Global Confidence, Uncertainty, and Business Cycles*

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This paper investigates the role of global confidence cycles, measured as the common factor across a wide range of survey-based business or consumer confidence indicators in global macroeconomic fluctuations over 1985–2019. We estimate a factor-augmented vector autoregression model, where global confidence shocks are identified through recursive restrictions. We report three main results. First, the global confidence cycles—in particular, that of consumer confidence—have played a key role in global business cycle fluctuations, explaining over a third of total variations. Second, while global business confidence shocks are in nature demand driven, global consumer confidence seems to reflect both demand and supply shocks, in line with "animal spirit" and "news" views on the relationship between confidence and economic activities. Third, the shifts in global confidence are not necessarily accounted for by uncertainty shocks. Instead, confidence acts as an important channel in the transmission of uncertainty shocks. The results are robust to alternative identification using a novel set of external instruments, alternative variable orderings, and different uncertainty measures.

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1. Introduction

The outbreak of the COVID-19 pandemic has refocused attention on the importance of economic sentiments, often defined as a combination of confidence and uncertainty, in global business fluctuations

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(Baker et al. 2020a, 2020b; Baldwin and Di Mauro 2020; Leduc and Liu 2020; Ludvigson, Ma, and Ng 2020). Uncertainty about the spread of the crisis and its impact on future economic developments and policies is still widespread. Global financial markets became highly volatile after the pandemic, reflecting the huge uncertainty and tumbling confidence, and economic agents quickly and dramatically downgraded their forecasts of economic growth. Using a wide range of cross-country confidence, uncertainty, and macroeconomic indicators, this paper investigates the role of economic sentiments, with a specific focus on economic confidence, in global macroeconomic fluctuations over the recent three decades.

A variety of theories have been developed to shed light on the role of economic confidence in macroeconomic fluctuations. The theories suggest at least two types of distinctive, although not exclusive, views on the role of confidence. Classical theories, dating back to Pigou (1927), Keynes (1936), and Akerlof and Shiller (2010), have long claimed that purely psychological waves of optimism and pessimism, or so-called animal spirit, could cause business cycle fluctuations. More recently, the theories have been further developed by reformulating macroeconomic models with rational expectations, or New Keynesian models, with economic sentiment as an endogenous variable in business cycle fluctuations (Angeletos and La'O 2013; Bacchetta and Van Wincoop 2013; Benhabib, Wang, and Wen 2015; Acharya, Benhabib, and Huo 2021). Another group of studies instead advocate so-called news or information views that a relationship between confidence and macroeconomic activity arises because confidence measures contain fundamental information about the current and future states of the economy (Cochrane 1994; Beaudry and Portier 2004; Angeletos and La'O 2013). For instance, the studies developed empirical models where economic agents have access to information on future productivity.[1]

[1]Recent literature often simultaneously takes these natures of confidence into account in modeling (Barsky and Sims 2012; Blanchard, L'Huillier, and Lorenzoni 2013; Levchenko and Pandalai-Nayar 2020). Specifically, they disentangled confidence into permanent (news) and transitory (surprise) technology components and a noise (animal spirits) component, and quantified the effects of each component. See the further discussions on the role of confidence in business cycles in Section 3 and Online Appendix A.1 (the online appendix is available at http://www.ijcb.org).

There has been rich empirical evidence on the role of confidence as a source of business and financial cycles (Eickmeier 2007; Beaudry, Dupaigne, and Portier 2011; Bachmann and Sims 2012; Møller, Nørholm, and Rangvid 2014; Karnizova and Khan 2015; Leduc and Liu 2016; Dées and Zimic 2019; Levchenko and Pandalai-Nayar 2020; Nowzohour and Stracca 2020). By using novel data and empirical methodologies, the studies augment the standard macroeconomic models with confidence indicators to investigate their role in domestic business cycles. Others propose novel identification schemes that enable one to sort out the shocks in economic sentiments that are orthogonal to other macroeconomic shocks, and examine their causal impacts on macroeconomic developments.[2]

Despite the great strides in the literature, to our investigation, there are some important questions left unanswered. Most existing work is based on country-specific evidence, focusing on a few large advanced economies. Hence, the role of confidence cycles from a global perspective is little studied. The size, significance, and persistence in the transmission of global confidence shock and, more importantly, the nature of global shocks is not clearly understood. While shifts in economic sentiment are generally regarded as originating in the demand side of the economy, other studies focus on the news contents on future productivity embedded in confidence measures, which could be supply driven (Barsky and Sims 2012, Dées and Zimic 2019, and Levchenko and Pandalai-Nayar 2020). In addition, few studies compare the role of confidence and uncertainty shocks. While it is generally agreed that uncertainty is an important source of fluctuations in economic confidence, the two concepts are not identical in definitions, information, and their relation to economic activities (Nowzohour and Stracca 2020).

Against this backdrop, this paper seeks to fill the gaps by answering the following questions:

- Is there a global confidence cycle?
- What is the role of global confidence shock on global macroeconomic and financial cycles?

[2]Another group dealt with cross-border spillovers of confidence, mostly from large economies to smaller open economies (Fei 2011; Colombo 2013).

- How do we compare the impact of confidence to that of economic uncertainty?

Using the global confidence cycle, defined as the common global factor of survey-based business or consumer confidence indicators across countries, we investigate how the cycle drives global factors of industrial production, employment, inflation, and interest rates. We follow the standard estimation process of the factor-augmented vector autoregression (FAVAR) model that consists of two steps. In the first step, the dynamics of global variables are characterized as a global block in a structural VAR framework. In the second step, a country-specific block is estimated to examine the impact of global confidence shocks on domestic variables. Given that the main focus of this paper is on the role of global confidence in global business cycle fluctuations, the results are presented based on the estimation of the *global* block of the model.

In estimating the model, a set of global variables is constructed by using a wide range of cross-country data. With this novel data set, we estimate a structural VAR model of the global variables to investigate the role of global confidence shocks. More specifically, measures of global confidence, uncertainty, business, financial, and inflation cycles are obtained using dynamic factor models. The estimated global factors are then further explored to identify the global confidence shock in a FAVAR framework, where the identification of shocks is achieved by means of Cholesky restrictions (Barsky and Sims 2012; Jurado, Ludvigson, and Ng 2015; Baker, Bloom, and Davis 2016; Leduc and Liu 2016). In this framework, it is assumed that global confidence shock is transmitted to other global variables with a time lag, while confidence indicators respond to other macroeconomic shocks within the period.[3]

Main results are summarized as follows. First, global confidence cycles—in particular, that of consumer confidence—have played a key role in global macroeconomic and financial fluctuations (Nowzohour and Stracca 2020). The responses of global industrial production, unemployment, inflation, and interest rates were all statistically

[3]The confidence indicators are thus ordered last. This assumption will be relaxed in Section 4 as robustness checks.

significant and sizable following global consumer and business confidence shocks, the results of which are in line with those in the earlier studies on the predictive power of confidence. Over the period of 1985–2019, global confidence shocks explained more than a third of total variations in global industrial production and unemployment rates, respectively.

Second, the results suggest that global consumer confidence shocks reflect a combination of global demand and supply shocks. While a positive global consumer confidence shock unambiguously raised global industrial production, employment, and interest rates, the impacts on global inflation were mixed over time. In line with the findings in the recent literature (e.g., Levchenko and Pandalai-Nayar 2020), the consumer confidence shocks seem to widely reflect productivity shocks and animal spirit of economic agents, which could be driven by a variety of factors including future expected changes in global macroeconomic and financial conditions as well as commodity prices and global trades. Meanwhile, global business confidence or global uncertainty shocks appear to be demand driven in line with what other literature generally suggests.

Third, the global confidence cycles have acted as an important channel in the transmission of uncertainty shocks—in particular, financial and macroeconomic uncertainty. Although the two concepts (i.e., confidence and uncertainty) are not entirely uncorrelated to each other, reflecting common information (Nowzohour and Stracca 2020), the results point out that the confidence shocks were not necessarily determined by a certain type of uncertainty. The empirical results suggest that global consumer and business confidences respond significantly to uncertainty shocks, possibly propagating the impacts on the global economy. Meanwhile, there was little evidence that the uncertainty measures responded significantly to confidence shocks.

Finally, the empirical results in this paper are robust to alternative identification strategies. Considering the potential simultaneity between confidence indicators and other macroeconomic and financial variables, we estimate VAR models by exploiting a novel set of high-frequency external instruments (Stock and Watson 2012; Mertens and Ravn 2013). To separate confidence shocks from uncertainty shocks, we adopt the methodology as in Jarociński and Karadi (2020). In addition, we also test alternative Cholesky restrictions that reverse the ordering of the variables (i.e., placing the confidence indicators at the first, rather than the last) and compare the results with our baseline model.[4] The results were broadly consistent across different identification schemes.

As distinguished from the large group of related studies, this paper aims to contribute to the literature in several ways. First, it provides new empirical results regarding (the evidence and) the role of global confidence cycle. To our knowledge, this paper is one of the first to quantify the impact of global confidence cycles on global business cycle fluctuations and examine the nature of the shocks that drive global confidence cycles. In addition, unlike most earlier studies, the paper examines the relationship between the role of global confidence and uncertainty. While it provides some evidence on the role of confidence as a transmission channel of uncertainty shocks, the results also suggest that global confidence shocks reflect other types of information than uncertainty shocks. Finally, with a variety of empirical results based on different identification schemes, this paper contributes to the studies on the identification of confidence and uncertainty shocks.

Section 2 explains empirical models and data. In Section 3, with the measures of global business and consumer confidence cycles, we estimate the global block of FAVAR model and quantify the impact of global confidence and uncertainty shocks on global indicators. Section 4 presents the results of sensitivity checks with different identification strategies and specifications. Section 5 concludes. Additional empirical results and the literature review are presented in the appendix.

