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Cross-Country Uncertainty Spillovers: Evidence from International Survey Data*

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Abstract

Using a large international survey of professional forecasters, we construct measures of economic uncertainty surrounding output growth, inflation, the interest rate, exchange rate and current account. We then analyze uncertainty spillovers across major advanced and emerging economies using large multi-country Bayesian Panel VARs. We consider how our results change if our uncertainty measures reflect: disagreement among forecasters (idiosyncratic uncertainty); the variance of their mean forecast errors (common uncertainty); or both types of uncertainty. We show that the US is an important but not dominant source of uncertainty, affecting other economies through interest rate and exchange rate uncertainty. This reflects the major role played by US monetary policy and the dollar in the global financial system. Crucially, though, the Eurozone followed by the UK and China are also important sources of uncertainty. We also find that, on average, foreign interest rate and exchange rate uncertainty are more important than foreign output growth uncertainty. While spillovers in idiosyncratic uncertainty are more frequently observed, failing to account for common uncertainty can lead us to overestimate the role played by smaller economies.

Keywords: Uncertainty Shocks, Spillovers, Bayesian Panel VAR, Stochastic Search Variable Selection, Consensus Forecasts.

JEL: C11, C33, F44, F47.

1 Introduction

Following Bloom's seminal work (2009), a large body of literature has sought to measure the adverse effects of domestic uncertainty on the economy (see Jurado et al., 2015, Bachmann et al., 2013, Scotti, 2016, Carriero et al., 2018 among many others). However, despite deepening trade and financial integration, it is still unclear to what extent uncertainty shocks occurring in a specific economy can affect other economies. Recent studies have also begun to distinguish between different components of uncertainty, for instance, analyzing: uncertainty around output growth (Berger et al., 2016); the relative importance of macroeconomic and financial uncertainty (Davidson et al., 2022 and Ludvigson et al., 2021); and economic and monetary policy uncertainty (Baker et al., 2015 and Husted et al., 2020). Again, though, the roles played by different uncertainty components in cross-country spillovers remains unknown.

This paper seeks to address these issues by analyzing international spillovers in uncertainty between seven major advanced and emerging economies.[1] While some studies use econometric or text-based uncertainty proxies, we build on a growing literature using survey data. Specifically, we utilize *Consensus Economics'* large international survey of professional forecasters. This facilitates a more granular approach where five components of uncertainty are constructed for each economy. These capture uncertainty surrounding output growth, inflation, the interest rate, exchange rate and current account. Like other recent studies (Lahiri and Sheng, 2010; Istrefi and Mouabbi, 2018 and Ozturk and Sheng, 2018) we distinguish between different survey-based empirical proxies for our five uncertainty components. We consider three survey-based proxies of uncertainty: (i) disagreement among our forecasters reflecting idiosyncratic uncertainty, (ii) the conditional variance of participants' mean forecast errors which captures common uncertainty, the perceived variance of future aggregate shocks and (iii) aggregate uncertainty which combines the two previous measures.

[1] This includes the US, Canada, the Eurozone, UK, Japan, China and India.

To analyze spillovers in uncertainty we estimate three large multi-country Panel VARs (PVARs) corresponding to our three survey-based proxies of uncertainty. PVARs allow us to jointly model uncertainty and macro-financial variables for each economy. Importantly, they also allow for interdependencies between individual economies. The great flexibility of our empirical strategy, however, comes with a cost. Modeling interdependencies between individual economies and allowing for different components of uncertainty leads to high-dimensional PVARs which are difficult to estimate. We circumvent these problems by estimating our PVARs using Bayesian estimation methods. Specifically, we extend the Stochastic Search Specification Selection (S^4) Bayesian PVAR approach of Koop and Korobilis (2016). S^4 is an algorithm for sorting through restrictions in a data based fashion, estimating interdependencies between economies which are empirically important and deleting unimportant ones. The latter leads to a model which is much more parsimonious, surmounting overparameterization concerns.

Koop and Korobilis (2016) consider whether one economy can affect another with a time lag through the VAR coefficients or contemporaneously through the error covariance matrix. We modify these restrictions so that they are more granular, focusing on whether one economy's uncertainty components can affect another economy's uncertainty components or macro-financial variables. We can then examine which restrictions are imposed before producing our impulse response functions and forecast error variance decompositions. Using these different results, we can investigate three issues. First, we can uncover which economies are sources of uncertainty spillovers and which economies are vulnerable to foreign uncertainty. Second, we can disentangle which components of uncertainty are most important and whether this varies across economies. Third, we can assess whether our results change depending on the uncertainty proxy used.

Our paper shows that there are considerable spillovers in uncertainty between different economies. While the US is an important transmitter of uncertainty it does not play a dominant role. Instead, we find that uncertainty spillovers originate from each economy with the Eurozone followed by the UK and China also playing a sizable role. These dynamics cannot be captured by approaches which assess the effects of a single global uncertainty shock, highlighting the importance of our high-dimensional VAR-based approach.

In terms of the relative importance of different uncertainty components, we find that the US affects other economies through interest rate and exchange uncertainty, important transmission channels linking the US to the global economy. We also find that across economies foreign output growth uncertainty has the most muted affect with foreign exchange rate and interest rate uncertainty playing a more important role. This aligns with the recent literature on domestic uncertainty shocks which finds that financial uncertainty is more important than macroeconomic uncertainty (Davidson et al., 2022 and Ludvigson et al., 2021). We also show that although similar results are obtained when using idiosyncratic and aggregate uncertainty as a proxy, failing to account for common uncertainty can lead us to overestimate the role played by smaller economies.

The rest of the paper is structured as follows. Section 2 discusses how our paper relates to the literature. Section 3 describes how we measure uncertainty using survey data and provides an overview of our dataset. Section 4 describes how our multi-country PVARs sheds light on uncertainty spillovers at different levels of granularity. We then present our results on uncertainty spillovers between different economies and different components of uncertainty in Section 5. Section 6 concludes.

