Global Uncertainty, Macroeconomic Activity and Commodity Price

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Abstract

We construct a homogeneous proxy of global macroeconomic uncertainty by employing a rich global dataset covering both advanced and major emerging economies. Our proxy displays significant independent variations from popular regional or country-specific uncertainty measures, and can serve as an alternative to the global economic policy uncertainty index when one needs to identify uncertainty shocks at the aggregate global level. We examine dynamic impacts among global macroeconomic uncertainty and other global macroeconomic variables, and provide two meaningful applications of our proxy by linking it to the price formation mechanism of oil and by disentangling the global common and country-specific components involved in uncertainty shocks. We show that the well-documented relationship between uncertainty and real activities is not only a regional issue, but also a global phenomenon. Global uncertainty, which works as aggregate demand shocks, plays a key role in determining commodity prices. In addition, to complement the conventional within-country analysis of uncertainty impact, we show that the global common components in uncertainty shocks account for a substantial fraction of business cycle fluctuations in a certain economy. Our findings are robust according to a variety of robustness analysis.

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1 Introduction

The Global Financial Crisis of 2007-2009 brought to the surface the need for understanding macroeconomic uncertainty as an important source of business cycle fluctuations. Since the seminal work of Bloom (2009), the cause and impact of uncertainty had drawn 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 little research that develops a homogeneous global uncertainty measure, and investigates the macroeconomic impacts of uncertainty in the global context. Our paper attempts to fill this gap.

Understanding the macroeconomic impact of uncertainty in the global context is extremely important. First, considering the oil 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. Meanwhile, Leduc and Liu (2016) points out that uncertainty shock essentially works as the aggregate demand shock, indicating that uncertainty shocks are the underlying drivers of oil price movements. Also, given that oil is a primary commodity over the world, the price of oil is unlikely to be determined by the macroeconomic status of a single country; rather, oil prices tend to be set by the overall global economic conditions of both advanced and major emerging markets. 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 time-varying uncertainty across countries.[1] Macroeconomic uncertainty, even if it originates within one country, may have an impact beyond that country or even its region. Such spillover effects would not be captured in a satisfactory manner by the existing methodologies, unless they measure uncertainty at the global level. Constructing a global uncertainty measure to identify the global common components complements the conventional single-country studies that investigate the impact of country-specific uncertainty on the business cycles of 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 measure may serve as a underlying instrument for regional and country-specific measure. 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 proxy. To achieve this goal, we employ a comprehensive dataset that contains 33 world major economies, covering both advanced and major emerging economies.[3] The dataset for each economy includes primary macroeconomic indicators such as GDP, CPI, interest rate, and etc. The time span we analyze in this study is the period from 1980 to 2016. We follow the classical econometric framework as in Jurado et al. (2015), which measures macroeconomic uncertainty as the conditional variance of the unforecastable component common to a set of macroeconomic variables.[4] This methodology, along with the abundant dataset, allows us to construct a homogeneous global macroeconomic uncertainty proxy.

After constructing a new proxy of global uncertainty, we analyze its basic properties, and we then compare it to other popular uncertainty measures. Next, we revisit the relationship among uncertainty and other key macroeconomic variables in the international context. We further provide two meaningful applications of our global uncertainty proxy. First, we pay particular attention to tracing out the dynamic responses of oil prices given global uncertainty shocks. By introducing the uncertainty in a standard Structural Vector Autoregressions (SVAR) framework (Bloom, 2009), we show that global uncertainty plays an important role in the price formation mechanism of oil. The results are robust when we adopt the benchmark framework for the oil market that was introduced by Kilian (2009).[5] Second, the existing literature has exhaustively 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 global uncertainty proxy, we are able to disentangle the macroeconomic impacts of uncertainty shocks induced by global common and country-specific components.

Our proxy displays significant independent variations from popular regional or country-specific uncertainty measures, reflecting the conceptual differences of the respective uncertainty indicators. Our global uncertainty proxy is more strongly correlated with the comparable measure for OECD countries discussed by Mumtaz and Theodoridis (2017) and, to a modestly lesser

3. The inclusion of the emerging countries is important and direct follows the ideas in Jurado et al. (2015) that macroeconomic uncertainty is not equal to the uncertainty in any single series. Instead, it is a measure of the common variation in uncertainty across many series. Our paper extend this idea to the international context.

4. 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.

5. We are aware of recent extensions and discussions on Kilian (2009)'s framework. More details, see Hamilton (2019) and Baumeister and Hamilton (2019). However, we stick to this method since it is the benchmark approach in oil market analysis.

extent, with the Jurado et al. (2015)'s estimate of macroeconomic uncertainty in the US. This suggests that global macroeconomic uncertainty is closely related to broader regional uncertainty, which might not seem surprising given our target, which is to proxy uncertainty at the global level. Different from these regional or country-specific uncertainty measures, our proxy highlights the influential events in emerging markets such as the revolutionary wave in the late 1980s and the 1997 Asian financial crisis. Our estimate of global macroeconomic uncertainty appears to be more modestly correlated with estimates of the global economic policy uncertainty index based on Baker et al. (2016) and Davis (2016), which aims to capture global uncertainty from the perspective of economic policy.

Our empirical results show that 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 percent increase in global uncertainty is associated with a reduction in GDP of 0.54 percent and an increase in unemployment of 0.20 percent. Our results are in line with the US-based research, such as that of Bloom (2009) and Jurado et al. (2015). This suggests that the significant impact of uncertainty shocks on real economic activity is not only a regional issue, but also a global phenomenon.

Regarding the world commodity market, we show that a one percent increase in global uncertainty triggers a 0.38 percent decline in oil prices. Moreover, shocks in uncertainty account for nearly 5.5% of the variations in the price of oil. The results indicate that uncertainty is one of the most influential driving factors of the oil price. Our findings are also robust when adopting an alternative analysis framework, such as that discussed in Kilian (2009). These results show that the global uncertainty shock, which works as aggregate demand shock, plays a critical role in the price formation mechanism of oil, one of the most important international commodities.

By distinguishing between global and country-specific uncertainty shocks, we show that even after controlling for country-specific components, global components can explain a substantial fraction of variations in macroeconomic performance in a given economy. However, we also document that the magnitude of global uncertainty impacts is relatively moderate compared to that of country-specific uncertainty impacts, which provides some support for the within-country analysis such as Bloom (2009) and Jurado et al. (2015). In sum, all of these findings point to the importance of distinguishing between global and country-specific components when investigating the macroeconomic impact of uncertainty shocks.

The global economic policy uncertainty index based on Baker et al. (2016) and Davis (2016) is the most widely utilized uncertainty measure at the aggregate global level, and it has been used in dozens of studies. We compare our empirical results with those produced using by this popular global uncertainty measure. The comparisons show that the global macroeconomic uncertainty has a significantly stronger explanatory power on fluctuations in oil prices as well as on real activities. Meanwhile, global macroeconomic uncertainty also accounts for a larger fraction of the business cycles in a certain economy. However, global economic policy uncertainty is typically more related to financial variables, such as stock returns. Overall, our results show that our global macroeconomic uncertainty proxy can at least serve as an alternative to global economic policy uncertainty index when one needs to identify uncertainty shocks at the aggregate global level.

The contribution of this paper is twofold. First, and most importantly, we construct a new homogeneous proxy for global macroeconomic uncertainty by employing a rich global dataset covering both advanced and major emerging economies. Compared to the global economic policy uncertainty index, our proxy aims to capture the global uncertainty that is related to the macroeconomic fundamentals. Our proxy can be unitized by many other studies. Since uncertainty shock in general works as aggregate demand shocks, our global uncertainty proxy also complements the aggregate demand index as discussed in Kilian (2009). Second, based on this newly constructed global uncertainty measure, we are able to answer two research questions of particular interest. We investigate the price formation mechanism of oil, complementing research that has investigated the determinants of oil price movements (e.g. Kilian, 2009). We distinguish the macroeconomic impacts of global common uncertainty shocks from those caused by 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 GDP and CPI. Mumtaz and Theodoridis (2017) investigates the common dynamics of uncertainty across the OECD countries. Carriero et al. (2018) assesses the international commonality in macroeconomic uncertainty for 19 industrialized countries. Cesa-Bianchi et al. (2014) evaluates the global realized volatility based on equity prices, exchange rates, and 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 from 1989 to 2014. Our paper builds on these works, and complements them by constructing a new homogeneous global uncertainty measure based on world macroeconomic dynamics. Furthermore, we provide two meaningful applications to explicitly show how our new measure can shed light on important research questions that are of particular interest in recent economic studies.[6] Our work explores the common macroeconomic uncertainty that encompasses both developed and major developing economies. Given the increasingly important role of developing countries 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 provides our conclusions.

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.[7] 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 observable economic indicators.