2. Empirical Methodology

The global block of the FAVAR model consists of seven global variables—confidence (for both business and consumer), uncertainty, industrial production, unemployment rate, inflation, and interest rates (with a 10-year maturity). In addition, to compare the role of

[4] See, for instance, Stock and Watson (2012, 2018) and Jurado, Ludvigson, and Ng (2015) for a detailed discussion of the identification issues.

confidence and that of economic uncertainty, a variety of uncertainty measures are employed in alternative models.[5]

2.1 Dynamic Factor Estimation

Global variables of the monthly series are estimated by applying the standard dynamic factor model as in Kose, Otrok, and Whiteman (2003) and Kose, Otrok, and Prasad (2012). We characterize the cross-country co-movement of confidence and investigate the extent to which the confidence is global. Despite its popularity in characterizing global business and financial cycles, few studies apply the techniques to the measures of confidence or uncertainty.[6] In addition, the rare studies have employed business and financial indicators in a monthly frequency in estimating the dynamic factor model partly due to the unavailability of monthly GDP data.

Along with global confidence and uncertainty, global business and financial cycle indicators are also estimated in a version of the alternative models. The models identify global factors for cross-country industrial production, unemployment rate, inflation, and interest rates, respectively. These exercises will first shed light on how the synchronization of confidence compares with that of macroeconomic and financial activities. This is an important question in light of recent studies that highlight the role of confidence in business and financial cycles—in particular, its role in transmitting shocks across borders (Colombo 2013; Dees and Brinca 2013; Levchenko and Pandalai-Nayar 2020). For instance, a pattern of confidence synchronization that mirrors co-movement in real activity could provide some evidence for the confidence channel.

[5] Although some results are presented in Section 3, see also Online Appendix A.2 for more details on the global uncertainty measures.

[6] As explained in the preceding studies, the dynamic factor model framework is suitable for our analysis for a variety of reasons. First, dynamic factor models are designed to extract a small number of unobservable common elements from the covariance or co-movement between (observable) macroeconomic time series across countries. Thus, the model allows for a more parsimonious representation of the data in terms of the latent factors. From a theoretical standpoint, dynamic factor models are appealing because they can be framed as reduced-form solutions to a standard dynamic stochastic general equilibrium (DSGE) model.

All the global variables are estimated by the following dynamic factor models:

$$\begin{aligned} u_{i,t} &= \beta^*_{u,i} f^*_{u,t} + e_{u,i,t} \\ c_{i,t} &= \beta^*_{c,i} f^*_{c,t} + e_{c,i,t} \\ y_{i,t} &= \beta^*_{y,i} f^*_{y,t} + e_{y,i,t} \\ l_{i,t} &= \beta^*_{l,i} f^*_{l,t} + e_{l,i,t} \\ \pi_{i,t} &= \beta^*_{\pi,i} f^*_{\pi,t} + e_{\pi,i,t} \\ r_{i,t} &= \beta^*_{r,i} f^*_{r,t} + e_{r,i,t}, \end{aligned} \tag{1}$$

where $u_{i,t}$, $c_{i,t}$, $y_{i,t}$, $l_{i,t}$, $\pi_{i,t}$, and $r_{i,t}$ represent uncertainty, (business and consumer) confidence, industrial production, unemployment rate, inflation, and interest rate in country i at month t, respectively, while $f^*_{j,t}$ $(j \in \{u,\ c,\ y,\ l,\ \pi,\ r\})$ are the global common factors for uncertainty, confidence, industrial output, unemployment, inflation, and interest rate at month t, respectively.[7] Asterisks denote global parameters or variables. Following the earlier studies, it is assumed that the global factors follow an AR(3) process although the increase (or decrease) of AR terms changes little the dynamic factor estimates.

As is standard in the literature, the importance of each factor is measured using a variance decomposition. The volatilities of business and consumer confidence, macroeconomic and financial variables are decomposed into volatility components such as each of the estimated factors and the idiosyncratic term. This is achieved by applying the

[7]The main assumptions in the estimation of the global factors follow those in Kose, Otrok, and Whiteman (2008) and Kose, Otrok, and Prasad (2012). While some studies provide evidence for additional sources of cross-country co-movement among macro variables, such as group-specific or regional factors, we focus here on the global component of the cross-country confidence indicators. Indeed, as will be explained in more detail in Section 3, the single global confidence factor alone explains quite a sizable portion—up to 60 percent—of fluctuations in country-specific confidence indicators and identifies well global events such as global recessions. The factor loading of the global factor is statistically significant and positive, in most countries supporting the idea of the global factor.

variance operator to each equation in the system. For instance, the variance of the confidence in country i ($c_{i,t}$) is decomposed as follows:

$$Var(c_{i,t}) = \left(\beta^*_{c,i}\right)^2 \; Var(f^*_{c,t}) + \; Var(e_{c,i,t}). \tag{2}$$

Then, the fraction of variance attributable to the global factor is computed as

$$\frac{\left(\beta^*_{c,i}\right)^2 \; Var(f^*_{c,t})}{Var(c_{i,t})}. \tag{3}$$

2.2 FAVAR Framework

In its structural form, the global block of the FAVAR system is represented by

$$B_0 Y_t = \alpha + \sum_{p=1}^{\tau} B_j Y_{t-p} + \varepsilon_t, \tag{4}$$

where Y_t consists of the seven global variables as explained above. The vector ε_t consists of a shock to the global confidence (*"global confidence shock"*), uncertainty measure (*"global uncertainty shock"*), and the other types of structural macroeconomic and financial shocks corresponding to the variables. As is common in the VAR literature, the impulse responses of the global variables following global consumer or business confidence shocks are mainly examined. The contributions of the global confidence shocks to forecasting errors or historical developments of the global variables are also quantified.[8]

2.3 Identification and Estimation

Our baseline strategy for the identification of global confidence shocks is to employ recursive restrictions by using Cholesky

[8]Due to the flexibility of the model, the FAVAR framework has been widely used in identifying the dynamic relationships among global variables or the transmission of global shocks into domestic variables. The model thus provides some advantages over the standard dynamic factor models that often assume no contemporaneous or serial correlations among the economic factors, or the factor structural VAR model that assumes zero contemporaneous impacts of country-specific variables.

decomposition of variance-covariance as in Baker, Bloom, and Davis (2016), Leduc and Liu (2016, 2020), and Levchenko and Pandalai-Nayar (2020). The global confidence indicators are ordered *last*, assuming that a structural shock in business or consumer confidence does not affect other global variables within a month, while other structural shocks influence the confidence indicators. This identifying assumption implies that the economic and financial developments drive the confidence.[9]

That said, the direction of causation between confidence (or uncertainty) and economic activity still remains debatable. For instance, in a monthly SVAR model for the United States, Barsky and Sims (2012) show the results when confidence variables are ordered first. This assumption can be supported by the empirical observations on the leading nature of confidence documented in the related literature.[10] The assumption is also in line with empirical findings in the recent strand of literature that the confidence cycles reflect news on future productivity and animal spirit of economic agents that are not correlated with the current economic fundamentals. Meanwhile, Stock and Watson (2012, 2018) seek to avoid estimation bias due to potential simultaneity between uncertainty measures and other macroeconomic and financial indicators by employing the external instrument identification scheme.[11] In this regard, to check the sensitivity of the baseline results, we additionally consider two alternative identification schemes: (i) an external instrument scheme, and (ii) a Cholesky restriction that orders the uncertainty and confidence first.

Bayesian method is used in estimating the FAVAR model. The procedure draws 2,000 iterations with 1,000 burn-ins. In reporting the impulse response functions, we present the median of the 1,000

[9]More specifically, the global variables are ordered: global output, unemployment, inflation, interest rates, uncertainty, and confidence. Similarly, Jurado, Ludvigson, and Ng (2015) employ a Cholesky identification where uncertainty measure (the VIX) is ordered last. They assume that the VIX is endogenous to other structural shocks, while other macroeconomic variables are not contemporaneously explained by the uncertainty shock.

[10]This will be explained further in Section 3.

[11]In the literature, this identification approach is also referred to as IV SVAR or proxy VAR. Hence, we interchangeably use the terms throughout the paper.

draws and 90 percentile confidence intervals for each forecasting horizon. In the Bayesian estimation, the independent normal-Wishart priors are used.[12]

2.4 Data

Following the earlier studies including Barsky and Sims (2012), Leduc and Liu (2020), and Levchenko and Pandalai-Nayar (2020), we include various macro and financial indicators in our VAR system. First, levels of business and consumer confidence indicators are employed. Households and firms may have different anticipation on the future development of economic conditions, thereby generating the different responses of macro variables to each shock. Furthermore, as discussed in the previous section, we consider uncertainty to have a better understanding on its relationship with global confidence and on its distinct feature in the business cycles. Unemployment rates and year-on-year growth rates of industrial output are employed as proxies for business cycle fluctuations. Finally, the interest rate and consumer price index inflation variables are also included to consider and to control for different types of shocks—global demand and supply shocks and monetary policy shocks.[13]

All the variables are based on a monthly frequency. There is by now a large literature that documents the co-movement of fluctuations in real or nominal aggregates across countries. However, many existing studies employed quarterly data, partly due to the unavailability of monthly GDP (gross domestic product) data. By employing monthly data, we can consistently compare the evolution of the estimated global business and financial indicators and their contributions to the variations in cross-country data with the corresponding results on confidence data.[14]

[12]When we tested alternative priors, including the Minnesota priors, there were few material differences in the results.

[13]In some alternative models, national stock prices, implied stock market volatilities, and oil prices are also considered as auxiliary variables. Main results remain unchanged even when the auxiliary variables are included.

[14]With monthly data, we can also quantify the spillover effects of confidence shocks more accurately. In the case of quarterly data, a certain part of the spillover effects could be regarded as common shocks among the variables.