2 Relationship to the Literature

Economic uncertainty is the uncertainty faced by consumers, firms and policymakers about the future and the possible path of macroeconomic and financial variables. From a theoretical standpoint, uncertainty can also be defined as the expected change in the second moment of a distribution which is mean preserving. Although uncertainty is an ambiguous concept, the literature has made considerable progress in documenting its causes and consequences (see Bloom, 2014 for a review). It is well understood that bad events tend to cause uncertainty to vary. For example, Bloom (2009) uncovers 17 uncertainty shocks from 1962 to 2008 - all but one are associated with events which lower economic growth. Such events include the OPEC oil price shocks and Asian financial crisis.

While there are a some channels through which uncertainty can positively effect the economy (see, for example, growth options theory and the Oi-Hartman-Abel effect discussed in Oi 1961; Hartman 1972; Abel 1983), the empirical literature predominately uncovers an adverse affect and countercyclical relationship with the business cycle. These adverse consequences can stem from "real options" effects (McDonald and Siegel 1986, Dixit and Pindyck, 1994) where firms and households postpone investment and consumption. Uncertainty can also cause borrowing costs to increase (Arellano et al., 2010; Christiano et al., 2014; Gilchrist et al., 2014) and cause households to raise their precautionary savings. While these channels have been primarily discussed in a domestic context, in today's globalized world the same channels are also likely to be at work when considering foreign uncertainty shocks.

In this paper, we focus on whether uncertainty shocks are transmitted across economies. The existing literature primarily addresses this through the concept of a global uncertainty shock, econometrically estimated from a broad set of variables. In these papers, international uncertainty is typically proxied by stochastic volatility, the time-varying second moment of time series variables. Cuaresma et al. (2020) and Carriero et al. (2019), for example, deploy large-scale VARs with stochastic volatility. Using data on advanced economies, they can then jointly estimate a measure of international uncertainty and its effects on each economy. Cross et al. (2019) instead focus on three small open economies in their VAR with stochastic volatility, allowing them to jointly estimate both international and domestic uncertainty shocks.

Other studies use factor models with stochastic volatility to decompose the effects of global and country-specific uncertainty. Focusing on OECD economies, Mumtaz and Theodoridis (2017) decompose changes in real and financial variables into contributions from country-specific and global uncertainty. This approach is generalized by Mumtaz and Musso (2019) who also allow for region-specific uncertainty. Again, focusing on OECD economies, Berger et al. (2016) obtain global and country-specific measures of output growth uncertainty. For each country, they then assess the impacts of uncertainty using small country-specific VARs. An overarching finding across studies using econometric measures of uncertainty is that global uncertainty often plays a more important role than domestic uncertainty. However, it remains unclear which countries and components of foreign uncertainty dominate.

A smaller strand of the literature on international uncertainty spillovers focuses on cross-country economic policy uncertainty (EPU) spillovers. These can be readily investigated using measures of EPU constructed by Baker et al. (2016) through textual analysis of newspapers. Klössner and Sekkel (2014) look at EPU spillovers among the G7 excluding Japan, finding the UK and US to be important EPU transmitters. However, they do not directly consider the effects of foreign EPU on the domestic macroeconomy. Caggiano et al. (2020) and Biljanovska et al. (2021) consider EPU spillovers from the US to Canada and the UK, and between Europe, China and the US respectively. In both cases they find that foreign EPU shocks reduce economic activity in other parts of the world.

Other PVAR approaches considering uncertainty shocks include Miescu (2019) and Casarin et al. (2018) who take advantage of the panel structure of the data but do not allow for interdependencies and spillovers between economies. Cesa-Bianchi et al. (2019) take a distinct approach using a large-scale PVAR to analyze the relationship between uncertainty, proxied using stock market volatility, and economic growth. They assume that both variables are driven by a global growth shock, global financial shock and two country-specific shocks. Using their framework, uncertainty shocks play a smaller role.

Instead of considering one single measure of global uncertainty or spillovers in a single component of uncertainty, we are the first study which considers the economic effects of international spillovers in five components of economy-specific uncertainty. Our survey data allows us to construct comparable measures of output growth, inflation, short-term interest rate, current account and exchange rate uncertainty across economies. This has the advantage that we can understand dynamics and interdependencies between major advanced and emerging economies at a more granular level. After all, it is possible that uncertainty shocks propagate only within some sets of economies, but not others. Or that a specific component of uncertainty plays a more dominant role.

The second theme of this paper is the measurement of uncertainty. Since uncertainty is unobservable the literature has proposed various empirical proxies.[2] While we have discussed volatility based estimates of uncertainty, there are other means to econometrically estimate uncertainty. Some studies have focused on the common unpredictable component of a large set of variables (Jurado et al., 2015 and Ludvigson et al., 2021) while others assess whether realized forecast errors occur in the tail of the historical forecast error distribution (Rossi and Sekhposyan, 2015, 2017). To analyze policy uncertainty, another strand of the literature constructs uncertainty proxies using textual analysis (see Baker et al., 2016, Husted et al., 2020, Larsen, 2017 and Castelnuovo and Tran, 2017 among many others). Regardless of the approach used, however, with the exception of Baker et al. (2016) and Rossi and Sekysposen (2017), few studies construct comparable cross-country measures of uncertainty. Furthermore, while individual studies capture different components of uncertainty, no single study compares the relative importance of different components in a unified framework.

In the present paper, we use an international survey of professional forecasters from *Consensus Economics* to construct measures of uncertainty. The justification for using surveys is that, in stable and certain times, a set of professional forecasters might be expected to

[2]Cascaldi-Garcia et al. (2022) and Castelnuovo (2022) provide recent reviews.

all produce similar forecasts. However, in uncertain times, they might be expected to produce divergent forecasts leading to measures relating to the forecast errors and dispersion of forecasts being used as proxies for uncertainty. In the next section of the paper we provide precise definitions of these proxies, but the point worth noting here is that there is an emerging literature using surveys to measure economic uncertainty. Additionally, by using survey data we can take a more disaggregated view and measure uncertainty surrounding a number of key variables for each economy included in our analysis.