To construct the global uncertainty measure, we simply follow the framework of Jurado

6. We provide the comparisons of our measures with other popular uncertainty proxies in the empirical section.

7. 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.

et al. (2015) and extend it to the multi-country framework. In Jurado et al. (2015), a crucial first step in our analysis is to replace the conditional expectation of variable of interest by a forecast, from which we construct the forecast error that forms the basis of our uncertainty measures. In our international context, we augment an autoregressive forecasting model with (i) a set of global factors (F_t^W) common to all variables (and all countries) in the system, (ii) a set of country factor (F_t^C) common to all variables in a certain country.[8] More specifically, let y_{jt} genetically denote a series that we wish to compute uncertainty in and whose value in period $h \geq 1$ is estimated from the factor augmented forecasting model

$$y_{jt+1} = \phi_j^y(L)y_{jt} + \gamma_j^W(L)F_t^W + \gamma_j^C(L)F_t^C + v_{jt+1,}^y \tag{1}$$

where $\phi_j^y(L)$, $\gamma_j^W(L)$, and $\gamma_j^C(L)$ are finite-order polynomials in the lag operator L of orders p_y, p_W and p_C, respectively, and v_{jt+1}^y is an idiosyncratic prediction error for the series.[9] An important feature of our analysis is that the one-step-ahead prediction error of y_{jt+1}, and of each factor in F_{t+1}^W and F_{t+1}^C is permitted to have time-varying volatility σ_{jt+1}^y, σ_{t+1}^W, σ_{t+1}^C, respectively. This feature generates time-varying uncertainty in the series y_{jt}.[10] Uncertainty is then the conditional expectation of this time-varying squared forecast error, which is computed using a stochastic volatility model.[11] This model allows for shocks to the second moment of a variable to be independent of the first moment ensuring that these estimates capture a mean preserving increase in volatility rather than a rise in volatility that accompanies a deterioration in the mean (as is often seen in survey forecasts used widely in uncertainty proxies).

When the factors have autoregressive dynamics, a more compact representation of the systems above is the factor augmented vector autoregression (FAVAR). Let $Z_t \equiv (F_t^{W\prime}, F_t^{C\prime})'$

8. This type of hierarchy model is commonly used in the literature of international economics, for example, Kose et al. (2003), Kose et al. (2012) and Mumtaz and Theodoridis (2017). We extract dynamic factors using the principal components method. Following Kose et al. (2012) among others, our procedure draws the country-specific factor conditional on the global factors. This imposes orthogonality between the global and country-specific factor innovations.

9. Note that for each y_{jt}, we only include the relevant country factor that y_{jt} belongs to when estimating the model. We also experiment the model with quadratic terms of global and country-specific factors in the model to capture possible nonlinearities. This setting does not significantly change the results below.

10. We follow Jurado et al. (2015) to allow for stochastic volatility in both the estimates of the factors used to augment the VAR and the variables included in the VAR. This results in four sources of time variation in the forecast errors due to the stochastic volatility of the VAR shocks, the factors, the covariance between these two, and an autoregressive term due persistence in the volatility of the VAR shocks. Without stochastic volatility the forecast error would not vary with t but only with h.

11. We use the STOCHVOL package in R as in Jurado et al. (2015), to estimate the volatilities by which uses Markov Chain Monte Carlo (MCMC) methods. The forecasting residuals are estimated with least squares and those residuals are used to estimate stochastic volatility model where volatility follows an AR(1) process with an intercept term.

be a $r = r_W + r_C$ vector which collects the r_W and r_C estimated factors, 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

$$\begin{pmatrix} \mathcal{Z}_t \\ Y_{jt} \end{pmatrix} = \begin{pmatrix} \Phi^{\mathcal{Z}} & 0 \\ \Lambda_j' & \Phi_j^Y \end{pmatrix} \begin{pmatrix} \mathcal{Z}_{t-1} \\ Y_{jt-1} \end{pmatrix} + \begin{pmatrix} \mathcal{V}_t^{\mathcal{Z}} \\ \mathcal{V}_{jt}^Y \end{pmatrix}, \tag{2}$$

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

where Λ_j' and Φ_j^Y are functions of the coefficients in the lag polynomials in Eq. (1), 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

$$\Omega_{jt}^{\mathcal{Y}}(h) \equiv \Phi_j^{\mathcal{Y}} \Omega_{jt}^{\mathcal{Y}}(h-1)(\Phi_j^{\mathcal{Y}})' + E_t(\mathcal{V}_{jt+h}^{\mathcal{Y}}(\mathcal{V}_{jt+h}^{\mathcal{Y}})'). \tag{3}$$

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,

$$\mathcal{U}_{jt}^y(h) = \sqrt{1_j' \Omega_{jt}^{\mathcal{Y}}(h) 1_j}. \tag{4}$$

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 in each country equal weight proportional to their GDP share, which is same to the construction of economy policy uncertainty index in Davis (2016). As a result, the individual uncertainty in series of major economy like the US contributes more to the estimates of aggregate global uncertainty. This method has appealing features of arguably clear economic meanings. As an alternative, we also adopt a statistical method and construct a latent common factor estimate of global macro uncertainty as the first principal component of the covariance matrix of individual uncertainties.[12]

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. (2). 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 number for these factors. We include four lags ($p = 4$) when estimating the model. This selection is supported by a careful inspection of residual autocorrelation. Besides, including more or less lags would not have significant impact on our estimates of global uncertainty. To concentrate 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 of the world. The choice of the starting date reflects our desire to maximize the sample size in the time dimension while including as many countries as possible. Where necessary, the variables are log differenced to induce stationarity. Finally, we standardize all of the series used in this study.

The dataset we use to construct a homogenous global uncertainty index covers the information from 33 world major economies, over the time span from 1980Q1 to 2016Q4. Our estimates

12. We experiment both the GDP share and factor structure as weighting schemes to generate the global uncertainty. These two methods generate very similar results. In the following empirical sections, we report the results based on the GDP share. The results based on the factor structure are available upon request.

are mainly based on the latest version of the Global VAR (GVAR) dataset.[13] The construction of the 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.

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 in 2016.

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. 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.[14] In sum, we mainly utilize the abundant information from the GVAR dataset to construct a homogenous measure of global uncertainty, and we complement it with the dataset of Mumtaz and Theodoridis (2017) for the robust

13. 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.

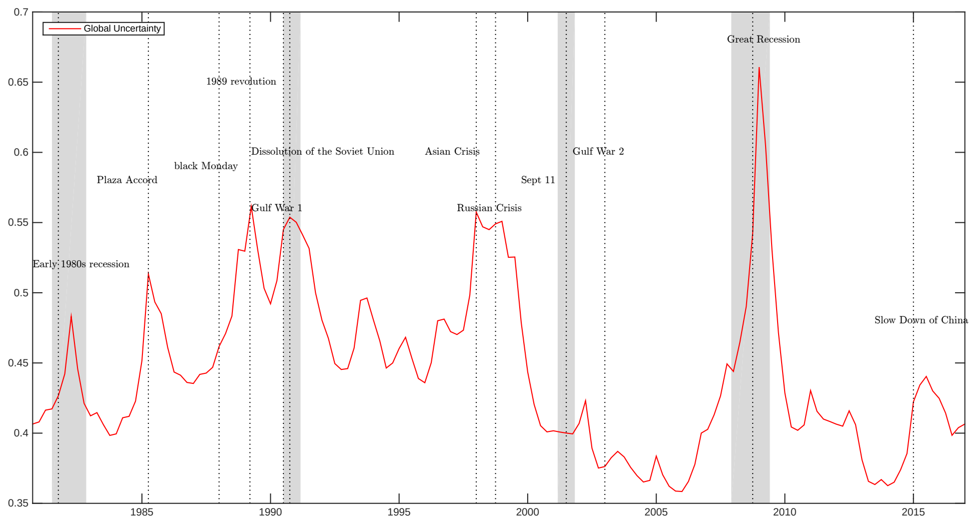
14. The appendix in Mumtaz and Theodoridis (2017) reports a full list of the series included and the data sources.

analysis and cross comparison. Our data reflects our desire to capture the comprehensive global economic conditions covering both developed and major developing counties.