Over the sample period of 1985–2019, the series are found to be stationary. That said, long-term trend components are removed through statistical methods such as the local mean model (as in Stock and Watson 2012) and the Hodrick-Prescott filter. In estimating the global variables using the dynamic factor model, the data availability somewhat differs across the variables, although a sufficient number of countries are equipped with all the variables. The database includes a set of 39 countries (25 advanced economies and 14 emerging market economies).[15]

3. Empirical Results

This section presents the main empirical results. First, the fluctuations of the global variables are examined by using a dynamic factor framework.[16] Then, the dynamic relationships among the variables are investigated based on the estimation of the global block of the FAVAR estimation.[17]

3.1 Global Confidence Cycle and Global Uncertainty Measures

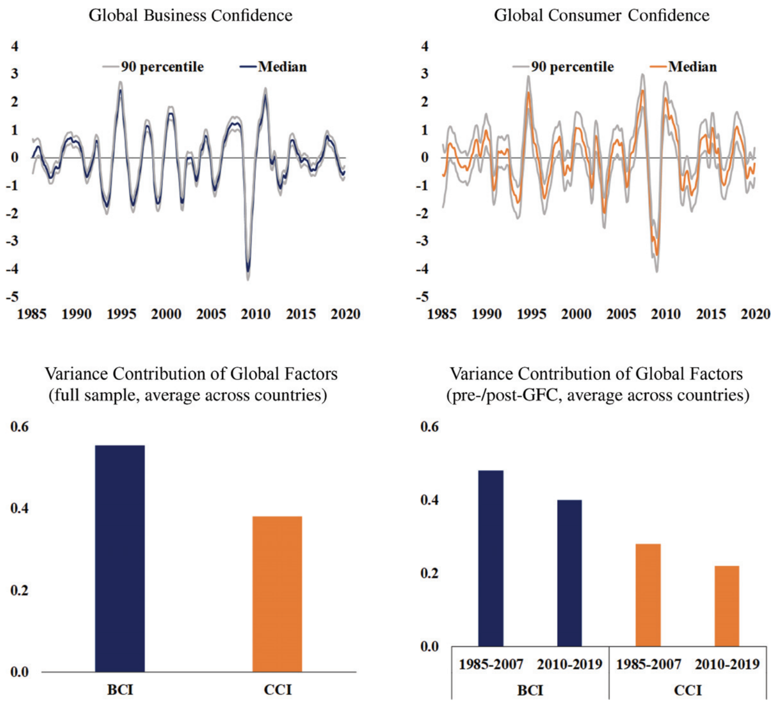
Figure 1 (the first row) presents the evolution of the global factors of business confidence and of consumer confidence over 1985–2019. The global factors declined sharply during the global financial crisis in 2008–09 and exhibited less volatility outside this episode. This is consistent with the narrative that the global financial crisis was truly a significant global event with a synchronous collapse in business and consumer confidence. Although not as pronounced as during

[15] To check the robustness of the results using this database, we also replicated the VAR estimation using an alternative (smaller) balanced set of countries. Results are available upon request.

[16] While key features of the estimated global factors are discussed in this section, the details for the estimates and their economic implications are summarized in Online Appendix A.2.

[17] Country-specific results based on the domestic block of the FAVAR model also suggest that international transmission of global confidence shocks into domestic variables is significant in most countries, although the effects are more pronounced in advanced economies than in emerging market economies. Such heterogeneity may reflect cross-country differences in various factors—including monetary and exchange rate regimes as well as the trade and financial openness. The analysis is beyond the coverage of this paper and will be left for future extensions.

Figure 1. Global Business and Consumer Confidence Factors



Note: Global factors are extracted from business or consumer confidence in 25 countries, using a dynamic factor model. Solid blue and orange lines are median draws based on 3,000 posterior Bayesian draws. Gray lines indicate 5th–95th percentiles confidence bands. Variance contributions of global factors are based on simple averages across countries. "BCI" and "CCI" indicate business confidence and consumer confidence, respectively. (For figures in color, see the online version of the paper at http://www.ijcb.org.)

the global financial crisis, the global confidence factors clearly fluctuated around other global recessions in 1986 and 1991, and the slowdowns in 1998, 2001, 2011–12, and 2014–15. Since 2018, both global business and consumer confidence have registered a clear downward trend, reflecting increasing global economic and policy uncertainty due to factors such as the U.S.–China trade war.

The second row of the figure presents the contributions of the global business and consumer confidence factors to the variations in cross-country confidence indicators.[18] The global factors, on average across countries, explained 57 and 38 percent, respectively, of total variations in business and consumer confidence indicators. The contributions are at least as sizable as those of the global factors for cross-country output and unemployment (as shown in Online Appendix A.2) and suggest that the "global confidence cycle" per se does in fact exist.[19]

That said, the results also point out that there are certain differences between business and consumer confidence indicators. For example, global consumer confidence seems to lead global business confidence by a few months. Meanwhile, the cross-country co-movement of business confidence is stronger than consumer confidence. Put another way, idiosyncratic country-specific terms played relatively more important roles in explaining the dynamics of consumer confidence than business confidence. It could be the case that the differences may reflect different types of information contents specific to each confidence indicator, and thus they could have a heterogeneous relationship with the global macroeconomic and financial cycles.

Another important feature of global confidence cycles—in particular, global business confidence—is that they exhibit quite high cross-correlations with global business, inflation, and financial factors as presented in Online Appendix A.2 (Figure A.1). For instance, global business confidence showed quite a high contemporaneous correlation (up to 0.9) with global industrial production. Global business confidence also showed sizable correlations (around 0.4) with

[18] As the sample includes the global financial crisis of 2008–09, a natural question emerges on whether the results are picking up outlier effects from the crisis. To check this, we estimate the baseline model over, before, and after the crisis. The figure presents the share of variance explained by the global factors. While it is true that global factors played a much more significant role during the crisis, their role remains sizable outside the crisis period as well. For instance, over 40 percent of variance shares in business confidence were explained by global factors during 1985–2007 and 2010–19. This corroborates our main result about the relevance of the global confidence cycle.

[19] Although only a few studies have examined the global dimension of confidence, this finding is in line with Dées and Güntner (2017) and Nowzohour and Stracca (2020), which confirm the existence of the global dimension of confidence shocks and their effects.

global inflation, global interest rates, oil prices, and global equity prices.[20]

3.2 Confidence as a Driving Force of Global Business Cycle

The foregoing exercises suggest that the global confidence cycles share substantial amounts of common information with the global business and inflation cycles. Nonetheless, the results also point out that global business and consumer confidence indicators may deliver different information on the future developments of economic and financial variables. In addition, the global confidence cycles and global uncertainty measures broadly display distinct movements, while they are negatively correlated.

Against this backdrop, we estimate a seven-variable VAR model that includes uncertainty (the VIX used as a proxy), business and consumer confidence measures, and other global variables (industrial production, unemployment rate, inflation, and interest rates) together in a single framework. As was emphasized in Section 2, considering the specifications in the previous studies and the lead-lag relations among the variables (Online Appendix A.2), we order the global macro and financial variables (global output, unemployment, inflation, and interest rates) first, followed by uncertainty index, and consumer and business confidence indicators. By doing so, we can identify different types of confidence and uncertainty shocks, all being orthogonal to each other. We then finally conclude on whether the confidence and uncertainty measures simply reflect common shocks or they play an independent role in global business cycle fluctuations.[21]

[20] Compared with the evolution of global confidence cycles, the fluctuations in global uncertainty, prima facie, appear to be more frequent and flicky, although the uncertainty factors do identify critical events, including the global financial crisis. The movements in global uncertainty thus may be less endogenous to business and financial cycles than confidence indicators. See Online Appendix A.2 for the details.

[21] Since multiple measures of confidence and uncertainty measures are considered together, we estimate a number of models with different variable orderings and compare the corresponding empirical results. To gauge the explanatory power of each measure of confidence and uncertainty, we also estimate the models that only include either global consumer or business confidence, or a global uncertainty index. The results are presented in Section 4.

3.2.1 Impulse Responses to the Uncertainty and Confidence Shocks

Figure 2 presents the dynamic responses of the global variables, following three types of shocks: uncertainty (panel A), business confidence (panel B), and consumer confidence (panel C) shocks.

Uncertainty Shock. Global uncertainty shocks exhibited countercyclical properties. Following a one-standard-deviation increase in global uncertainty, the global industrial production declined by up to 1.5 percentage points while global unemployment rates rose by around 1 percentage point. Following the uncertainty shock, global interest rates (10-year bond yields) were significantly reduced by around 1.2 percentage points. Global inflation decreased by 0.3 percentage point although the dynamic responses became insignificant one year after the shock. The negative responses of output and inflation following the uncertainty shocks are consistent with, inter alia, the *wait-and-see* effect that economic agents would optimally pause their investments in productive activities and purchases in durable goods and wait until the uncertainty is not there anymore.

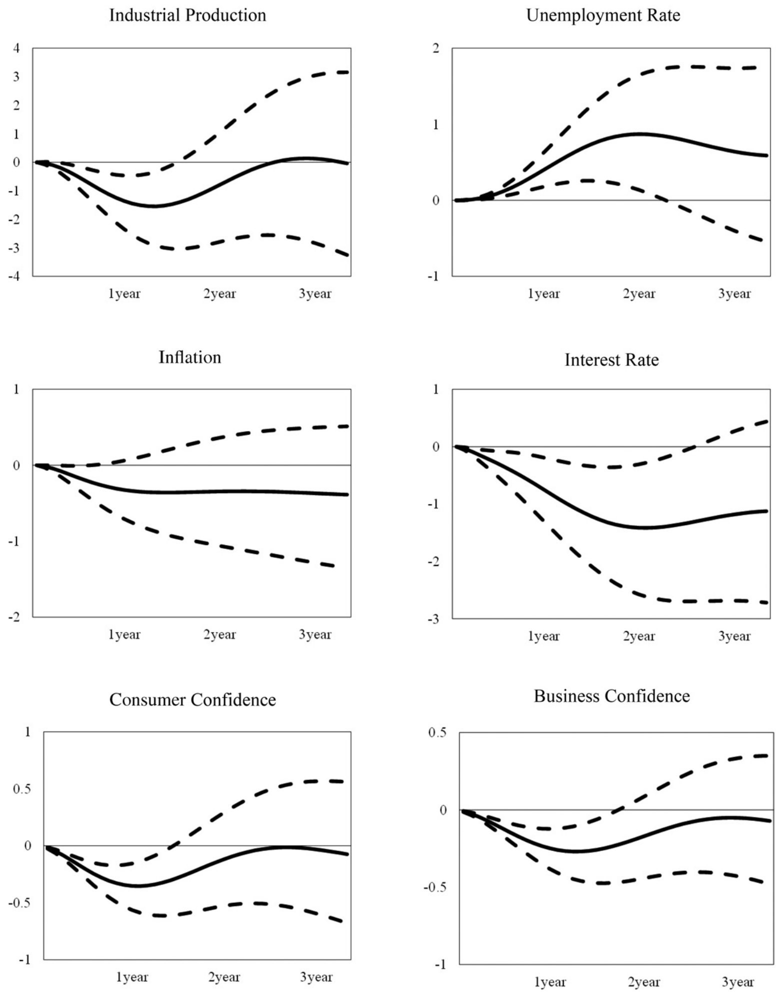
Furthermore, the result suggests that the confidence acts as a transmission channel of uncertainty shock, as argued by Ilut and Schneider (2014) and many others. Both consumer and business confidence indicators responded negatively up to two years following the increase in uncertainty. This is in contrast to the insignificant response of the VIX following business and consumer confidence shocks, as will be explained below.