Despite data dating back to 1989 on a wide range of variables, forecasts from *Consensus Economics* have seldom been used to consider international spillovers with the exception of Lahiri and Zhao (2019). Lahiri and Zhao (2019) do not explicitly focus on uncertainty. Rather they use GDP growth forecasts to consider the propagation of shocks among industrialized and emerging Asian economies. Using GDP growth forecasts rather than actual values facilitates the analysis of the transmission of shocks at a monthly frequency.

Two studies using *Consensus Economics* survey data to analyze uncertainty shocks are Ozturk and Sheng (2018) and Istrefi and Mouabbi (2018). Both these studies follow Lahiri and Sheng (2010), decomposing aggregate uncertainty into idiosyncratic and common uncertainty using forecast data. Ozturk and Sheng (2018), construct country-specific and global uncertainty measures using forecasts of macroeconomic variables for 45 economies. Istrefi and Mouabbi (2018) use forecasts of short and long-term interest rates to examine the effects of domestic interest rate uncertainty shocks on nine industrialized economies. Both studies find that idiosyncratic and common uncertainty shocks both have an adverse affect on the real economy with the latter tending to produce more negative responses.

3 Measuring International Uncertainty Spillovers

In the following subsection we discuss how survey data can be used to construct uncertainty proxies and the different dimensions of uncertainty our survey data can capture. We then provide an overview of our dataset and the measures used in our analysis.

3.1 Measuring Uncertainty Using Survey Data

We first discuss and evaluate the uncertainty proxies which can be constructed based on our survey data. Surveys of professional forecasters capture participants' probabilistic assessments about the future path of macroeconomic and financial variables. As discussed below, this means that survey-based measures of uncertainty are conceptually more similar to some econometric estimates of uncertainty. In contrast, text-based estimates of economic policy uncertainty relate more closely to the coverage of political events and announcements.

A popular survey-based proxy in the literature is disagreement among professional forecasters which is given by the dispersion of the different point forecasts (see e.g. Bachmann et al., 2013). This is often referred to as idiosyncratic uncertainty. This measure assumes that in times of low uncertainty, participants are more likely to agree on the future path of economic variables. In contrast, when uncertainty is high, a broader range of opinions will lead to a higher degree of disagreement. While disagreement and uncertainty are positively correlated, a number of studies have argued that disagreement among survey participants is not always a reliable proxy (Zarnowitz and Lambros, 1987, D'Amico and Orphanides, 2014, Rich and Tracy, 2010, 2018). For instance, disagreement may be low when forecasters agree that there is high uncertainty in the future (Zarnowitz and Lambros, 1987). Disagreement may also capture different opinions rather than uncertainty (see, for example, Diether et al., 2002).

Recently, Lahiri and Sheng (2010) uncover the circumstances under which disagreement is a reliable proxy for uncertainty. They find that disagreement is an appropriate proxy in stable times and at shorter forecast horizons. However, during unstable times we must account for common uncertainty, the uncertainty shared by all forecasters due to exposure to the same future shocks. Common uncertainty aligns with the concept of uncertainty presented in Jurado et al. (2015) who, using an econometric model, define uncertainty as the unforecastable component common to a large number of series. Using survey data, however, common uncertainty can be captured by the conditional variance of participants' mean forecast errors. By combining disagreement among forecasters and forecast error variances we then obtain a measure of aggregate uncertainty (Lahiri and Sheng, 2010).

Following the framework devised by Lahiri and Sheng (2010) and used by Istrefi and Mouabbi (2018) and Ozturk and Sheng (2018), for each component of uncertainty, we therefore construct three uncertainty proxies: forecaster disagreement reflecting idiosyncratic uncertainty, the conditional variance of forecasters' mean forecast errors representing common uncertainty and the combination of the two, aggregate uncertainty. Aggregate uncertainty, $U_{t,h}$, at time t about a variable h periods in the future, can therefore be decomposed as follows:

$$U_{t,h} = D_{t,h} + V_{t,h}, \tag{1}$$

where $D_{t,h}$ is forecaster disagreement and $V_{t,h}$ is the conditional variance of their mean forecast errors. To define these two quantities, let $f_{k,t,h}$ be the forecast made by forecaster k for $k = 1, \ldots, K$ at time t about a variable at time $t+h$ and $f_{t,h}$ be the average taken across forecasters. Disagreement is the variance taken across forecasters,

$$D_{t,h} = \frac{\sum_{k=1}^{K} (f_{k,t,h} - f_{t,h})^2}{K}. \tag{2}$$

If we let y_{t+h} be the realization of a variable at time $t+h$, then the forecast error of the

k^{th} forecaster is

$$e_{k,t,h} = y_{t+h} - f_{k,t,h}. \quad (3)$$

The mean forecast error, $e_{t,h}$, is the average taken across all K forecasters. An estimate of $V_{t,h}$, can be obtained using $e_{t,h}$. Specifically, we follow Lahiri and Sheng (2010) and filter the mean forecast errors for possible autocorrelation before estimating GARCH models. In most cases, we identify a GARCH (1,1) as an adequate choice but our findings are not affected by the exact specification. Engle (1983) and Lahiri and Sheng (2010) argue that this approach provides us with better proxy for ex-ante uncertainty compared to ex-post squared errors of mean forecasts.

3.2 An Overview of Our Dataset

Our monthly survey data is obtained from *Consensus Economics*, a private firm which collects point forecasts of key economic and financial variables at the beginning of each month. An important advantage of this dataset is that forecasts are collected across many advanced and emerging economies. Since the surveys have a near uniform design for all economies, this facilitates the construction of comparable measures of uncertainty across countries. In each economy, professional forecasters are drawn from government agencies, international banks, consultancies and research institutions. The survey has a high number of participants who participate over a long period or the full sample. Additionally, the name of each forecaster is published. This increases the incentive to provide accurate forecasts since implausible numbers could harm the reputation of a forecaster.