3 Empirical Results

3.1 Estimates of Global Macroeconomic Uncertainty

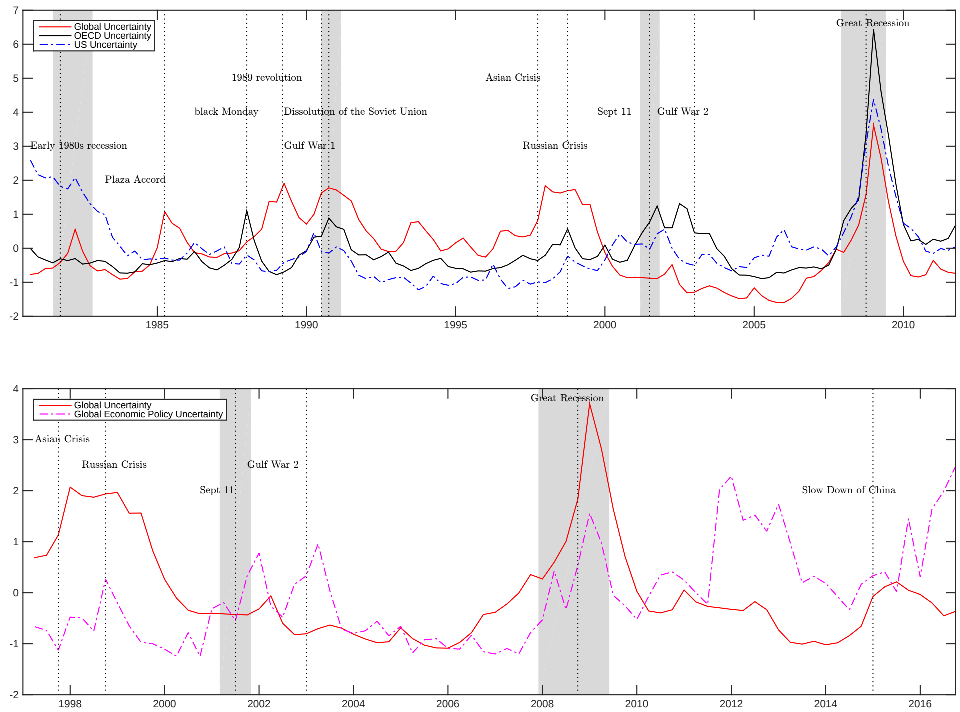
FIGURE 1 Global Macroeconomic Uncertainty Proxy



Notes: We construct the global macroeconomic uncertainty measure by estimating the FAVAR model in Eq. (2) with the data from 33 world major economies.

We present estimates of our global macroeconomic uncertainty proxy 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 uncertainty shows spikes around the 1981-1982 recessions, the 1990-1991 recessions, and the Great Recession of 2007-2009. However, we also document the noticeable decoupling between our global uncertainty measure and the US business cycle patterns when uncertainty is mainly coming from emerging markets, such as the revolutionary wave in the late 1980s and the 1997 Asian crisis period. The dotted vertical lines in Figure 1 further indicate that the uptrends in global uncertainty have largely coincided with influential global events. For example, 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 were severe global

FIGURE 2 Comparison of Uncertainty Measures



Notes: We obtain the US macroeconomic measure from Jurado et al. (2015), OECD measure from Mumtaz and Theodoridis (2017) and global economic policy measure from Davis (2016). The global economic policy measure constructed in Davis (2016) has a relative short time span, which starts from 1997.

economic contractions, which are also associated with a surge in global uncertainty. Along with major economic crises, major institutional and political events such as the signing of the Plaza Accord, the the revolution of 1989, Gulf War I and dissolution of the Soviet Union are also related to a surge in global uncertainty. More recently, the slowdown of economic growth in China has also triggered a rise in uncertainty at the international level.

It is also of interest to compare our global proxy to other popular country-specific and regional macroeconomic uncertainty measures: US uncertainty (Jurado et al., 2015) and OECD uncertainty (Mumtaz and Theodoridis, 2017). Figure 2 plots the standardized series of these macroeconomic uncertainty measures, together with another widely used global uncertainty index, the global economic policy uncertainty index (Davis, 2016).[15] Figure 2 shows that these measures share some commonalities in their long-run movements. For example, all of these measures are clearly countercyclical. However, further analysis of these plots also indicates that our global proxy exhibits considerable differences from the country-specific or regional

15. Note that the global economic policy measure in Davis (2016) has a relatively short time span.

uncertainty measures. For example, as discussed above, aside from the recent Great Recession, our global uncertainty proxy shows spikes during the period of the revolution of 1989 and the Asian financial crisis. In contrast, country-specific or regional measures mainly report the dynamics of uncertainty in advanced countries, which fails to capture uncertainty shocks in the emerging countries.

To translate the graphical pattern into a statistical representation, we report the correlations of the uncertainty measures in Table 2. As expected, our global measure is more correlated with the regional macroeconomic uncertainty measure of OECD than it is to the country-specific measure of the US. Also, the global economic policy uncertainty measure differs the most from our global proxy. The reason for this may lie in how these two measures are constructed.[16] The global economic policy uncertainty aims to capture uncertainty related to economic policy. Our proxy reflects uncertainty related to macroeconomic fundamentals.

Table 3 further reports the summary statistics of our uncertainty proxy, as well as other indices. Table 3 also displays the first-order auto-correlation coefficient, along with 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 decline 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 macroeconomic 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 compared to the US uncertainty measure, but more persistent compared to OECD and economic policy uncertainty measures.

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

In sum, our global macroeconomic uncertainty proxy shares some commonalities with pop-

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

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.

ular country-specific and regional uncertainty measures, as well as with the economic policy uncertainty index. However, we also document substantial heterogeneity. Our proxy highlights the uncertainty-related events not only in the advanced economies, but also in the rapidly developing emerging countries. This property is in line with our desire to proxy uncertainty at the aggregate global level, capturing the comprehensive global economic conditions covering both advanced and major emerging counties.

3.2 Global Uncertainty and Macroeconomic Dynamics

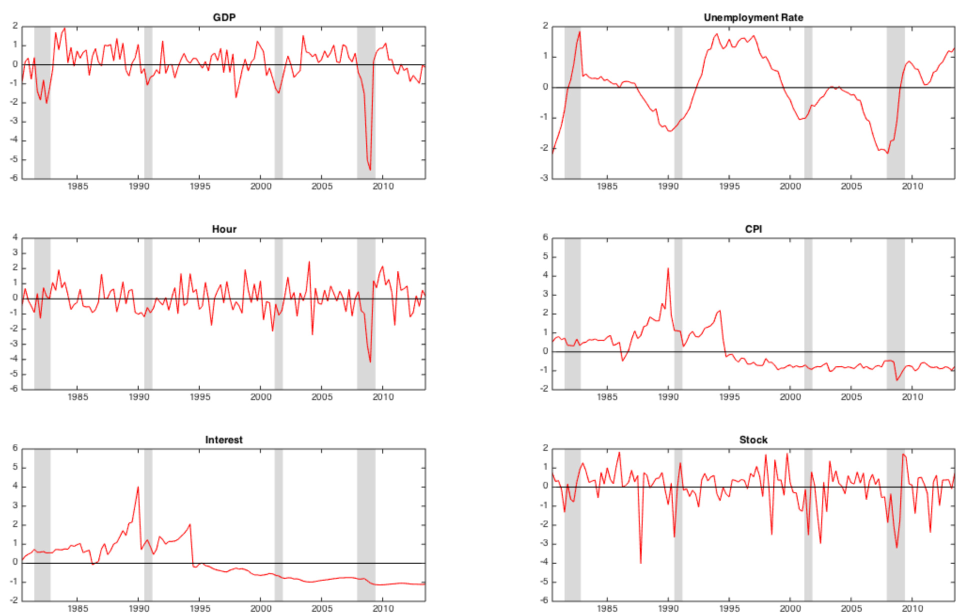
Existing empirical studies on uncertainty have often found important relationships between real activity and uncertainty proxies. In particular, these proxies are countercyclical, and VAR estimates suggest that they have substantial impacts on output and employment, given an innovation in these uncertainty measures.[17] In this section, we extend these existing literature to the global context. To achieve that, we first construct the global macroeconomic factors. The construction of global macroeconomic factors follows the strands of literature that investigates the world business cycle (e.g. Kose et al., 2012, 2003, 2008; Mumtaz and Surico, 2009). Second, we relate these macroeconomic variables to global uncertainty and investigate the dynamic responses.

We first plot the dynamics of the global factor series for each macroeconomic variable,

17. 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.

as shown in Figure 3. These global factors are generated by the simple principle component method. Overall, the patterns of each series capture the major global events. For example, the trough of the stock series matches the major stock market crashes across 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.[18] These results are in line with earlier studies such as Mumtaz and Surico (2009).

FIGURE 3 Global Macroeconomic Factors



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

We now use a standard VAR model to investigate the dynamic responses of these key macroeconomic variables to innovations in global uncertainty. We estimate impulse-response functions (IRFs) using a seven-variable model similar to that employed by Bloom (2009) and

18. 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 3.5.

—henceforth, VAR-7:[19]

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

Following Bloom (2009), we adopt a standard recursive method to achieve the identification. This identification scheme assumes that the uncertainty shocks have a contemporaneous impact only on the financial variable of stock prices. Figure 4 shows the dynamic responses of major global factors given a one percent increase in global uncertainty. 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 that is based on single-country analysis.[20] Figure 5 plots the responses of the major financial variable, stock price, given the uncertainty shocks. We show that a one percent of uncertainty shocks triggers a 0.24 percent decline in the stock price. Our findings support the theory that an increase of uncertainty leads to risk aversion of investors or even causes a panic sentiment in the financial market, which boosts the selling of stock shares and thereafter lowers stock prices.