The foregoing results are largely robust when other measures of uncertainty are employed. For instance, the dynamic responses of global variables to the uncertainty shocks, identified with the financial uncertainty, macroeconomic uncertainty (both compiled by Jurado, Ludvigson, and Ng 2015), and economic policy uncertainty (EPU) index (by Baker, Bloom, and Davis 2016), are overall similar to those with the VIX. More details are provided in Section 4.

Business Confidence Shock. In line with the findings in the existing literature, global business confidence shocks are, by and large, procyclical. Following a one-standard-deviation increase in global business confidence, global industrial output rose by 2.5 percentage points while global inflation and interest rates rose by 0.5

Figure 2. Impulse Response Following Confidence and Uncertainty Shocks: Model with CCI, BCI, and VIX

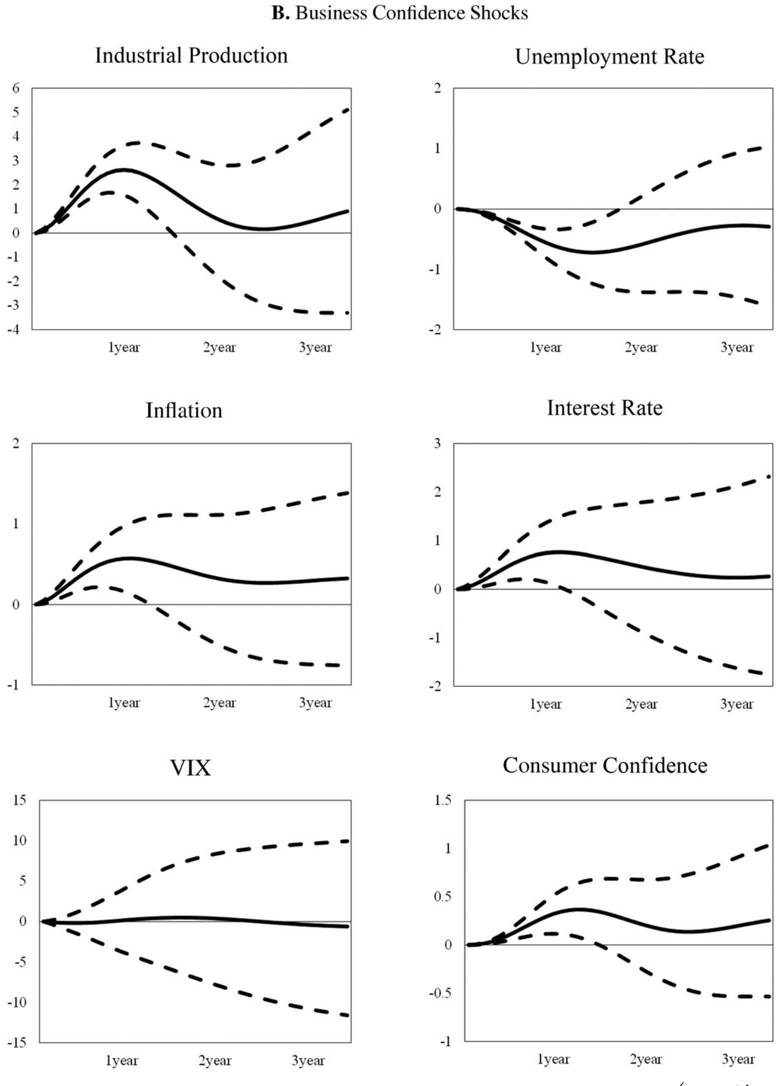
A. VIX Shocks



(*continued*)

and 0.4 percentage point, respectively. The shock led to a decline in global unemployment rates by 0.8 percentage point. Global inflation unambiguously showed significantly positive responses following a business confidence shock throughout forecasting horizons.

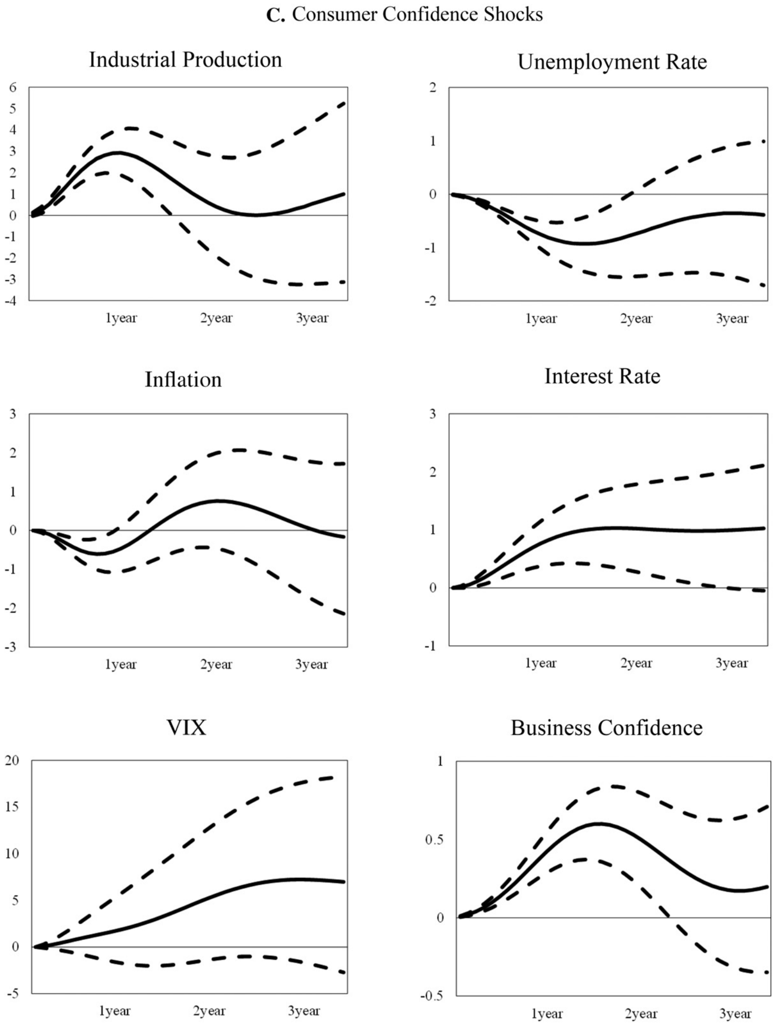
Figure 2. (Continued)



(continued)

The speed and persistence in the transmission of global business confidence shocks to other global variables seem short-lived (Nowzohour and Stracca 2020); the impacts on global unemployment rates

Figure 2. (Continued)



Note: The impulse responses are based on the global FAVAR model (that consists of global industrial production, unemployment rate, inflation, interest rates, uncertainty, consumer confidence, and business confidence) to a positive one-standard-deviation global uncertainty shock (panel A), global business confidence shock (panel B), and consumer confidence shock (panel C). Solid lines and broken lines indicate median (50th) and 5th–95th percentiles, respectively, among 1,000 successful Bayesian draws. Vertical axis indicates percentage points or unit changes and horizontal axis indicates months.

and inflation were maximized around two years after the shock, while the impacts on global output reached a peak around a year after the shock. All the results were statistically significant within 90 percent confidence intervals. The common positive reactions of industrial production, inflation, and interest rates following the shock, and their short-lived impacts collectively suggest that global business confidences shocks may largely reflect transitory demand-side shocks, presumably reflecting other uncertainty or animal spirit.[22]

Consumer Confidence Shock. Finally, positive global consumer confidence shocks have expansionary impacts on economic activity. The impacts were substantial and statistically significant over the sample period. Following a one-standard-deviation increase in the global consumer confidence, global industrial production rose by up to 2.8 percentage points, on a cumulative basis, and global unemployment rates decreased by around 1 percentage point, indicating the considerable boosting impacts. Following the same shock, global interest rates rose by around 1 percentage point. This may reflect in part the subsequent response of central banks to counter the expansionary conditions.

Contrary to the responses to positive business confidence shocks (and to decline in uncertainty), the dynamic responses of global inflation to positive global confidence shocks remained negative for a year after the shock, up to around −0.3 percentage point. This suggests

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[22]Although the main purpose of this paper is not on disentangling the confidence into their constituent shocks, we may interpret the impulse responses in light of the shocks, assuming that confidence measure conveys the information on permanent (*news*) and transitory (*surprise*) technology shocks, and noise (*animal spirits*) shocks (e.g., Beaudry, Dupaigne, and Portier 2011, Barsky and Sims 2012, and Blanchard, L'Huillier, and Lorenzoni 2013). For instance, following a framework of Levchenko and Pandalai-Nayar (2020), we may consider that confidence (C_t) consists of the three components:

$$C_t = \lambda_1 \varepsilon_{t-s}^{news} + \lambda_2 \varepsilon_t^{sur} + \lambda_3 \varepsilon_t^{noise},$$

where ε_{t-s}^{news} is s-period-ahead news shocks, and ε_t^{sur} and ε_t^{noise} are surprise total factor productivity (TFP) shock and noise shock, respectively.

Prior studies report that the news shock on a future improvement in TFP would lead to long-lasting and increased demand for the global economy, while surprise TFP innovation has similar impacts but for shorter periods. It is also well documented that a non-technology noise shock accounts for a material share of global fluctuations at short frequencies.