In our paper, we use data from 1996:04 - 2016:07 for seven advanced and emerging economies: the United States (USA), Canada (CAN), the Eurozone (EU), the United Kingdom (GBR), Japan (JPN), China (CHN) and India (IND). For each economy, we construct our five components of uncertainty, using forecasts on: industrial production growth (IP), CPI inflation (CPI), the 3-month short-term interest rate (IR), dollar exchange rates (FX) and the current account relative to GDP (CA). This enables us to capture the most important dimensions of uncertainty for an economy since we account for monetary policy (interest rate and inflation uncertainty, see Istrefi and Mouabbi, 2018 and Istrefi and Piloiu, 2014); the business cycle (industrial production growth uncertainty, see Kuang and Mitra, 2016); and the international economy (exchange rate and current account uncertainty).[3]

For consistency across components of uncertainty, we consider a 12 month ahead forecasting horizon. Forecasts for interest rates and exchange rates are fixed horizon forecasts, however, the forecasts for industrial production, inflation, and the current account are fixed event forecasts. We therefore adopt an established approach (see Patton and Timmermann, 2011, Dovern et al., 2012) for transforming fixed event forecasts to fixed horizon forecasts with further details provided in Appendix A.

For each economy, we therefore construct five components of uncertainty and proxy each component in three ways with the exception of the current account. Since current account data is unavailable at a monthly frequency across economies, we do not calculate the conditional variance of the mean forecast errors, $V_{t,h}$, for the current account. This means that we do not have a measure of common current account uncertainty and our aggregate and idiosyncratic current account uncertainty measures are the same.

We provide plots of our uncertainty measures for each economy and uncertainty component in Figure 1. For brevity, we focus on our aggregate uncertainty measures. We can clearly see that while there is some commonality in uncertainty across economies and components of uncertainty, there is also considerable heterogeneity. For instance, we see common spikes in IP, CPI and IR uncertainty during the global financial crisis. However, the EU also experiences heightened IP uncertainty during the debt crisis between 2011-2013. Similarly, periods of low IR interest rate uncertainty correspond to country-specific zero lower bound periods

[3]If a series is unavailable for one economy, we use a suitable alternative. Details are given in Appendix A.

(Istrefi and Mouabbi, 2018). FX and CA uncertainty exhibit slightly different patterns. For example, as China resumed exchange rate reform in mid 2010, FX uncertainty began to rise. Similarly, as the Japanese yen strengthened amid the implementation of negative interest rates in 2016, both IR and FX uncertainty rose. CA uncertainty is more noisy but has generally been higher since the global financial crisis. This initial look at the data again suggests that using a disaggregated, VAR-based approach is likely to reveal new insights.

For each economy, we also include data on industrial production growth and stock price growth. This allows us to consider the effects of uncertainty spillovers on the real and financial sectors of each economy. This means that when either considering idiosyncratic or aggregate uncertainty, our PVAR has 49 endogenous variables (i.e. five uncertainty variables and two macro-financial variables for each of the 7 economies). However, when considering common uncertainty, our PVAR has 42 endogenous variables since we do not have proxies for common current account uncertainty. We also include six exogenous controls. The first three control for different aspects of global uncertainty and include the CBOE Volatility Index (VIX), global economic policy uncertainty and global oil price uncertainty. We also include a time trend, a global financial crisis dummy and an Asian financial crisis dummy.[4] Further details on data sources are provided in Appendix A.

Given the lack of consensus, we follow the empirical literature estimating three PVARs. First using disagreement as a proxy of uncertainty, second using the conditional variance of forecast errors and finally using the combination of both. By considering a model with disagreement alone, we also overcome a possible criticism of common and aggregate uncertainty, ensuring that forecast error variances (which use realizations of variables in their construction) and the realizations themselves are not included in the same model. Disagreement also has the advantage of being available in real time and unaffected by data revisions.

[4]We also checked for stochastic volatility by comparing generalized impulse response functions from homoskedastic country-specific VARs and country-specific VARs with stochastic volatility. The results were qualitatively similar.

Figure 1: Aggregate Uncertainty Measures

Note: All measures shown are standardized.

4 Econometric Methods

In this section, we describe our econometric methods. As previously discussed, a VAR-based approach allows us to relax the assumption that there is a single global uncertainty shock. Instead, we can undertake a more granular examination of international uncertainty spillovers. In particular, we allow for cross-country heterogeneity in terms of the propagation of uncertainty shocks and the relative importance of different components of uncertainty. The main challenge faced is that our PVARs are high-dimensional and can suffer from overparameterization problems. To overcome this, we use Bayesian methods to estimate our large multi-country PVARs. These require a prior and a method of posterior computation. In terms of the former, we discuss how existing methods are extended to explore and summarize international uncertainty spillovers. For the latter, we use the Markov Chain Monte Carlo (MCMC) algorithm developed in Koop and Korobilis (2016) and the reader is referred to that paper for details. Further details are also provided in Appendix B.

Our multi-country PVAR[5] model is defined as:

$$y_{it} = A_{1,i}Y_{t-1} + ... + A_{p,i}Y_{t-p} + \varepsilon_{it}, \tag{4}$$

where y_{it} is a vector of G dependent variables for economy i $(i = 1, ..., N)$ at time t $(t = 1, ..., T)$, $Y_t = (y'_{1t}, ..., y'_{Nt})'$, $A_{p,i}$ is a $G \times NG$ matrix and $p = 1, ..., P$ denotes lags. The errors ε_{it} are distributed as $N(0, \Sigma_{ii})$. This specifies the model for economy i. Our PVAR has two additional features.

First, economy i variables depend on lags of other economies' variables. It is this feature which allows for what are called dynamic interdependencies (DIs), see Canova and Ciccarelli (2009). DIs relate to dynamic relationships. If, for instance, US variables last month have an

[5]For simplicity, this notation does not include an intercept or exogenous right-hand side variables. In our empirical work, exogenous variables are included and our data is standardized so we do not include an intercept.

affect on Japan this month, then we say there is a DI from the US to Japan. The magnitude of the DI is measured by an appropriate block of coefficients in the coefficient matrices $A_{p,ij}$ for $p = 1, ..., P$. If every coefficient in this block is zero, then there is no DI from the US to Japan. Investigating whether DIs exist between i and j, thus, involves checking the restriction that $A_{p,ij} = 0$ for $p = 1, ..., P$.