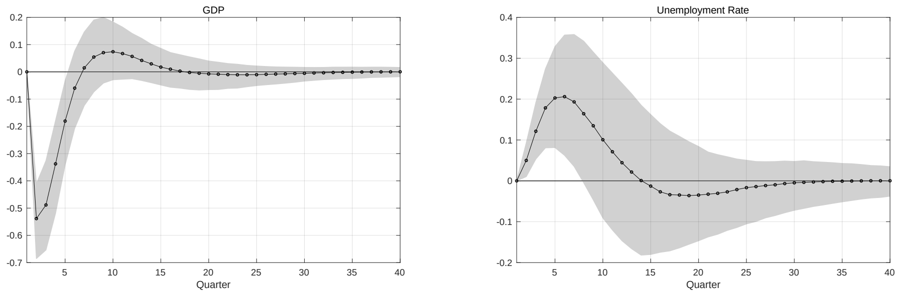
Table 4 reports the variance decomposition results. We show that global uncertainty can explain around 9% variation in GDP fluctuations, and 6% in unemployment. These results provide further evidence of the vital role of uncertainty in determining the world business cycle. Table 4 also shows that uncertainty shocks can explain a significant fraction of variations in other global factors of interest such as working hours, CPI, and interest rates.

19. 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.

20. "Real Options" effect, "Precautionary Savings" effect and "Financial Frictions" effect are three commonly accepted mechanisms through which the uncertainty shocks affect the real activities.

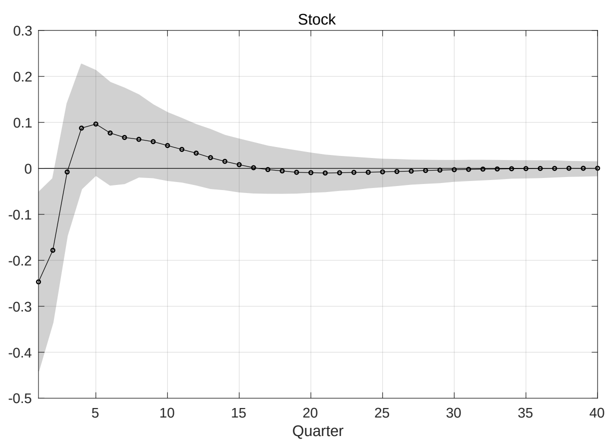
This is a preprint posted to SRN at 10.2139/ssrn.3280848

FIGURE 4 IRFs of Global Macroeconomic Activities



Notes: The solid dotted line represents the IRFs of GDP and unemployment rate given one percent global uncertainty shock. Shaded areas represent 68% confidence bands over 10,000 bootstrap repetitions.

FIGURE 5 IRFs of Global Financial Market



Notes: The solid dotted line represents the IRFs of global stock returns given a one percent global uncertainty shock. Shaded areas represent 68% confidence bands over 10,000 bootstrap repetitions.

TABLE 4 Variance Decomposition: Uncertainty

	GDP	Unemployment	Hours	CPI	Interest Rate	Uncertianty	Stock Price
Explained by:				Uncertianty			
K=4	8.385%	1.712%	2.581%	0.511%	0.503%	81.914%	3.673%
K=12	8.910%	3.825%	3.543%	1.685%	1.581%	60.125%	4.317%
K=40	8.965%	5.745%	4.034%	2.899%	2.830%	48.849%	4.495%

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

3.3 Global Macroeconomic Uncertainty: 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 prices have a significant relationship with real activity in the US and other countries.[21]

In the 2000s, along with the emerging literature on the impact of uncertainty on real activity, dramatic oil price volatility has triggered intensive debate in the literature on the possible drivers of oil price movements (e.g. Kilian, 2008, 2009; Lippi and Nobili, 2012; Peersman and Van Robays, 2009; Singleton, 2013). Among the literature investigating the price formation mechanism of oil, 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.[22] 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 for aggregate demand shocks. Leduc and Liu (2016) provides both empirical results and a theoretical framework to show that uncertainty shocks essentially work as aggregate demand shocks. As a result, a question of particular interest is how the commodity price (of oil) will respond to one particular type of aggregate demand shocks—macroeconomic uncertainty shocks.[23]

In this section, we provide an important application of the global uncertainty measure by

21. 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).

22. 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.

23. 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 Peersman, 2012).

revisiting the debates over the key determinants of oil prices. Given that oil is a world primary commodity, the price of oil is unlikely to be determined by the macroeconomic status of a single country, but will rather be set by overall global economic conditions. Therefore, a global uncertainty measure is needed to understand the price fluctuations of oil. Based on our global macroeconomic uncertainty proxy, we are able to contribute to the debates on estimating the extent to which the steep volatility in oil prices is determined by uncertainty shocks. We adopt two econometric frameworks to investigate this question. First, we estimate the impact of uncertainty on oil prices in a typical macroeconomic economic SVAR model that includes GDP growth, inflation, and etc. Second, following Kilian (2009), we estimate an alternative structural model that considers world oil production, real price of crude oil, and global economic activity.[24]

More specifically, we augment the previous VAR-7 framework to analyze the impacts of macro uncertainty on oil prices. We place the oil price as the last component, and we employ the recursive method to achieve identification. This identification scheme is arguably realistic, because the oil price shocks are unlikely to affect global real economic activities contemporaneously.[25]

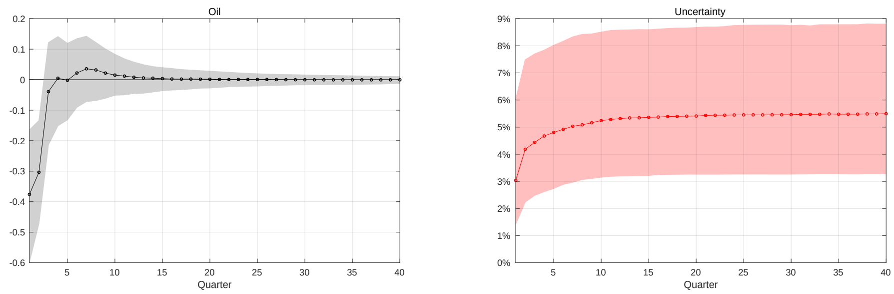
The left panel of Figure 6 reports the dynamic responses of oil prices given global uncertainty shocks. As expected, we document that macroeconomic uncertainty shocks have a significant impact on oil prices. In particular, oil prices experience an instant decline of 0.38 percent, which dies out quickly in the following 4 periods.[26] The right panel of Figure 6 and Table 5 present the variance decomposition results. We show that uncertainty can explain nearly 5.5% of the variance in oil price movements in the long run. Moreover, among all the macroeconomic variables, uncertainty plays the top 3 most important role in driving the oil price fluctuations, together with GDP and interest rates. All of these findings point out the importance of macroeconomic uncertainty in oil price formation mechanism, cautioning future studies to take uncertainty into account when investigating oil price movements.

24. 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 3.5.

25. Our estimation results are also robust to the alternative identification scheme. For more discussions on this issue, see Section 3.5.

26. 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



Notes: The solid dotted line represents the IRFs of oil price given a one percent global uncertainty shock, as well as the variance decomposition results. Shaded areas represent 68% confidence bands over 10,000 bootstrap repetitions.

TABLE 5 Variance Decomposition: Uncertainty

	Oil Price							
Explained by:	GDP	Unemployment	Hours	CPI	Interest Rate	Uncertianty	Stock Price	Oil Price
K=4	9.165%	1.517%	1.179%	3.722%	4.126%	4.673%	1.556%	72.528%
K=12	9.246%	2.171%	1.277%	4.448%	4.614%	5.317%	1.656%	69.751%
K=40	9.216%	2.437%	1.303%	4.893%	5.148%	5.495%	1.652%	68.023%

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

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

$$A_0 z_t = \alpha + \sum_{i=1}^{4} A_i z_{t-i} + \varepsilon_t, \tag{5}$$

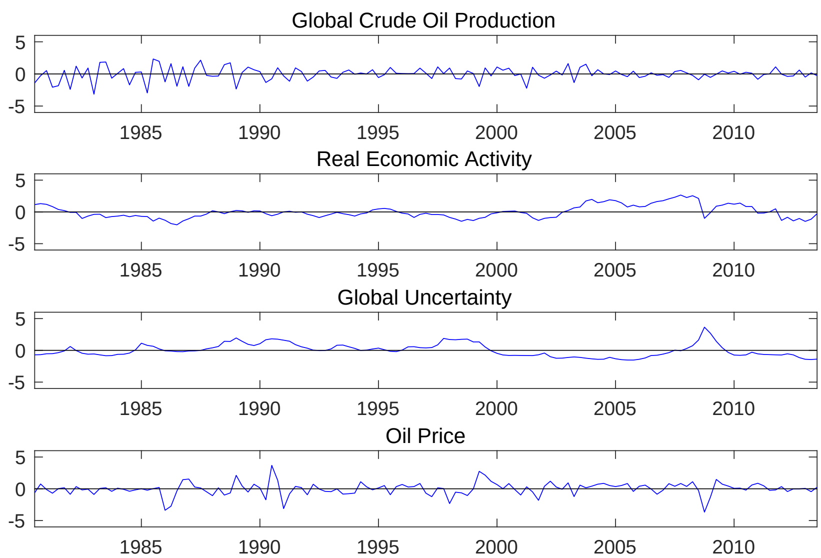
where ε_t denotes the vector of serially and mutually uncorrelated structural innovations, and the SVAR is based on the quarterly data for $z_t = (\Delta prod_t, rea_t, uncer_t, rpo_t)'$.[27] $\Delta prod_t$ is the percent change in global crude oil production, rea_t denotes the index of real economic activity constructed in Kilian (2009), $uncer_t$ refers to the global uncertainty measure, and rpo_t is the real price of oil. Figure 7 plots the historical rates of these series. Following Kilian (2009), we adopt the standard recursive method to achieve the identification. In the baseline case, we assume global uncertainty has a contemporaneous impact only on oil prices, but not on oil production and economic activity. More specifically, we postulate that A_0^{-1} has a recursive structure such