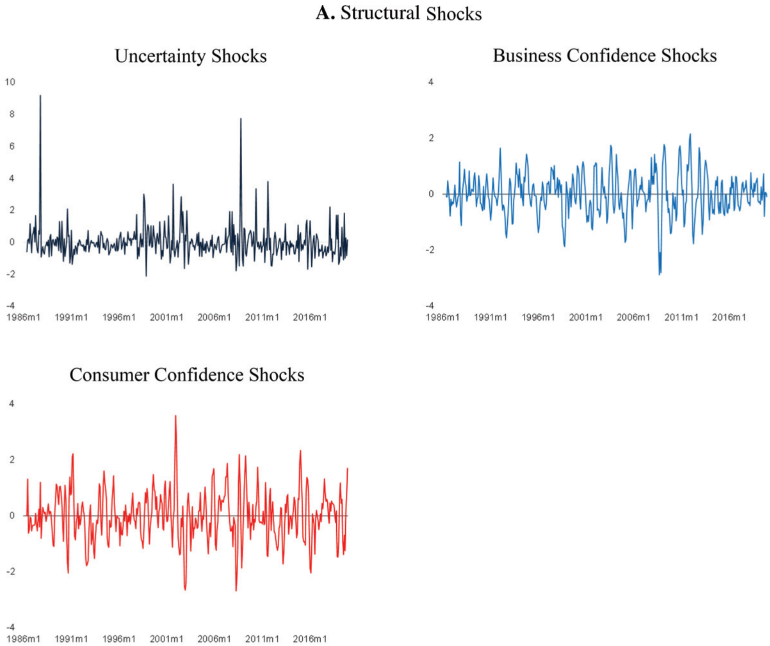
that the confidence shocks may reflect supply shocks, at least partly, such as surprise or news shocks on productivity or shifts in consumer confidence due to changes in other supply factors including global commodity prices or global value chains. After one year, however, the impacts turn to somewhat positive although insignificant (on a non-cumulative basis, the positive impacts are significant).[23]

Similar to global business confidence, the impacts of global consumer confidence shock on all the global variables were maximized around one to two years after the shock. The impacts appear to die out before three years after the impact. Given theoretical and empirical results in the literature that *demand* (or animal spirits) shocks generally do not have long-lasting effects on output, these results may suggest that global consumer confidence is mainly associated with the shocks which tend to have short-lived impacts, such as animal spirits and transitory TFP shocks, rather than the shocks of which impacts are more persistent, such as news shocks. In this context, the above impulse responses following global confidence shocks are somewhat different from the findings by the studies on country-specific confidence that point to the major role of (persistent) news shocks (Barsky and Sims 2012, Blanchard, L'Huillier, and Lorenzoni 2013). Instead, they are more consistent with recent studies on the role of the confidence shocks in international business cycle co-movement (Levchenko and Pandalai-Nayar 2020).

Although more supporting evidence would merit, this finding may suggest that news shocks are more likely to be country specific in nature, less correlated across economies, while other types of confidence shocks—animal spirits and TFP surprise—are more likely to be more synchronized across countries at short frequencies. Levchenko and Pandalai-Nayar (2020), for instance, show that aggregates in a small open economy (represented by Canada) respond by far more strongly to the noise shock (labeled as "sentiment shock" in their paper) than surprise TFP and news shocks originated from the United States. Based on this finding, the authors argue that

[23]Similar to our results, based on the SVAR model of U.S. GDP, consumption, inflation, real interest rate, and consumer confidence over 1960–2008, Barsky and Sims (2012) found that positive confidence innovations were associated with an increase in real economic activities and interest rates and a substantial *drop* in inflation.

Figure 3. Structural Uncertainty and Confidence Shock: Model with VIX, CCI, and BCI



(*continued*)

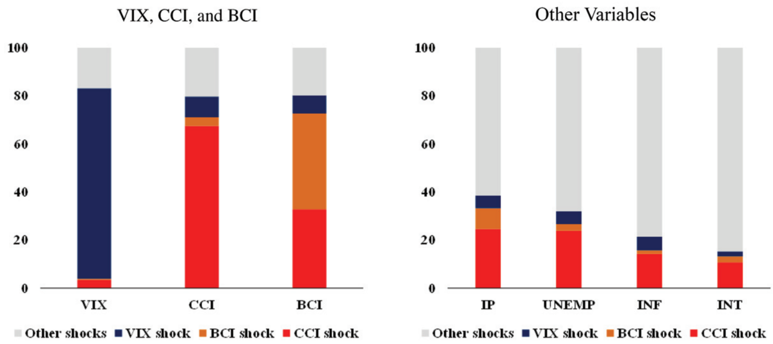
noise shock is more important than other shocks in generating cross-border co-movement of business cycles in the short run. It could be the case that the latter shocks are easily spreadable via news and social media and trade linkages, while the former is hardly transmittable across jurisdictions due to the barriers in the economic and social system. In fact, Levchenko and Pandalai-Nayar (2020) report that the U.S. news shocks do not have any significant impacts on Canadian TFP.

3.2.2 Structural Shocks

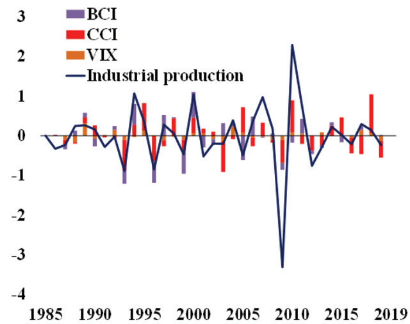
The different natures of confidence and uncertainty shocks as discussed above are reflected in the structural shocks estimated from the FAVAR model. As shown in panel A of Figure 3, uncertainty and business confidence shocks were the most pronounced around the

Figure 3. (Continued)

B. Forecast Error Variance Decompositions



C. Historical Contributions of Global Industrial Production



Note: Structural shocks (panel A), forecasting error variance contributions (panel B), and historical decomposition (panel C) of uncertainty (VIX), consumer confidence (CCI), and business confidence (BCI) shocks estimated with the global FAVAR model (that consists of global industrial production, unemployment rate, inflation, interest rates, uncertainty, consumer confidence, and business confidence). FEVD decomposition is based on 40 months forecasting horizon. All results are based on median among 1,000 successful Bayesian draws. Vertical axis indicates percent.

global financial crisis in 2008–09, and they were also highly volatile around the global recessions in 1986 and 1991, the Asian financial crisis in 1998–99, or the euro-area debt crisis in the early 2010s. The troughs of global business confidence cycle or global uncertainty cycle overall coincided with or followed the occurrence of such global events.

Meanwhile, the global consumer confidence shocks appear to identify other types of global events such as the oil price crisis in 1990–91, the boom and collapse of U.S. dot-com bubble in 2001–02, the global commodity price surge in early 2008, as well as the U.S.–China trade war in 2018–19, events that originated in both demand and supply sides of the global economy. Importantly, the global recessions or other global events mentioned above were generally preceded by the trough of the global confidence cycle, suggesting the predictive power of consumer confidence as discussed in Berry and Davey (2004), van Aarle and Moons (2017), Shapiro, Sudhof, and Wilson (2020), and (Online Appendix A.1).

3.2.3 Variance Decompositions and Historical Decompositions

Figure 3 (panel B) then presents the variance contributions of three types of shocks to the variations in confidence and uncertainty indicators (left panel) and other global variables (right panel). The results first show the relationship between global confidence and uncertainty. Around one-third and one-tenth of total variations in global business confidence were explained by global confidence shocks and global uncertainty shocks, respectively. On the contrary, the global business confidence shocks little explained consumer confidence or uncertainty. The contributions of global uncertainty shocks to global consumer confidence were similar to the contributions to business confidence. Again, global confidence (both consumer and business) appears to act as an important transmission channel of uncertainty shocks. In addition, global consumer confidence shocks spill over to global business confidence significantly.

As is evident in the right panel of the figure, among the three types of shocks, the global consumer confidence shocks took the lion's share, by explaining around a quarter of total variations in both industrial production and unemployment rates. The shocks also explained sizable—around 20 and 15 percent, respectively—variations in inflation and interest rates. Business confidence shocks explained a sizable portion in industrial production (around 10 percent), while the contributions to the other variables were smaller. The contribution of uncertainty shocks was less than 10 percent.

One may argue that the greater share of consumer confidence shocks explained above was mainly due to the variable ordering.

To check this possibility, we ordered the global business confidence before global consumer confidence (although this assumption is less convincing in light of cross-correlations between the two variables) and compared the results. In this case, the contributions of consumer and business confidence shocks to global industrial production were 20 percent and 18 percent, respectively, and their contributions to the global unemployment rate were 20 and 10 percent, respectively. The results were overall consistent with the baseline results and reconfirm the critical role of global consumer confidence shocks. When global uncertainty was ordered last, the contribution of uncertainty shocks little changed, suggesting that the uncertainty measures are more or less exogenous to the confidence indicators.

Historically, the contributions of the shocks were significantly negative around the global recessions in 1991 and 2009 or global slowdowns in 1998, 2001, and 2014, as depicted in panel C of Figure 3. The shock apparently contributed to the declines (or spikes) in the global industrial production (unemployment rate) around the global events. Again, the results suggest that global consumer confidence shocks contributed the most to the declines in industrial production around the global recession and downturns.

3.2.4 Contribution of Confidence Shocks: Alternative Confidence and Uncertainty Measures

Figure A.6 in Online Appendix A.3 presents variance contributions of global confidence shocks to other confidence and uncertainty measures (panel A) and global macroeconomic and financial variables (panel B) when alternative uncertainty measures are employed. Consistent with the model that employs the VIX as an uncertainty measure, the global consumer confidence is mostly explained by its own shocks. Neither business confidence nor uncertainty measures accounted for much of the portion of consumer confidence. One exception is macroeconomic economic uncertainty, which explains around 20 percent of variations in consumer confidence, as seen in the left chart of the second row. This may be due to the information contents on future macroeconomic uncertainty in consumer confidence (Barsky and Sims 2012; Levchenko and Pandalai-Nayar 2020). As explained above, much of the portion of business confidence was explained by consumer confidence shocks in all models. The explanatory power of the uncertainty measures for business confidence shocks was minor except for macroeconomic uncertainty.

Panel B shows the variance contributions of global industrial production, unemployment rate, inflation, and interest rates accounted for by business and consumer confidence shocks as well as uncertainty shocks. Clearly, the contributions of consumer and business confidence shocks do not change much regardless of the type of uncertainty measures employed in the model except macroeconomic uncertainty. This suggests that macroeconomic uncertainty accounted for much of the extent to which confidence shocks transmit into global macroeconomic variables.