But it is also possible that static relationships exist between economies. For instance, a rise in US uncertainty might occur at the same time as Japanese uncertainty. Contemporaneous links between the errors in economy i and j are allowed for through the second additional assumption that $cov(\varepsilon_{it}, \varepsilon_{jt}) = \Sigma_{ij}$. This is called a static interdependency (SI) and relates to the error covariance matrix in the PVAR. That is, SIs between two economies exist if Σ_{ij} is non-zero. Thus, checking the restriction that $\Sigma_{ij} = 0$ is equivalent to checking for SIs between i and j.

Koop and Korobilis (2016) develop Bayesian methods for the multi-country PVAR to explicitly consider the DI and SI restrictions described above. An advantage of Bayesian methods is that they produce posterior probabilities for any parameter and these can be used to produce posterior inclusion probabilities (PIPs) for every possible DI and SI. These PIPs provide us with the probability that each DI or SI should be included in the model.

In this paper, we extend the S^4 methods of Koop and Korobilis (2016) to allow for a more detailed investigation of cross-economy linkages. With 49 endogenous variables in our idiosyncratic and aggregate uncertainty models, 35 of which are uncertainty variables, $35 \times 49 = 1715$ impulse response functions are of interest. By carefully tailoring the S^4 algorithm, we can use PIPs to provide simple summaries of what the data tell us about international uncertainty spillovers between economies before considering our impulse response functions.

Specifically, we begin by noting that DIs and SIs, as defined by Canova and Ciccarelli (2009), exist if any economy i variable impacts on any economy j variable. For every economy, we have five uncertainty variables and two macro-financial variables. Koop and Korobilis

(2016) answer the general question: does economy i affect economy j? We instead set up our restrictions so that we can consider the more specific question: do uncertainty variables $r = 1, ..., 5$ in economy i (for $i = 1, ..., 7$) affect economy j's (for $j = 1, ..., 7$) real and financial sectors $s = 1, 2$ or uncertainty variables $r = 1, ..., 5$? We can then consider uncertainty spillovers at the economy level, using PIPs to summarize which economies are the main sources of uncertainty and which economies are most affected by foreign uncertainty spillovers.

Having provided an overview of spillovers of uncertainty at the economy level, we can then analyze uncertainty spillovers at the component level. We focus on generalized impulse response functions (GIRFs) which show the effect of a shock to uncertainty variable r (for $r = 1, ..., 5$) in economy i (for $i = 1, ..., 7$) on sector s (for $s = 1, 2$) of economy j (for $j = 1, ...5$). We also compute Diebold Yilmaz (2014) spillover indices based on generalized forecast error variance decompositions (GFEVDs). We calculate GIRFs and GFEVDs as in Koop, Pesaran and Potter (1996), Pesaran and Shin (1998) and Lanne and Nyberg (2016). We note that GIRFs and GFEVDs are invariant to the way the variables in the PVAR are ordered. This is an attractive feature in our case where we have a large number of variables and do not wish to impose unrealistic assumptions through a specific ordering.

5 Results

In this section, we present empirical results from three different high-dimensional PVAR(1) models with exogenous variables as described in Section 3. The three different PVARs arise due to our separate use of three uncertainty proxies, D_{t+h}, V_{t+h} and U_{t+h}, reflecting idiosyncratic, common and aggregate uncertainty respectively. For brevity, we abbreviate these to D, V and U in the figures below.

First, we begin at a low level of granularity, discussing which economies are sources of uncertainty and which economies are most affected by these foreign uncertainty spillovers.

For each uncertainty proxy, we consider these spillovers at the economy level by summarizing our PIPs, the probability that a given DI or SI between economies is selected for inclusion in the model. Second, we consider a higher level of granularity, not only examining cross-country spillovers but how a shock to each component of uncertainty affects the real and financial sectors of the seven economies analyzed. We do so by summarizing our GIRFs for each uncertainty proxy. Third, remaining at a high level of granularity, we use our GFEVDs to present Diebold-Yilmaz (2014) directional spillover indices.

5.1 International Uncertainty Spillovers at the Economy Level

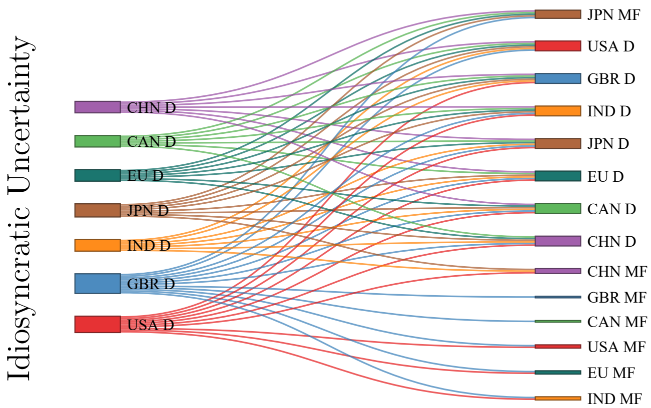
For each of our seven economies, we have five uncertainty and two macro-financial variables. Therefore the number of potential interdependencies is huge. To consider spillovers in uncertainty at the economy level, we group our variables into two blocks for each economy: an uncertainty block (D, V or U) and a macro-financial block (MF). A block of variables (uncertainty or macro-financial) can affect any other block (uncertainty or macro-financial) within an economy or in a different economy. This affect can take place contemporaneously (SI) or with a lag (DI). The probability that a DI or SI is included in the model is captured by the corresponding PIP. We summarize these PIPs using Sankey diagrams. If a PIP ≥ 0.5, then that interdependency is deemed important and shown as a link in the Sankey diagram. In practice, we found almost no PIPs to be near 0.5 with the vast majority clustering near 0 or 1. This pattern is reassuring in terms of detecting clear-cut interdependence.