27. The VAR is estimated on quarterly data using four lags and a constant. We adopt the data from 1980 to 2013. Note that we are using the quarterly data since our global uncertainty measure is only available at the quarterly frequency.

that the reduced-form errors ε_t can be decomposed according to $e_t = A_0^{-1}\varepsilon_t$:

$$e_t \equiv \begin{pmatrix} e_t^{\Delta prod} \\ e_t^{rea} \\ e_t^{uncer} \\ e_t^{rpo} \end{pmatrix} = \begin{bmatrix} a_{11} & 0 & 0 & 0 \\ a_{21} & a_{22} & 0 & 0 \\ a_{31} & a_{32} & a_{33} & 0 \\ a_{41} & a_{42} & a_{43} & a_{44} \end{bmatrix} \begin{pmatrix} \varepsilon_t^{oil\ supply\ shock} \\ \varepsilon_t^{aggregate\ demand\ shock} \\ \varepsilon_t^{uncertainty\ shock} \\ \varepsilon_t^{oil-specific\ demand\ shock} \end{pmatrix}. \tag{6}$$[28]

FIGURE 7 Historical Rates of Oil Market Variables

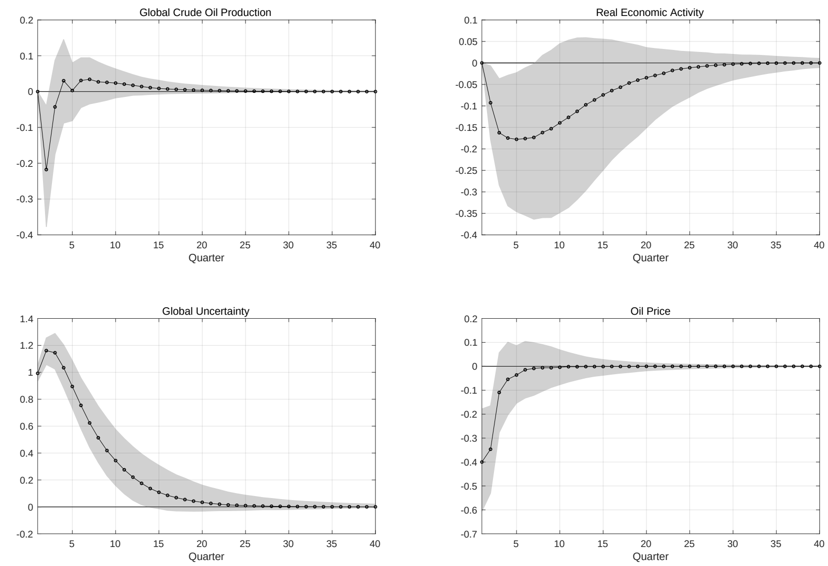


Notes: Estimates derived from model (5) and (6).

Figures 8 and 9 report the results when adopting Kilian (2009)'s framework. Our findings confirm that the global uncertainty shock, which works as aggregate demand shock, plays a critical role in determining oil price movements. In particular, after controlling for the supply and conventional aggregate demand factors, a one percent increase in global uncertainty leads to a 0.40 percent significant decline in oil prices. Meanwhile, the uncertainty shocks can again explain nearly 6% of oil price variances in the long run. Moreover, the impact of uncertainty shocks is comparable to the conventional aggregate demand shock, and it is much stronger as compared to supply-side factors. All of these results are in line with the macroeconomic SVAR model.

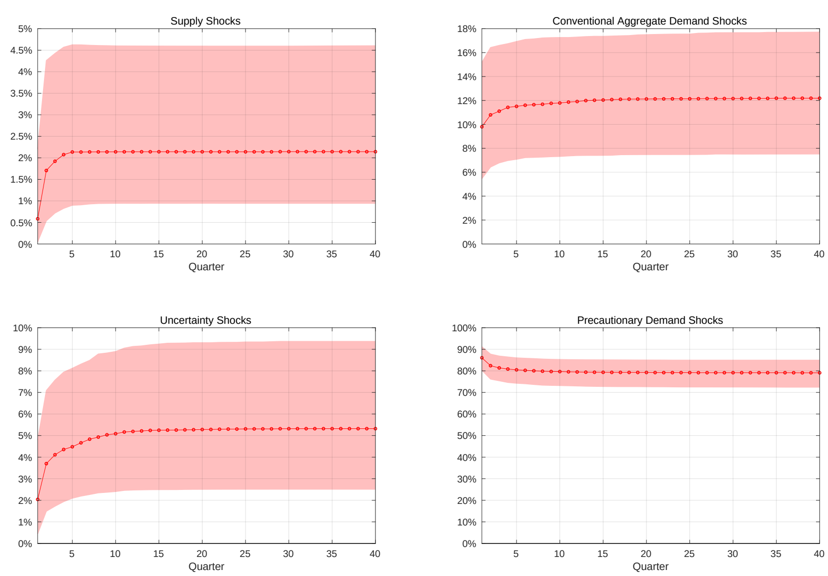
28. For more discussions on the validity of this identification scheme, see Kilian (2009). Our estimation results are also robust to the reasonable changes of this ordering scheme. We report the corresponding results in Section 3.5.

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



Notes: The solid dotted line represents the IRFs of oil market variables given a one standard deviation global uncertainty shock. Shaded areas represent 68% confidence bands over 10,000 bootstrap repetitions.

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



Notes: The solid dotted line represents the variance decomposition of oil market variables. Shaded areas represent 68% confidence bands over 10,000 bootstrap repetitions.

In sum, based the global uncertainty proxy, we are able to explore the implications set forth in the work of Kilian (2009) and Leduc and Liu (2016), and we investigate the impacts of global uncertainty shocks on oil price movements. Our results show that global uncertainty, which works as aggregate demand shock, plays a key role in determining commodity prices. These findings highlight the importance of second moment shocks, together with traditional level shocks, on the price formation mechanism in the oil market.

3.3.2 Uncertainty Shock: Global Common v.s. Country-specific Components

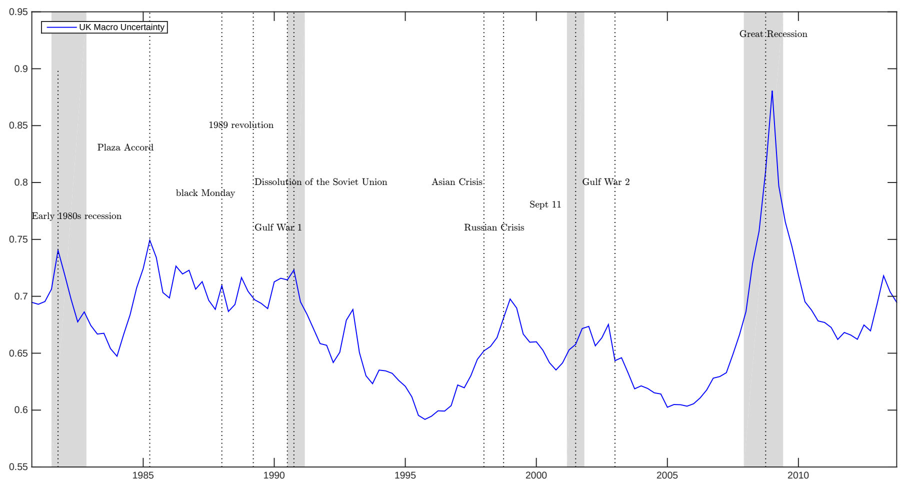
Recent literature has thoroughly discussed the impact of uncertainty shocks on a certain economy (e.g. Bloom, 2009; Carriero et al., 2017; Jurado et al., 2015). However, another strand of literature documents that globalization spurs the rising production, trade and financial integration across countries and has triggered a common business cycle at the global and country group levels (Kose et al., 2012, 2003, 2008; Stock and Watson, 2005). The world economies interact with each other on myriad levels, and therefore, the uncertainty shocks may transmit across countries through these cross-country linkages. In this regard, Mumtaz and Theodoridis (2017) provides detailed empirical evidence of the commonly dynamics of uncertainty across countries, and constructs a two country DSGE model to capture uncertainty spillover from one country to another.[29] However, most of uncertainty measures used in the existing literature, which is constructed based on domestic data, fail to disentangle the country-specific and global common components of uncertainty shocks.