From a different angle, we now examine how the contributions by each global confidence are affected by the inclusion of other global confidence or uncertainty. Figure A.7 in Online Appendix A.3 summarizes the variance contributions of global business confidence (panel A) or global consumer confidence (panel B) to the variations in global macroeconomic activities based on the five- or six-variable SVAR models that consist of global confidence and/or uncertainty indicators, as well as global business and financial variables. In panel A, for instance, "BCI" (red bars) presents the results based on the five-variable VAR model with only business confidence (i.e., BCI, and four business and financial variables), and "Other measures" (navy bars) indicates those from the six-variable VAR model (i.e., the five variables plus other confidence indicator or global uncertainty measure). The results suggest that when consumer confidence was included in the model, the contributions of the global business confidence to variations in industrial production or unemployment rates more than halved from 40 to 18 percent and from 25 to 8 percent, respectively. Again, similar to what was found in Figure A.6, this result reaffirms that a large portion of business confidence was due to consumer confidence.

The contributions of global consumer confidence shocks to industrial production and unemployment rates were not substantially decreased when business confidence or the VIX was added in the model (panel B). Again, consistent with our earlier experiments, the contribution declines by 5–10 percentage points when macroeconomic uncertainty measures are included in the model.

4. Results with Alternative Models

In Section 3, the dynamic responses of global variables were estimated following three different types of shocks (global consumer and business confidence and uncertainty) based on the baseline seven-variable model. In identifying the shocks, we relied on the Cholesky restriction which places uncertainty and confidence measures last, assuming that global confidence and uncertainty are likely to be endogenous to the global macro variables. In this section, we test the sensitivity of the results to different model specifications and identifying assumptions. More specifically, we estimate (i) the model with external instruments, (ii) the model that employs Cholesky restriction of an alternative variable ordering, and (iii) the model with alternative measures of global uncertainty.[24]

4.1 Proxy VAR Estimation

4.1.1 External Instrument Identification

We estimate the model with external instrument identification (or proxy VAR), as initially proposed by Stock and Watson (2012, 2018) and Mertens and Ravn (2013). This scheme has considerable appeal in that it exploits the information from external instruments while avoiding the potential simultaneity among the variables in a VAR model. Unlike the recursive VAR identification, it neither imposes any restrictions on the direction of causation nor rests on timing assumptions between the variables. It thus provides robust results regardless of the variable orderings.

A novel approach is proposed to identify both confidence and uncertainty shocks using high-frequency data. We exploit theory-consistent sign restrictions to the shocks, which corresponds to *the poor man's identification approach* in the proxy VAR estimation (Ca' Zorzi et al. 2020; Jarociński and Karadi 2020).

[24]In Online Appendix A.4, we additionally present the results from the model that excludes inflation and the model that employs only confidence or uncertainty exclusively.

In order for the instrumental variables to be valid, the following conditions are required:

$$rank(E[z_t \varepsilon_t^p]) = L \quad (L \neq 0) \qquad \text{(relevancy)} \qquad (5)$$

$$E[z_t \varepsilon_t^q] = 0 \qquad \text{(exogeneity)}, \qquad (6)$$

where z_t denotes the instrumental variables, ε_t^p are the structural shocks of interest (here, uncertainty and confidence shocks), and ε_t^q are the other structural shocks defined in Equation (4).

At least two different types of instrumental variables are required for the identification of two structural shocks. That said, as discussed in Online Appendix A.1, it is challenging to obtain such instrumental variables because a change in uncertainty tends to occur contemporaneously with shifts in confidence even within a higher frequency (Nowzohour and Stracca 2020). For instance, some sentiment measures which have been commonly used as the instrumental variables in the literature (e.g., changes of the VIX or gold prices) are likely to capture the information on both types of shocks together.[25]

4.1.2 Poor Man's Approach

We obtain instrumental variables for confidence and uncertainty shocks by analyzing the co-movement among daily asset prices—the VIX, gold prices, stock prices, as well as EPU index. The following three premises are considered. First, confidence is procyclical while uncertainty is countercyclical, thus negative cross-correlations are observed between them (Baker, Bloom, and Terry 2020; Nowzohour and Stracca 2020). Second, stock returns sensitively capture shifts in market participants' belief by altering net present value of

[25]For instance, some literature points out that the VIX delivers the information not only on the uncertainty but also on the other components significantly correlated to the confidence, including risk perception (Bekaert and Hoerova 2014), signals for future conditions (Pástor and Veronesi 2012, 2013). Similarly, gold price, another widely used fear-gauging measure, is determined by the uncertainty as well as macroeconomic conditions (O'Connor et al. 2015). Jones and Sackley (2016) and Bilgin et al. (2018) provide evidence of the linkage between uncertainty and gold prices, while Batten, Ciner, and Lucey (2010, 2014) report the dynamic relationships between gold prices and macroeconomic determinants, including business cycles and financial market sentiment.

wealth (Beaudry and Portier 2006; Farmer 2012, 2013). Third, news-based uncertainty measures, such as the EPU index, convey more exogenous information on economic uncertainty than market-based measures.[26]

Based on these premises, we take the following procedures to construct the instruments:

(i) We first filter out non-informative components from the daily shifts of market-based sentiment measures (the VIX and gold prices). We regard the shifts in such measures as the proxies for uncertainty or confidence shocks only when the direction of their movements is opposite to that of stock prices (S&P 500). The other remaining part is regarded as non-informative and set to zero.[27] In so doing, it is assumed that a rise in uncertainty or a decline in confidence would bring about negative impacts on the net present value of wealth, thereby putting instant downward pressures on stock prices, and vice versa.

(ii) The series is further disentangled into uncertainty- and confidence-specific components. We assign them as uncertainty surprises if their signs are identical to those of daily changes in the EPU index.[28] This is based on the observations that the market-based measure tends to co-move strongly and positively with the news-based uncertainty measures, driven by the common information on the economic uncertainty (Jones and Sackley 2016; Kelly, Pástor, and Veronesi

[26]For instance, while the VIX or gold prices reflect the implied uncertainty of asset prices, which could be driven by various factors such as liquidity, risk appetite, and demand-supply imbalances in the markets, the EPU index mainly reflects the uncertainty about policies in a whole economy. This is also consistent with our empirical results, as in Figure A.6 in Online Appendix A.3, where EPU shocks barely explained the variations in consumer and business confidence while other measures (the VIX or gold prices) explained them more.

[27]These may reflect other types of shocks—policy or financial—which are uncorrelated to uncertainty or confidence.

[28]Daily series of U.S. EPU index is employed considering the availability at a daily frequency.

2016). The series is otherwise regarded as the confidence surprises, which need not necessarily be accompanied by the comovement with the news-based uncertainty measure, at least contemporaneously.[29]

(iii) The daily series based on (i) and (ii) are compiled into monthly series for monthly VAR.

4.1.3 Estimation Results

Using the constructed instrumental variables, dynamic responses of global variables are estimated following global uncertainty and confidence (either consumer or business) shocks.[30]

Based on the relevancy (F-statistics) of the instrumental variables, the surprises computed from the VIX and gold prices are selected as the instruments for the global uncertainty shock ($IV_U = [VIX_U, Gold_U]$), while those computed from gold prices are finally employed for the identification of consumer confidence

[29]Following Pástor and Veronesi (2012) and Bekaert and Hoerova (2014), our approach posits that the market-based measure is an increasing function of the product of uncertainty, signal precision for future economic conditions, and other information. Also, following Baker, Bloom, and Davis (2016) and Nowzohour and Stracca (2020), the news-based measure is regarded as a positive linear function of uncertainty, while confidence is a decreasing function of signal precision.

$$\begin{aligned} M^{mkt} &= f([\text{Uncertainty}] \times [\text{Signal precision}] \times [\text{Others}]) \\ M^{news} &= g(\text{Uncertainty}) \\ \text{Confidence} &= h(\text{Signal precision}), \end{aligned}$$

where M^{mkt} and M^{news} denote market- and news-based sentiment measures, respectively, and "Others" indicates the other types of shocks. f and g are increasing functions, while h is a decreasing function.

[30]Due to their conceptual similarities, we estimate two separate six-variable VARs where each of the two confidence indicators is included interchangeably. It is also worth noting that, since two shocks are simultaneously identified in a VAR using external information, an additional restriction needs to be imposed on the variance-covariance matrix of the structural shocks to ensure the orthogonality of the shocks. (In a typical proxy VAR estimation which focuses only a single shock—e.g., Gertler and Karadi 2015—this restriction is not necessary.) A recursivity assumption is imposed, such that the uncertainty is ordered before the confidence. For the technical details on the identification of multiple shocks in a proxy VAR framework, see Mertens and Ravn (2013) and Ha and So (2021).

shocks ($IV_C = [Gold_C]$).[31] The instrumental variables prove sufficiently relevant to the reduced-form innovations in both uncertainty and consumer confidence; F-statistics on the first-stage regression for the two shocks are 15.2 and 22.0, respectively.[32]

The estimation results based on the external instruments confirm the robustness of our baseline results. Figure 4 presents the impulse responses of the global variables following the global consumer confidence and uncertainty shocks, which appear quite consistent with those based on the baseline recursive scheme. An increase in uncertainty, as shown in panel A, was significantly associated with declines in global industrial production, consumer confidence, interest rates, and inflation, and a rise in unemployment. Meanwhile, improvement in consumer confidence (panel B) was associated with the boost in global economic activity—leading to an increase in global production and market interest rates, and a decline in unemployment. Again, the responses of inflation were mixed over time, in line with the observations from the baseline model. The impacts of confidence shocks appear more sizable than those of uncertainty shocks, although the response of the variables was short-lived following both types of shocks, as discussed in Section 3.

Figure 5 presents the impulse responses to a one-standard-deviation global business confidence shock, which are based on the

[31]The results are largely robust across the selection of instrumental variable sets, in terms of the directions and shapes of impulse responses, although the relevancy is different depending on types or combinations of instruments.