We thus have two Figures summarizing the PIPs corresponding to the DIs (Figure 2) and SIs (Figure 3) detected in our three PVARs. Note that SIs are symmetric (e.g. if there are static spillovers from economy A uncertainty to economy B uncertainty, then there are static spillovers from economy B uncertainty to economy A uncertainty) so the links are in a neutral color. However, DIs are not symmetric (e.g. economy A uncertainty could dynamically affect economy B uncertainty, but the reverse might not necessarily occur). This means Sankey diagram relating to DIs should be viewed from left to right with the link color indicating which economy the spillover originates from.

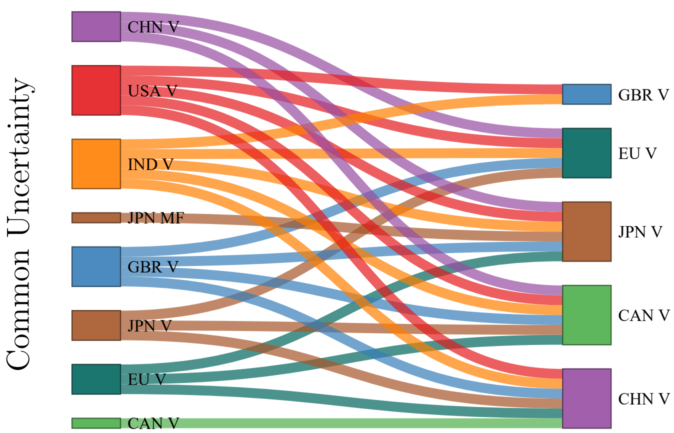
Our DIs, shown in Figure 2, demonstrate considerable evidence of international uncertainty spillovers with dynamic spillovers almost exclusively originating from the uncertainty block of different economies. Unsurprisingly, DIs indicate that uncertainty in the US plays a particularly strong role internationally regardless of the survey-based proxy used. Nonetheless, it is important to stress that the US does not play a dominant role as a source of foreign uncertainty to any domestic economy. Rather, spillovers originate from each economy and affect foreign uncertainty or the foreign real and financial sectors. For example, if we focus in on our aggregate uncertainty measure, we find that the Eurozone is also an important source of uncertainty. This is an intuitive finding suggesting that larger countries play a larger role in the transmission of international uncertainty. While China's role is growing, our results also coincide with studies which find that US uncertainty can affect China but not vice versa (Huang et al., 2018). The fact that there is not one simple source of uncertainty suggests that there may be no single global uncertainty measure. This illustrates the advantages of our VAR-based approach which disentangle the individual sources of uncertainty and how they spillover across economies.

We also find that dynamic spillovers from domestic uncertainty to domestic macro-financial blocks do not always occur, reinforcing the finding in the literature that foreign uncertainty can potentially play an even more important role than country-specific uncertainty. This finding, however, is not uniform across countries. For example, if we consider aggregate uncertainty, macro-financial variables in the UK, a small open economy, are only affected by foreign uncertainty arising from major trading partners, the Eurozone and US. In contrast, macro-financial variables in both the Eurozone and US are affected by their own uncertainty as well as foreign sources of uncertainty.

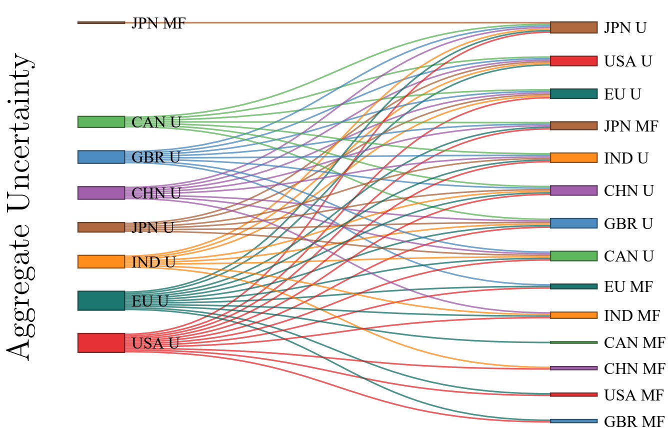
Figure 2: Dynamic Spillovers Across Economies



Top D Sources (No. of Links)	Top MF Receivers (No. of Links)
GBR (12)	JPN (5)
USA (10)	CHN (3)
JPN (8)	EU (2)



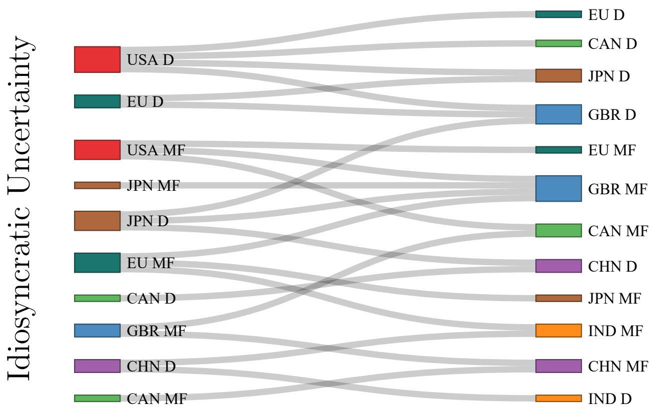
Top V Sources (No. of Links)
USA (5)
IND (5)
GBR (4)



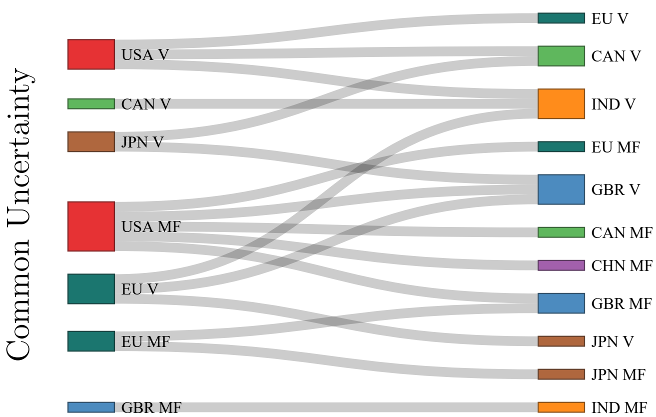
Top U Sources (No. of Links)	Top MF Receivers (No. of Links)
USA (12)	JPN (5)
EU (12)	IND (4)
GBR (8)	EU (3)
CHN (8)	
IND (8)	

Note: We report dynamic interdependencies where the posterior inclusion probability $\geq$ 0.5. We have two groups of variables: uncertainty variables proxied by disagreement (D), the variance of forecast errors (V) and their sum (U) and macro-financial variables (MF).