In this section, we utilize the newly constructed global uncertainty series to explicitly distinguish the global common and country-specific components when evaluating the impacts of uncertainty shocks. We illustrate our idea in the context of the UK. More specifically, we first construct the macroeconomic uncertainty measure for the UK, and we then investigate the interactions between the UK uncertainty and global uncertainty. We pay particular attention to the UK for two reasons. First, compared to the US, the UK is an arguably "small" open economy, which ensures that the empirical findings have some implications on the dynamic causal effect. Second, as a developed country, the UK provides abundant macroeconomic data of relatively higher quality, across a longer time span, compared to some other developing small

29. 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.

open economies.

FIGURE 10 Macroeconomic Uncertainty in the UK



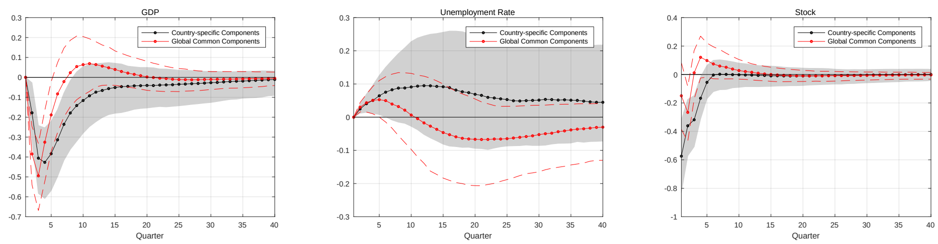
Notes: We utilize the same method of Jurado et al. (2015) as before to construct the UK macroeconomic uncertainty measure. We extract the data from Mumtaz and Theodoridis (2017).

Figure 10 plots the estimated macroeconomic uncertainty for the UK based on the same method as in Jurado et al. (2015). In general, this UK macroeconomic uncertainty series can capture major economic events of the UK, and is in line with the corresponding results generated by Mumtaz and Theodoridis (2017). Based this measure, we augment the single-country analysis as in Bloom (2009) and Jurado et al. (2015), and investigate the impacts of uncertainty shocks on macroeconomic fluctuations in the UK when including both global and country-specific uncertainty components. More specifically, we now estimate an eight-variable VAR model:

$$\begin{bmatrix} UK \;\; GDP \\ UK \;\; Unemployment \\ UK \;\; Hours \\ UK \;\; CPI \\ UK \;\; Interest \;\; Rate \\ Global \;\; Uncertianty \\ UK \;\; Uncertianty \\ UK \;\; Stock \;\; Price \end{bmatrix}.$$

Following Bloom (2009), we adopt the standard recursive method to achieve the identification. Global uncertainty is allowed to contemporaneously affect the country-specific uncertainty in the UK. This identification method is useful for separating the global common and country-specific effects, and has been adopted by many other studies (e.g. Canova, 2005; Carriero et al., 2018; Mumtaz and Surico, 2009).

FIGURE 11 IRFs of the UK Economy,
Global Common and Country-specific Components in Uncertainty

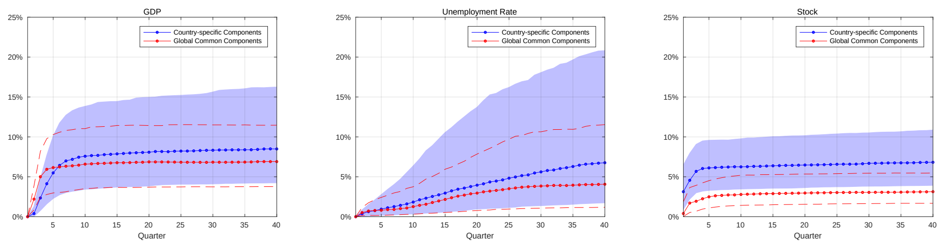


Notes: The black line represents the IRFs given the country-specific uncertainty shocks of the UK, the red line represents the IRFs given the global uncertainty shocks. We also report 68% confidence bands over 10,000 bootstrap repetitions.

We now distinguish between global and country-specific uncertainty shocks. We compare the responses of major UK macroeconomic indicators given global common and country-specific uncertainty shocks in Figure 11. This figure shows that even after controlling for the country-specific components, the effect of global common uncertainty shocks is significant, especially for variations in real output. The results confirm that in addition to the country-specific uncertainty which has been studied extensively, global common components in uncertainty also account for a substantial fraction of business cycle fluctuations in a certain economy. However, we should also note that the magnitude of the impact of global uncertainty shocks is relatively moderate compared to that of country-specific uncertainty shocks. These findings suggest the validity for the results in within-country analysis such as Bloom (2009) and Jurado et al. (2015). Figure 12 plots the variance decomposition results, which also support the observations we document above.

Overall, by formally purposing a global uncertainty proxy and exploring the arguments from Mumtaz and Theodoridis (2017) among other studies, we highlight the importance of identifying the global components when investigating the impact of conventional country-specific uncertainty. Global components can explain a substantial fraction of variations in macroeconomic performance in a certain economy.

FIGURE 12 Variance Decomposition of the UK Economy,
Global Common and Country-specific Components in Uncertainty



Notes: The blue line represents the variance explained by country-specific uncertainty, the red line represents the variance explained by global common uncertainty. We also report 68% confidence bands over 10,000 bootstrap repetitions.

3.4 Comparison with Global Economic Policy Uncertainty

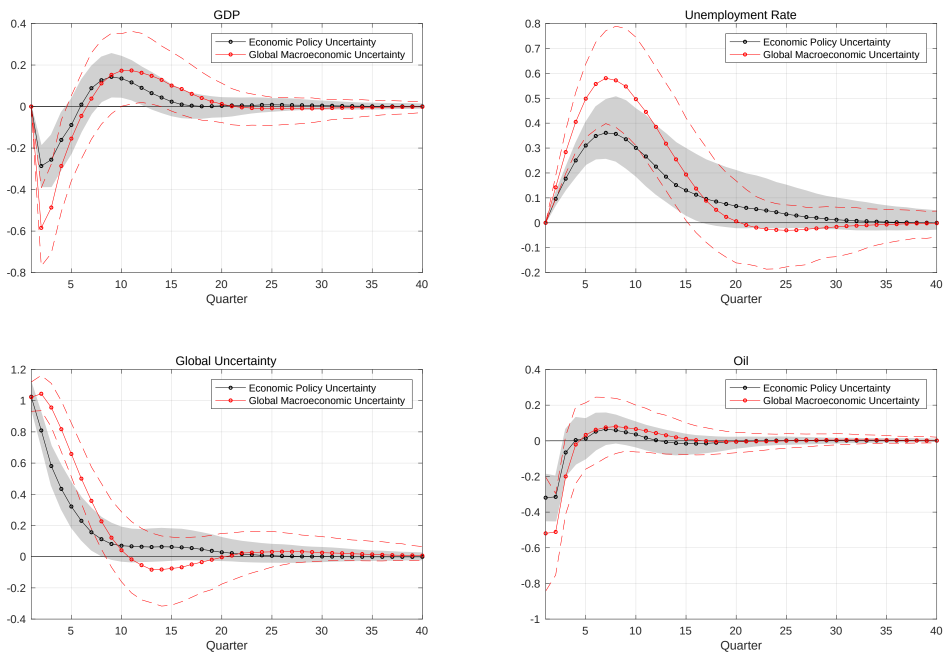
Another question of particular interest is the comparison between the macroeconomic impacts of our proxy and that of other global uncertainty measures. Among few global uncertainty measures, the global economic policy uncertainty index based on Baker et al. (2016) and Davis (2016) is the most popular global uncertainty index, and has been used in dozens of studies.[30] As a result, in this section, we make comparisons to this widely utilized index.

Before presenting our empirical results, it is useful to review the basic properties of two global uncertainty proxies. The global economic policy uncertainty index aims to capture uncertainty from the perspective of economic policy. The construction of this index is based on text readings, covering information from 20 countries and is available on a monthly basis. However, this index starts only from January 1997, due to the restriction set by the text reading method. Our proxy focuses on macroeconomic uncertainty, which reflects macroeconomic fundamentals. Our proxy could date back to 1980, so that it provides more abundant information on the historical perspective. However, due to the data limitations, our proxy is only available on a quarterly basis.

In Figures 13 and 14, we revisit the impact of uncertainty shocks on global macroeconomic activities and the price formation mechanism of oil. To make it comparable, we obtain the estimates by adopting the same econometric framework as in the previous sections, but we replace our macroeconomic uncertainty measure with the global economic policy uncertainty index. The black line is the IRFs given the economic policy uncertainty shocks. The red line reports the results of our global macroeconomic uncertainty measure. In Figures 15, we

30. See https://www.policyuncertainty.com/global_monthly.html for a full list of publications.

FIGURE 13 Global Macroeconomic Activities and Uncertainty: Comparison with Global Economic Policy Uncertainty



Notes: The black line is the IRFs given the economic policy uncertainty shocks, the red line reports the results of our global macroeconomic uncertainty proxy. We also report 68% confidence bands over 10,000 bootstrap repetitions.

disentangle the impact of global common and country-specific components with the global economic policy uncertainty index. Note that we only use the data starting from 1997 to ensure the validity of the comparison.