[32]To the extent that sentiments and other macrofinancial variables can mutually affect in a short interval, we also carry out the exogeneity tests for our instrumental variables by regressing the following univariate model (Piffer and Podstawski 2018; Levchenko and Pandalai-Nayar 2020):

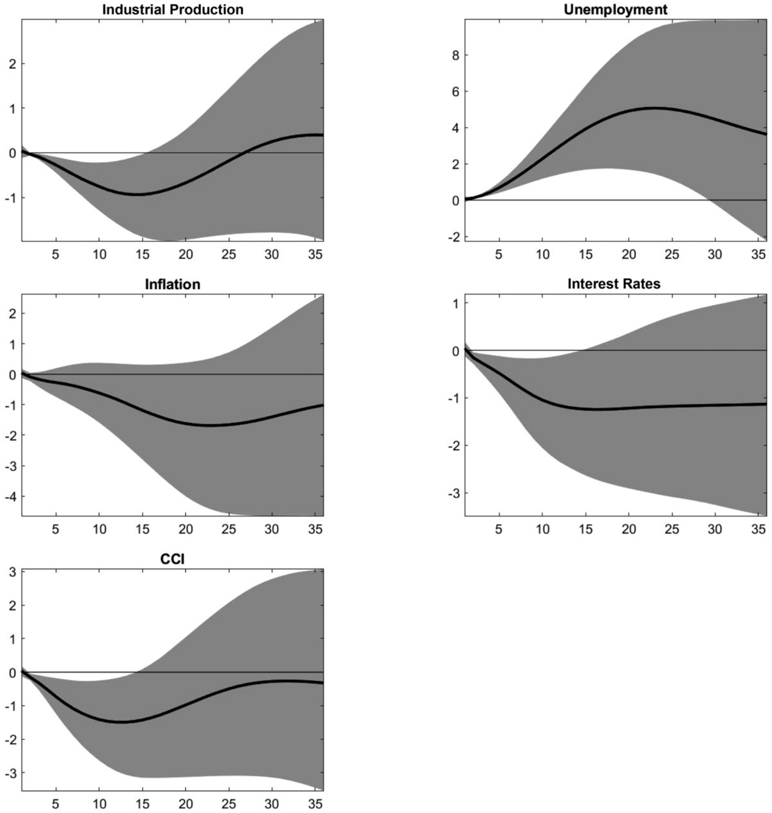
$$z_t = \alpha + \beta_i m_{i,t} + \theta_{i,t},$$

where z_t denotes our instrumental variables computed with the poor man's approach and m_i indicates the other structural shock. By testing the null hypothesis of $\beta_i = 0$, we can figure out whether our proxies are correlated with the other shocks instrumented by m_i. Regarding m_i, various types of financial, policy, and oil shocks are considered. As the estimation results are summarized in Tables A.2 and A.3 in Online Appendix A.3, the instrumental variables employed in our proxy VAR estimation are mostly uncorrelated with other structural shocks.

Figure 4. Impulse Response Following Consumer Confidence and Uncertainty Shocks: Proxy VAR Model with Poor Man's Approach

A. Uncertainty (VIX) Shocks

$IV_U = [VIX_U, Gold_U]$



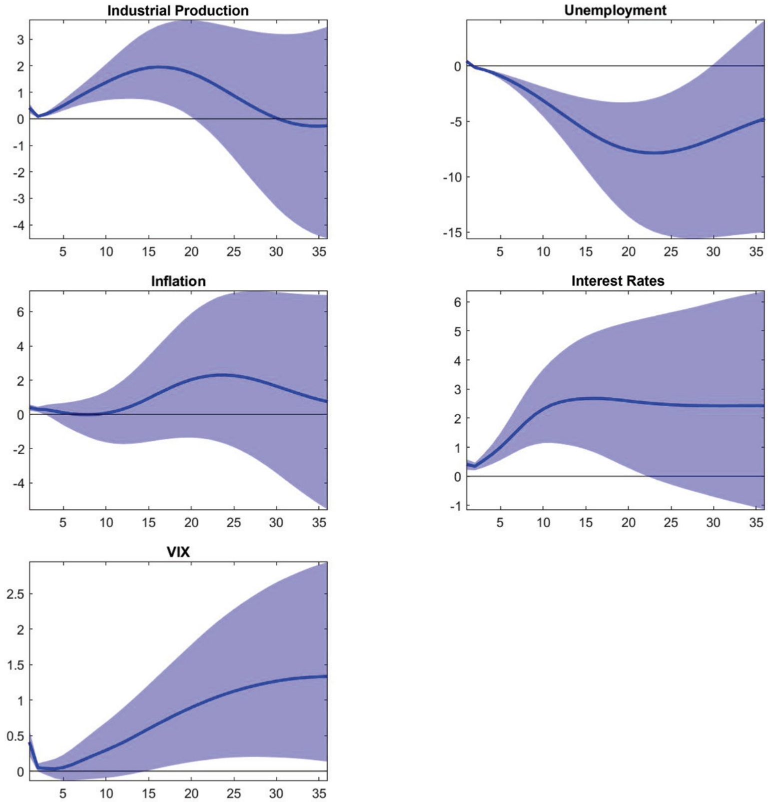
(*continued*)

estimation of the six-variable proxy VAR (global business confidence, uncertainty, and other global variables). Again, the results are in line with those observed in Section 3. The variables computed from gold prices are selected here to instrument for uncertainty and business confidence shocks ($IV_U = [Gold_U]$, $IV_C = [Gold_C]$). F-statistics

Figure 4. (Continued)

B. Consumer Confidence Shocks

$$IV_C = [Gold_C]$$

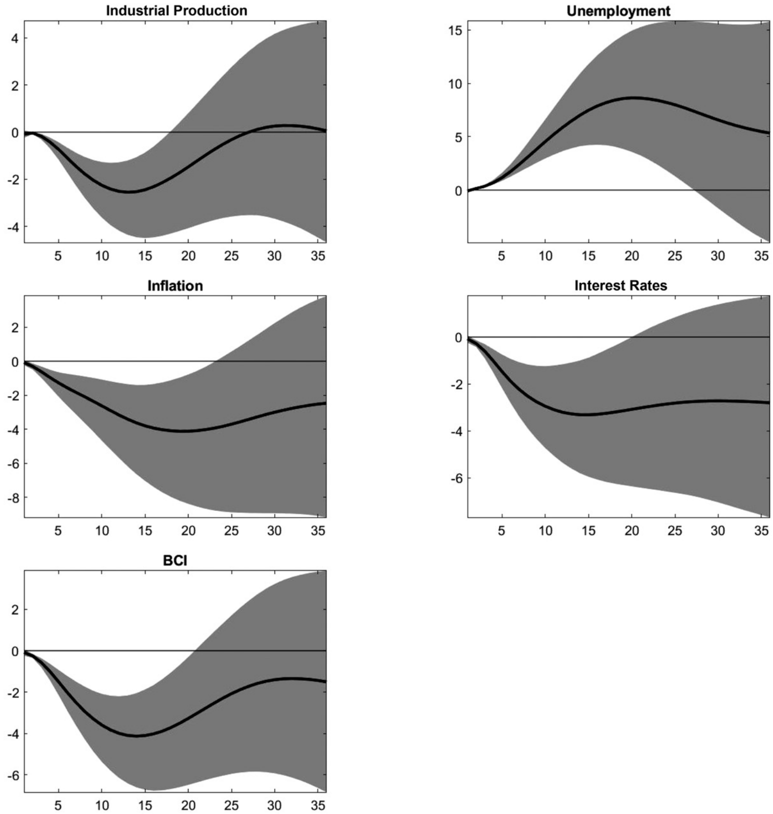


Note: The impulse responses are based on the six-variable VAR model (uncertainty, consumer confidence, and other global variables) that exploits the sets of external instrument $[VIX_U, Gold_U]$ for the global uncertainty shocks and $[Gold_C]$ for the global consumer confidence shocks. Each instrumental variable is decomposed into the ones to correspond to the shocks according to the poor man's approach. F-statistic on the first-stage regression for the uncertainty shocks is 15.2 (panel A) and for the confidence shocks is 22.0 (panel B). The responses are to a positive one-standard-deviation structural shock. Solid lines and shaded areas indicate median (50th) and 5th–95th percentiles, respectively, among 1,000 successful bootstrap draws. Vertical axis indicates percentage points or unit changes and horizontal axis indicates months.

Figure 5. Impulse Response Following Business Confidence and Uncertainty Shocks: Proxy VAR Model with Poor Man's Approach

A. Uncertainty (VIX) Shocks

$IV_U = [Gold_U]$



(*continued*)

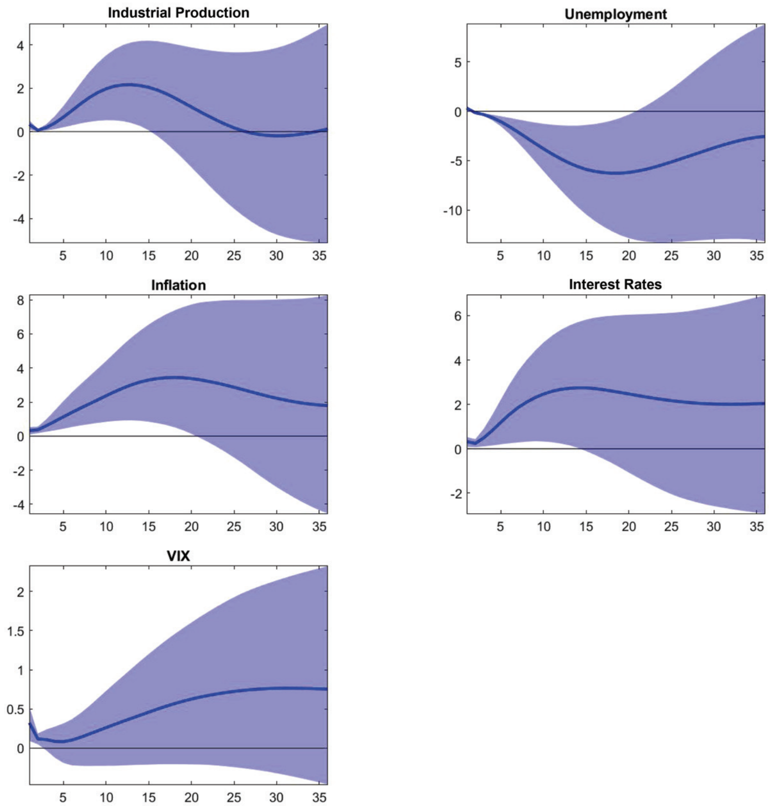
for the first-stage regression are 13.3 and 15.9 for uncertainty and business confidence shocks, respectively.[33]

[33]We also report additional results based on alternative sets of instrumental variables in Online Appendix A.4.