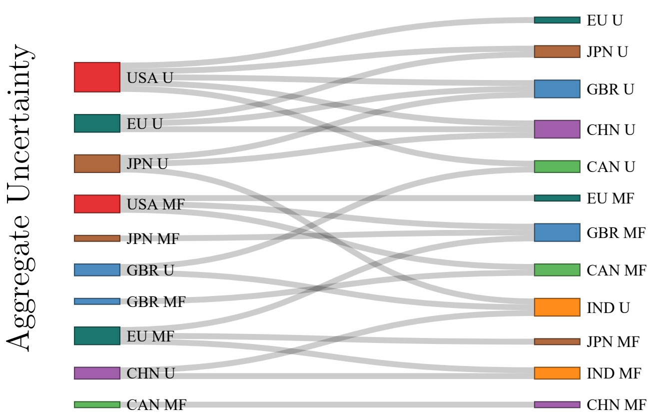
Figure 3: Static Spillovers Across Economies



Top D Connections (No. of Links)
JPN D (5)
USA D (4)
CHN D (4)



Top V Connections (No. of Links)
EU V (4)
USA V (3)
GBR V (3)
JPN V (3)
IND V (3)
CAN V (3)



Top U Connections (No. of Links)
USA U (5)
CHN U (5)
GBR U (5)
JPN U (5)
EU U (4)

Note: We report static interdependencies where the posterior inclusion probability ≥ 0.5. We have two groups of variables: uncertainty variables proxied by disagreement (D), the variance of forecast errors (V) and their sum (U) and macro-financial variables (MF).

If we consider other patterns in aggregate uncertainty, we can see that each of our emerging economies - China and India - also affect uncertainty and macro-financial variables in the other emerging economy. A similar pattern involving the UK and Eurozone is also uncovered. This provides some evidence in favor of region-specific uncertainty (see Mumtaz and Musso, 2019) which is driven by trade links and, for countries in Europe and North America, a common language (Balli et al., 2019).

The Japanese and Indian cases, however, highlight that it not always possible to decompose uncertainty into global, region-specific and country-specific parts. The Japanese and Indian macro-financial and uncertainty blocks experience the greatest number of uncertainty spillovers. This is likely to arise, in part, from their susceptibility to uncertainty spillovers originating from trading partners in multiple regions including the US, the Eurozone as well as China. The remaining economies experience a large number of uncertainty spillovers to their uncertainty variables with fewer spillovers to macro-financial variables. This may suggest that international uncertainty shocks also affect other economies by raising domestic uncertainty.

Still focussing on dynamic spillovers, if we consider our different survey-based empirical proxies, at first glance our results using idiosyncratic uncertainty and aggregate uncertainty look similar. Upon closer inspection, though, our aggregate uncertainty measure yields a more sensible ordering in terms of the top uncertainty sources. While the UK dominates in terms of idiosyncratic uncertainty, if we use aggregate uncertainty then Eurozone uncertainty affects the domestic real and financial sectors and all foreign macro-financial blocks apart from China. This demonstrates the importance of accounting for common uncertainty which primarily detects linkages between different uncertainty blocks.

If we now turn to Figure 3, we find fewer interdependencies in our SI figures than our DI figures. And in the SI graphs the uncertainty blocks appear to have less impact on macro-financial blocks than in the DI cases. For instance, US aggregate uncertainty (Figure 2) has many more dynamic linkages, including several with macro-financial blocks. In contrast, US aggregate uncertainty (Figure 3) is statically linked with disagreement measures in five other economies, but is not linked with the macro-financial block in any economy. This suggest that international spillovers between real and financial variable are sufficiently captured by SIs. However, the effects of uncertainty on these variables materialize with a delay as firms and households postpone decisions and borrowing costs rise as discussed in Section 2. This pattern could also arise from the timing of the underlying *Consensus Economics* surveys which tend to be conducted at the beginning of the month, making it unlikely that participants are able to respond to developments in industrial production and stock prices in the corresponding month.

Otherwise, however, Figure 3 reinforces many of our findings. While SIs are symmetric, we can again see that the US plays an important but not dominant role across all uncertainty measures. For instance, regardless of the uncertainty measure used, increases in the US always coincide with higher uncertainty in the Eurozone and Canada. We again also tend to see important relationships between the Eurozone and UK and China and India. Idiosyncratic and aggregate uncertainty also tend to produce simililar results but a closer look shows that in the case of aggregate uncertainty a wider range of countries play an important role.

5.2 International Uncertainty Spillovers at the Component Level

5.2.1 Impulse Response Analysis

In the preceding subsection, we discussed spillovers between economies at a low level of granularity. In this subsection, we consider a higher level of granularity. With up to 49 endogenous variables in each PVAR, we could discuss up to 49^2 GIRFs for each of our three uncertainty proxies. In the interest of brevity, we will focus on the question of whether and how different uncertainty components affect the real and financial sector of each economy.

We also continue to investigate how our results vary across different uncertainty proxies.

Having produced hundreds of GIRFs, we summarize industrial production growth (IP) and stock market growth (MSCI) GIRFs using Sankey diagrams and bar charts.[6] For our Sankey diagrams, a link is shown if a large uncertainty shock has a negative effect which is non-zero according to the 84 percent credible interval.[7] If the response is non-zero, we record the magnitude of the median GIRF's trough. The width of the links in our Sankey diagrams reflect the magnitude of these recorded responses. Results obtained using a 68 percent credible interval are provided in Appendix C with full GIRFs in the online only Appendix.