The comparison induces the following interesting observations.

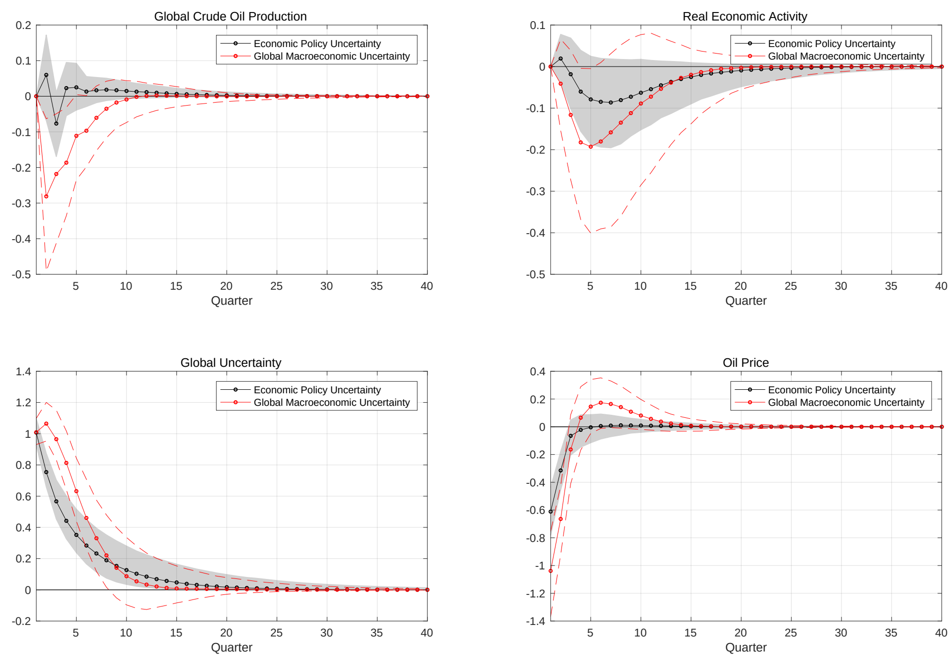
First, and most importantly, we show that our global macroeconomic uncertainty proxy has a significantly stronger impact on fluctuations in real activities as well as in oil prices. More specifically, Figures 13 documents that a one percent increase in global macroeconomic uncertainty shocks can trigger as much as a 0.60 percent decline in GDP growth, a 0.58 percent increase in unemployment rate and a 0.51 percent slump in oil prices. These impacts are much greater than the estimated 0.29 percent decline in GDP growth, 0.33 percent increase in unemployment rate and 0.32 percent slump in oil prices that are caused by economic policy uncertainty shocks. The results are robust when we adopt the alternative Kilian's framework and disentangle the impact of global common and country-specific uncertainty shocks.[31] All of these results point out that global macroeconomic uncertainty, which captures economic fundamentals, is a useful proxy to explain macroeconomic fluctuations.

Second, however, economic policy uncertainty is more related to financial variables. In Figures 15, we document a surge in stock returns given the economic policy uncertainty measure. The explanation could be related to the manner in which economic policy uncertainty measure is constructed. The text reading method can easily capture market sentiments during a financial volatile period. As a result, changes in economic policy uncertainty are associated with dramatic variations in stock prices.

In sum, our proxy has a significant explanatory power on fluctuations in real activities and the oil prices. Compared to the global economic policy uncertainty measure, which aims to capture policy uncertainty, our proxy mainly reflects uncertainty in the macroeconomic fundamentals. All of our findings indicate that our global macroeconomic uncertainty proxy can at least serve as an alternative to the global economic policy uncertainty proxy when one needs to identify uncertainty shocks at the aggregate global level.

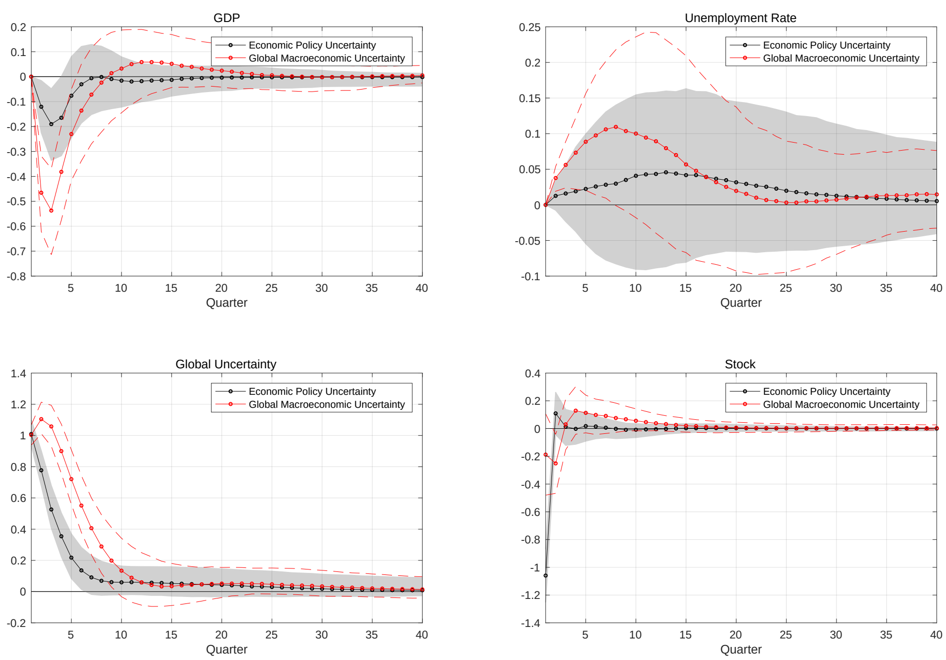
31. Note that we document a much stronger impacts of uncertainty on oil price in the Kilian's Framework. The reason could be we only use the data starting from 1997 to ensure validity of the comparison. However, in the recent period, the macroeconomic activities index has a weaker power to capture the world real activities. More arguments on this issue, see Hamilton (2019).

FIGURE 14 Oil Market and Uncertainty:
Comparison with Global Economic Policy Uncertainty



Notes: The black line is the IRFs given the economic policy uncertainty shocks, the red line reports the results of our global macroeconomic uncertainty measure. We also report 68% confidence bands over 10,000 bootstrap repetitions.

FIGURE 15 Common and Country-specific Uncertainty:
Comparison with Global Economic Policy Uncertainty



Notes: The black line is the IRFs given the economic policy uncertainty shocks, the red line reports the results of our global uncertainty measure. We also report 68% confidence bands over 10,000 bootstrap repetitions.

3.5 Further Discussions

3.5.1 Alternative Identification Scheme

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

Figure A1 reports the results in the VAR-7 framework, and Figure A2 and A3 report 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 still explain between 2% to 3% of the variations in oil price movements.

3.5.2 Alternative Country Set

One possible concern about our baseline results is that the global factors used in 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 in global interest rate in the 1990s may have been 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 the data only from OECD countries. In other words, we are estimating the impact of global uncertainty based on OECD common factors. Figures A4 and A5 in the Appendix present the main results. As expected, the baseline results are robust when we adopt only the OECD factors.

3.5.3 Global Uncertainty and Other Commodities

We also analyze the impacts of macroeconomic uncertainty on two other key international commodities: agricultural raw materials and metals.[32] We choose the composite index of agricultural raw materials and metals as commodity price measures, which contain major exported and imported goods such as rubber, cotton, iron, copper, and etc.

The left panel of Figure A6 shows the dynamic responses of the raw material prices, given the global uncertainty shocks. We document a significant decline in raw material price immediately after the uncertainty shocks, followed by a small overshoot and then a stabilization in the following fifteen quarters. The right panel of Figure A6 presents the variance decomposition results. We show that uncertainty can explain approximately 7.5% of the variance of raw material price movements in the long run. In Figure A7, we generate results for the metal price. Similarly, we document a significant decline in metal price given the uncertainty shocks. Figure A7 also shows uncertainty shocks can explain nearly 8% of the long-run variance in metal price fluctuations. In sum, the results related to agricultural raw materials 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)'s forecast-error-based uncertainty measure to the international context, and construct a new homogeneous global uncertainty proxy. Compared to the country-specific and regional uncertainty measures, our proxy highlights uncertainty-related events not only in the advanced economies, but also in the fast-developing emerging countries. The global uncertainty proxy developed in this paper can be utilized in many other studies, and can serve as an alternative when one needs to identify uncertainty shocks at the aggregate global level.