Figure 5. (Continued)

B. Business Confidence Shocks

$IV_C = [Gold_C]$



Note: The impulse responses are based on the six-variable VAR model (uncertainty, business confidence, and other global variables) that exploits the sets of external instrument $[Gold_U]$ for the global uncertainty shocks and $[Gold_C]$ for the global consumer confidence shocks. Each instrumental variable is decomposed into the ones to correspond to the shocks according to the poor man's approach. F-statistic on the first-stage regression for the uncertainty shocks is 13.3 (panel A) and for the confidence shocks is 15.9 (panel B). The responses are to a positive one-standard-deviation structural shock. Solid lines and shaded areas indicate median (50th) and 5th–95th percentiles, respectively, among 1,000 successful bootstrap draws. Vertical axis indicates percentage points or unit changes and horizontal axis indicates months.

4.2 Cholesky Identification with Alternative Variable Ordering

While Cholesky restrictions have been widely employed in identifying uncertainty or confidence shocks, the related studies have often employed different assumptions in identifying the shocks. For instance, in a monthly VAR, Jurado, Ludvigson, and Ng (2015) and Baker, Bloom, and Davis (2016) both employed recursive restrictions in identifying global uncertainty shocks, but ordered the variables differently. Jurado, Ludvigson, and Ng (2015) ordered the uncertainty index (the VIX) last by assuming that the VIX is likely to be endogenous to other structural shocks, while other macroeconomic variables are little explained by the uncertainty shock within a month. The reversed ordering was selected in Baker, Bloom, and Davis (2016). Although less amount of evidence is presented in the literature on the identification of confidence shocks, the studies have again imposed different types of recursive restrictions—Levchenko and Pandalai-Nayar (2020) ordered the confidence indicator last in the VAR system while Barsky and Sims (2012) ordered the variable first.

Against this backdrop, we test here the results based on a different ordering where confidence measure is placed first and orthogonalized with respect to other global variables. Figure A.8 in Online Appendix A.3 presents the impulse response of the global variables following a one-standard-deviation increase in the consumer confidence (panel A) and business confidence (panel B).

The effects of confidence shocks appear to be consistent, albeit stronger, on the global variables, compared with the baseline results. The global industrial production rose by up to around 4 percentage points while unemployment rates declined by over 2 percentage points following the consumer confidence shock, and the effects appear short-lived. The effects on inflation were negative within a year but turned positive afterward. Similarly, as depicted in panel B of Figure A.8, a one-standard-deviation increase in the global business confidence was associated with a rise in global industrial production, inflation, and interest rates, and declines in global unemployment rates. The effects on the global variables were weaker than those of consumer confidence shocks.

The results also confirm the sizable contributions of consumer and business confidence innovations to the variance of the global macroeconomic variables, under the alternative identification scheme (not shown here). All in all, the results are consistent across the two different orderings of the variables, in line with what was found in Jurado, Ludvigson, and Ng (2015) for the case of uncertainties.

4.3 Additional Results on Uncertainty Shocks

An important issue we raised throughout the paper is the differences between confidence and uncertainty. The baseline estimation brought us to the conclusion that uncertainty is associated more with *wait-and-see* impacts while confidence is likely to reflect other types of shocks, and moreover, plays a role as a potential catalyst in transmitting uncertainty shocks. In addition, as was shown in Section 3.2.4, the contribution of confidence shocks was broadly consistent across the models that employ different types of uncertainty shocks.

In this subsection, we present some additional empirical results on the distinct nature of uncertainty in terms of its correlation with confidence and its role in global economic activities. The robustness of our findings is checked by replacing the VIX, used as a proxy for global uncertainty, with a battery of other uncertainty measures.

4.3.1 Correlation between Confidence and Uncertainty Measures

Simple empirical exercises suggest the confidence and uncertainty measures are moderately correlated, supporting the possibility of common shocks. For instance, global business and consumer confidence have a positive correlation of 0.35. Similarly, the uncertainty measure (VIX) was negatively correlated with confidence; the correlations of uncertainty shocks with consumer confidence and business confidence were −0.26 and −0.20, respectively.[34]

More generally, Figure A.4 in Online Appendix A.2 presents cross-correlations of business (panel A) and consumer (panel B)

[34]Similarly, in our proxy VAR exercises, which take into account the correlation between uncertainty and confidence shocks, the covariance parameters were estimated to be negative, −0.36 (in the model with consumer confidence) and –0.41 (with business confidence).

confidence with various uncertainty measures. For instance, global consumer confidence was relatively highly correlated with financial uncertainty and economic policy uncertainty. Meanwhile, business confidence shocks were more correlated with macroeconomic uncertainty (correlation coefficients: –0.35). In addition, as shown in Figure A.4, while consumer confidence tends to co-move with uncertainty measures, business confidence tends to lag uncertainty measures by two to five months, suggesting more endogenous nature of the confidence.

4.3.2 Models with Other Uncertainty Measures

We now test other types of uncertainty measures in the five-variable FAVAR model, focusing on the variance contributions of each uncertainty measure to the global variables.[35] Table A.1 in Online Appendix A.2 summarizes the results.

When we employed the financial uncertainty as compiled by Jurado, Ludvigson, and Ng (2015) (the first row of the table), the contribution of uncertainty shocks was comparable to those based on VIX: the uncertainty shocks explained less than 10 percent of variations in the global variables, except global unemployment on which the impacts of the uncertainty shocks were more sizable and/or persistent, explaining around 30 percent of total variations.

Next, we employed macroeconomic uncertainty by Jurado, Ludvigson, and Ng (2015) (the second row). The variance contributions of the macroeconomic uncertainty to unemployment rate and to inflation were quite sizable, explaining over half of total variations in the variables. Its contribution to global industrial output is also substantial, explaining over a third of total variations.

When we employed the global EPU index in Baker, Bloom, and Davis (2016) (the third row), the impacts of uncertainty on global variables were also sizable although the results were less statistically significant. The variance contribution of the global EPU was similar to the VIX, by explaining below 10 percent of total variations in the global variables except that it explained a sizable portion (around a quarter) of global unemployment rates.

[35]The results on the contributions of uncertainty shocks changed little when we instead employ the six- or seven-variable model that also includes confidence indicators.

We examined the impact of other types of uncertainty measures: global monetary policy uncertainty in Husted, Rogers, and Sun (2020) and global geopolitical uncertainty in Caldara and Iacoviello (2018), and world pandemic uncertainty index in Ahir, Bloom, and Furceri (2018) (the fourth through the sixth row). The results were largely insignificant, suggesting that the uncertainty shocks did not systematically explain the global macroeconomic and financial variables, at least in an aggregate manner. That said, this does not imply that country-specific measures of such uncertainty do not explain domestic variables.

5. Concluding Remarks

The COVID-19 pandemic reignited the attention on the importance of economic sentiments. This paper examines the role of global confidence shocks that are transmitted into global macroeconomic and financial activities. To this end, we estimate a Bayesian FAVAR model using a broad range of cross-country data on business and consumer confidence, uncertainty, industrial production, unemployment rates, headline CPI inflation, and interest rates, all at monthly frequency.

The paper reports three main results. First, global confidence shocks have played a key role in global macroeconomic and financial fluctuations over the recent three to four decades. The dynamic responses of global variables were all very significant and sizable following global confidence shocks, but mostly short-lived. The global confidence shocks explained more than a third of total variations in global economic activities.

Second, the results suggest that global consumer confidence shocks appear to reflect a combination of global demand and supply shocks. The shocks are likely to widely reflect TFP shocks, financial and macroeconomic uncertainty, and animal spirit of economic agents. To the contrary, global business sentiment or global uncertainty shocks appear to be a demand shock consistent with what other literature indicates.

Third, global confidence plays an important role in the transmission of uncertainty shocks into global business cycles. Although the two concepts (i.e., confidence and uncertainty) are not entirely uncorrelated to each other, reflecting common information, the results point out that the confidence shocks were not necessarily determined by uncertainty. The empirical results suggest that global consumer and business confidence indicators respond significantly to uncertainty shocks, possibly propagating the impacts on the global economy. Meanwhile, there was little evidence that uncertainty measures responded significantly to confidence shocks.

The results are robust to alternative identification strategies. These include the identification using external instruments, alternative ordering of variables, and different types of uncertainty measures.

The empirical results in this paper bring us to several important policy implications going forward. First, more delicate policy coordination across countries is necessary to mitigate the adverse impacts from heightened uncertainty and subdued confidence since the onset of the COVID-19 crisis. Although our sample does not cover the post-COVID period, the pandemic has apparently left deep scars on global economic activity. Moreover, despite some promising signals of a swift recovery, the crisis is still at play in escalating formidably uncertainties and overshadowing economic agents' confidence in the future economic conditions in many economies and sectors. Due to the nature of the pandemic, such perils cannot be fully controlled by individual countries' efforts alone. Not only health but also economic policies must be globally collaborated to stand against the worldwide headwinds associated with heightened uncertainty and deteriorated confidence.

Next, along with country-specific indicators, the shifts in global confidence indicators should be closely monitored and their possible consequences must be thoroughly understood in policymaking. As discussed throughout the paper, the impacts of global confidence and uncertainty shocks are significant, multifaceted, and quickly spreading, possibly due to close financial or trade linkages. To offset adverse effects, multi-pronged countermeasures are required in response to the shocks in a timely manner. To avoid any policy missteps, it is also vital for them to be equipped with more advanced real-time monitoring tools for global confidence and uncertainty (e.g., now-casting).

There are several avenues for future work. First, as indicated in the introduction, this paper is focused on the global nature of the shock transmission. A follow-up work on the domestic transmission of the shocks will shed more light on the potential heterogeneity across countries in international spillovers. Second, while the analysis in the paper provides evidence on the important role of the global confidence cycle, it does not explore systematically whether the nature of the cycle is indicative of "news" or "sentiments." Such a distinction can shed further light on the causal implications of confidence for business and financial cycles.

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