the global and country-specific uncertainty shocks, complementing the single-country studies such as Bloom (2009) and Jurado et al. (2015).

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Appendix

A OECD Factors

FIGURE A1 IRFs of global uncertainty with OECD Factors

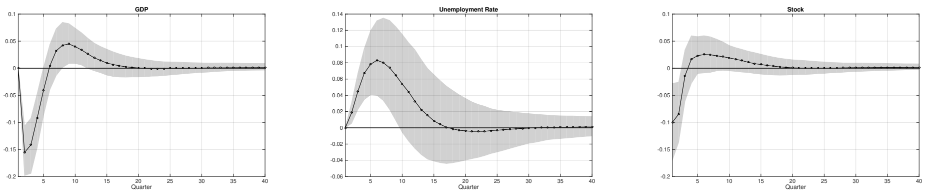
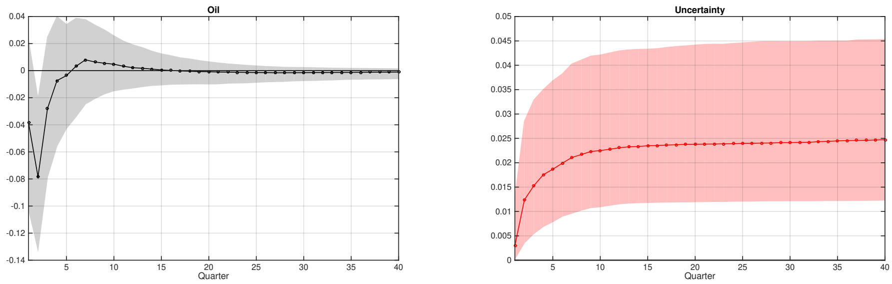


FIGURE A2 IRFs of global uncertainty on Oil Price with OECD Factors



B Alternative Identification Scheme

FIGURE A3 IRFs and Variance Decomposition of Oil Price:
Alternative Identification Scheme

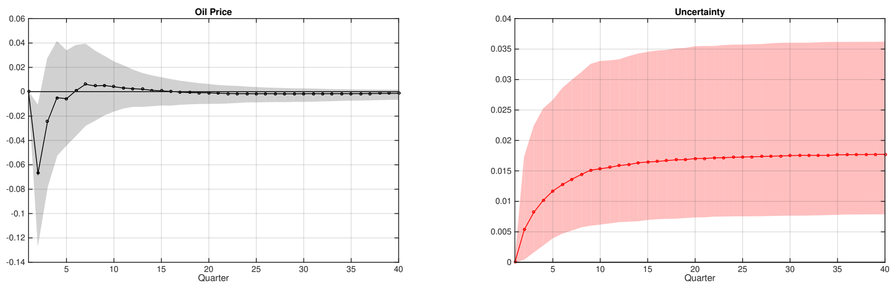


FIGURE A4 Responses of Oil Market Variables: Alternative Identification Scheme

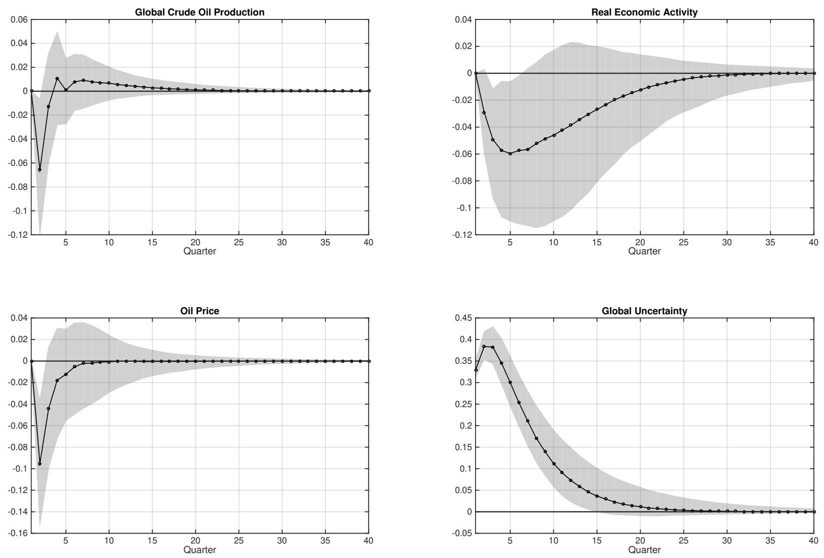
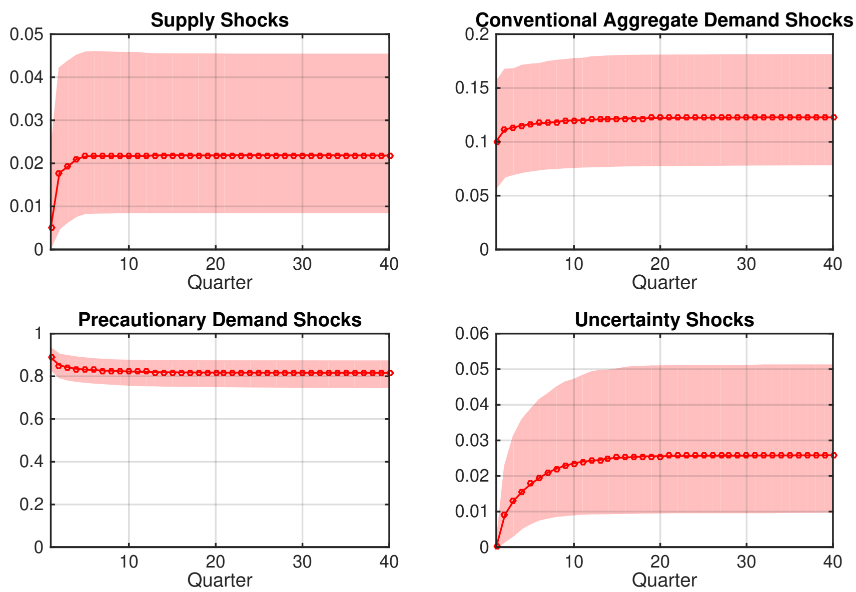