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

32. 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 shock 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 proxy in empirical research. First, our global uncertainty measure provides an alternative aspect to complement the aggregate demand shocks discussed in Kilian (2009), which are generally difficult to measure in empirical studies. We show that the second moment shocks of macroeconomic uncertainty, together with conventional aggregate demand shocks in level, are important drivers in oil price movements. Second, our global uncertainty proxy helps to distinguish the global common components from country-specific components in uncertainty shocks, complementing the single-country studies such as Bloom (2009) and Jurado et al. (2015).

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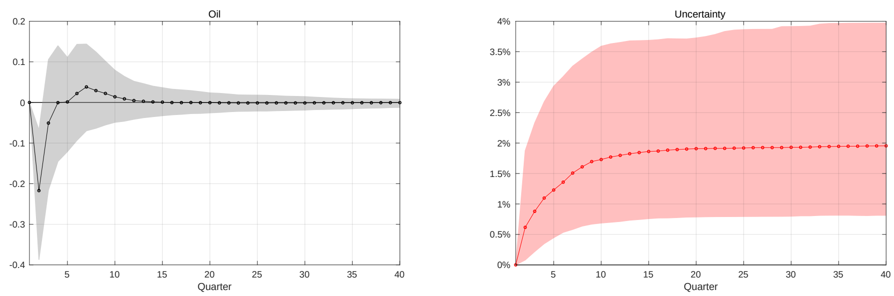
Appendix

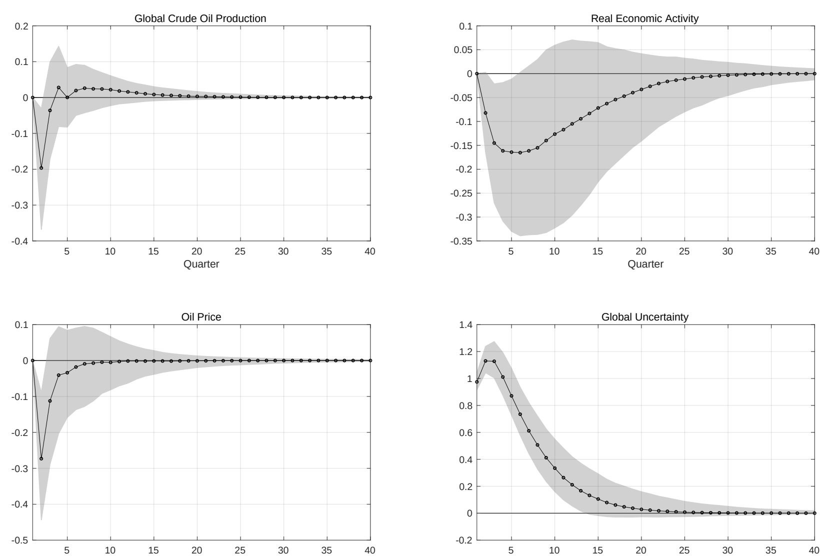
A Alternative Identification Scheme

FIGURE A1 IRFs and Variance Decomposition of Oil Price:
Alternative Identification Scheme



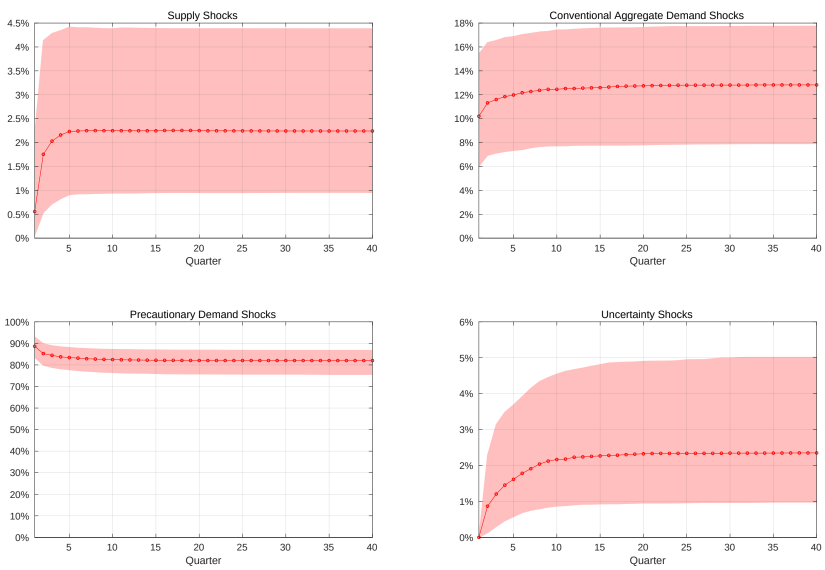
Notes: The alternative identification scheme restricts the global uncertainty shocks can have impact on all of the macroeconomic variables of interest only after one quarter.

FIGURE A2 Responses of Oil Market Variables:
Alternative Identification Scheme



Notes: The alternative identification scheme restricts the global uncertainty shocks can have impact on all of oil market variables of interest only after one quarter.

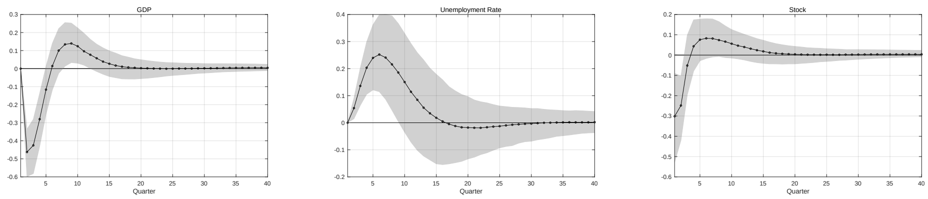
FIGURE A3 Variance Decomposition of Oil Market Variables: Alternative Identification Scheme



Notes: The alternative identification scheme restricts the global uncertainty shocks can only have impact on all oil market variables of interest after one quarter.

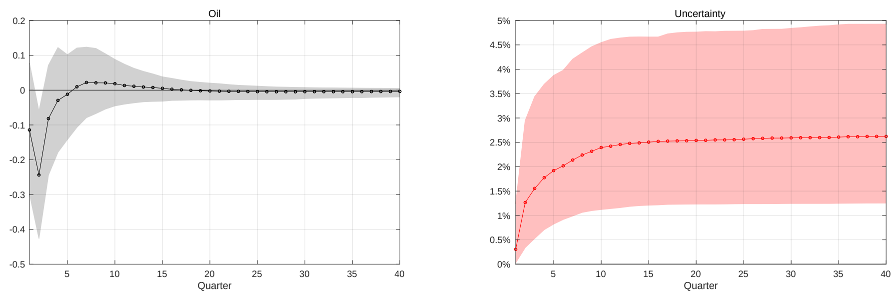
B OECD Factors

FIGURE A4 IRFs of Global Factors with OECD Factors



Notes: The global factors are constructed with only the data of OECD countries.

FIGURE A5 IRFs and Variance Decomposition of Oil Price with OECD Factors



Notes: The global factors are constructed with only the data of OECD countries.

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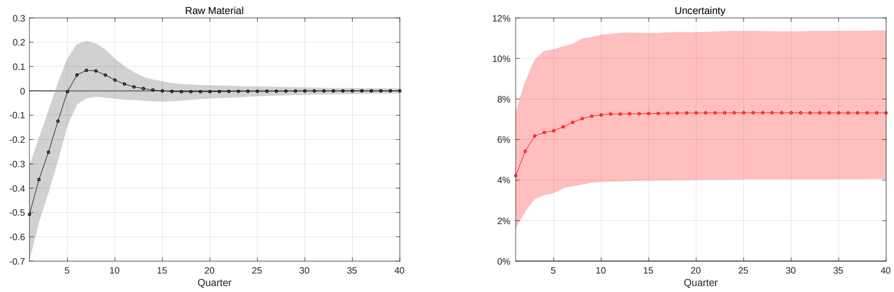
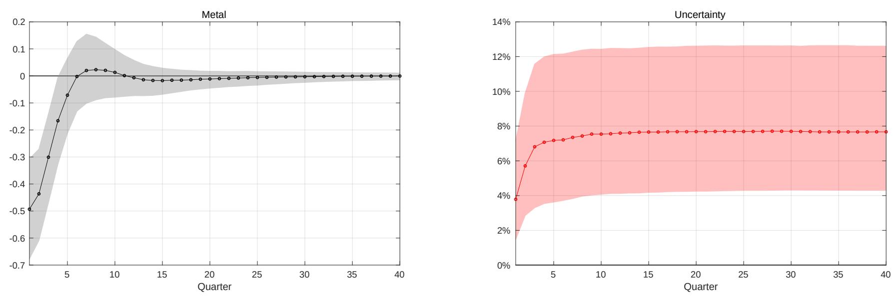
C Macro Uncertainty and Other Commodities

FIGURE A6 IRFs and Variance Decomposition of Raw Material Price



Notes: The agricultural raw material price indices are taken from the IMF's Primary Commodity Prices monthly data and subsequently aggregated to the quarterly frequency.

FIGURE A7 IRFs and Variance Decomposition of Metal Price



Notes: The metals price indices are taken from the IMF's Primary Commodity Prices monthly data and subsequently aggregated to the quarterly frequency.