FIGURE A5 Variance Decomposition of Oil Price: Alternative Identification Scheme



C Comparison with Economic Policy Uncertainty

FIGURE A6 Comparison with Economic Policy Uncertainty

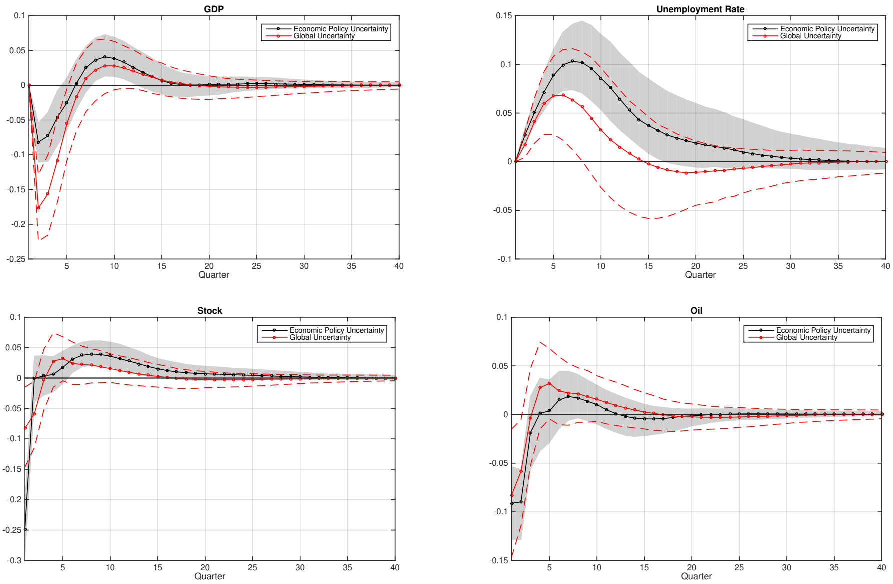
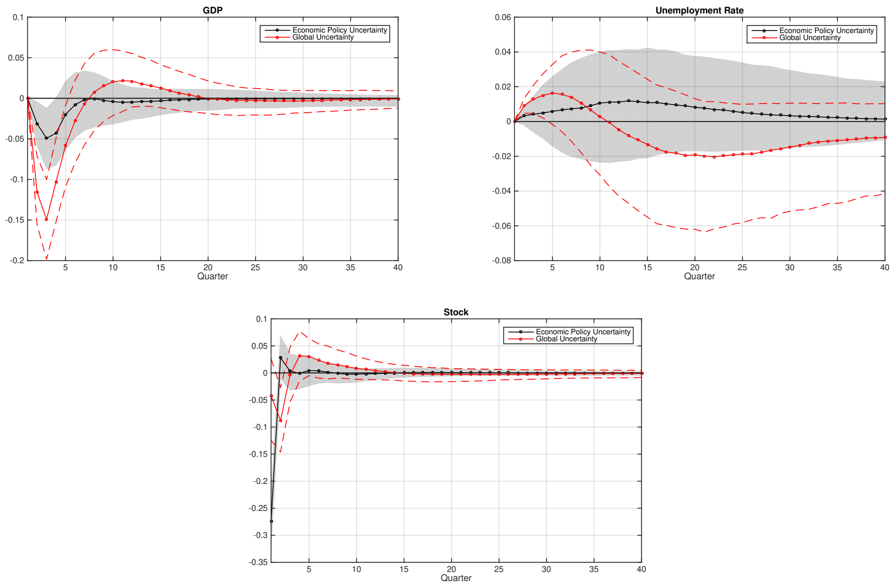


FIGURE A7 Comparison with Economic Policy Uncertainty



D Macro Uncertainty and Other Commodities

FIGURE A8 IRFs and Variance Decomposition of Raw Material Price

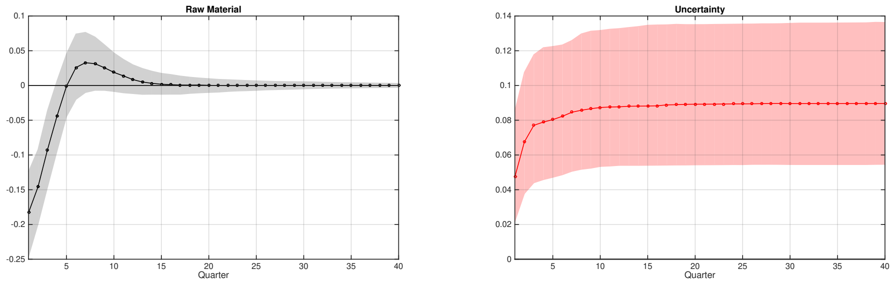


FIGURE A9 IRFs and Variance Decomposition of Metal Price