To provide further information on the magnitude of responses, for aggregate uncertainty, bar charts are produced by considering the effects of uncertainty shocks originating from each economy and taking the average of recorded responses across components. For instance, if we consider the effects of Eurozone uncertainty shocks on UK GDP growth, we have five recorded responses, one corresponding to each component of Eurozone uncertainty. We then take the average allowing us to capture how UK GDP growth responds to an adverse uncertainty shock in the Eurozone. It is worth noting that this summary measure is likely to understate the effect of foreign uncertainty spillovers. For example, UK GDP growth may be affected by one component of Eurozone uncertainty, say interest rate uncertainty, but remain unaffected by other Eurozone uncertainty components. In the same vein, we do not consider the effects of different uncertainty components taking the average across economies. This is because the role played by different components of uncertainty is heterogeneous across economies. For example, an economy may only be affected by exchange rate uncertainty in the US but remain unaffected by exchange rate uncertainty originating from other countries. In the subsequent subsection, however, we directly compare how the magnitude of different

[6] These have been rescaled to reverse standardization of the raw data.

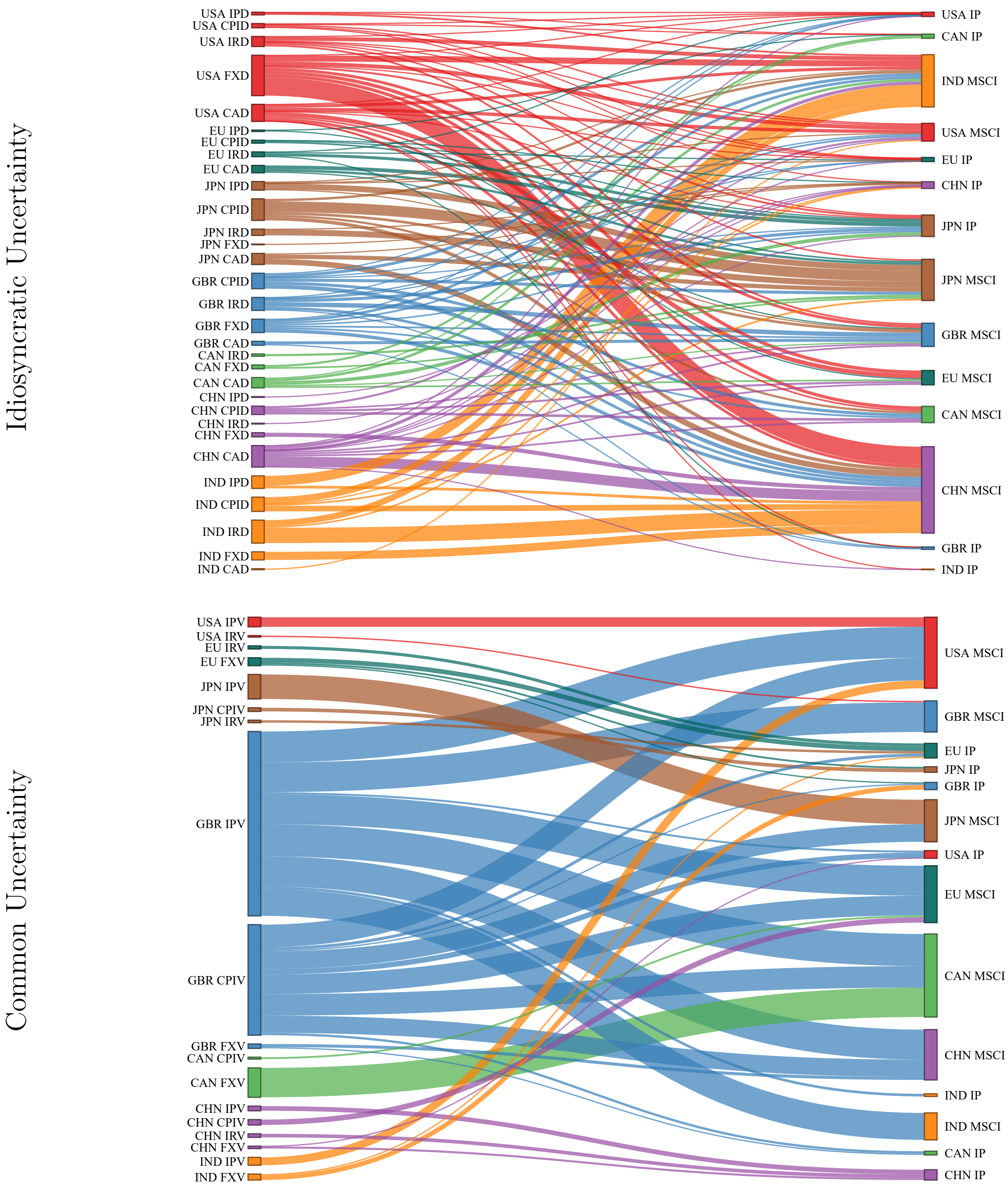
[7] We consider large uncertainty shocks equal to four standard deviations following Bloom, 2009, Jurado et al., 2015 and Istrefi and Mouabbi, 2018.

spillovers vary depending on the uncertainty component considered.

Patterns in idiosyncratic and common uncertainty spillovers are provided in Figure 4 while aggregate uncertainty spillovers and their magnitude are assessed in Figure 5 . If we first consider overarching trends, these Figures together with our GIRFs (many of which have credible intervals containing zero at all horizons) demonstrate that our flexible modeling approach and S^4 algorithm can effectively sort through the myriad of potential linkages, selecting important ones for inclusion and shrinking unimportant ones to zero. This is reassuring given our high-dimensional dataset and model. Our results also confirm that there are considerable international spillovers in uncertainty across economies for all three uncertainty proxies. Importantly, though, our results also show that different components of uncertainty play different roles, an issue we will delve into more deeply shortly.

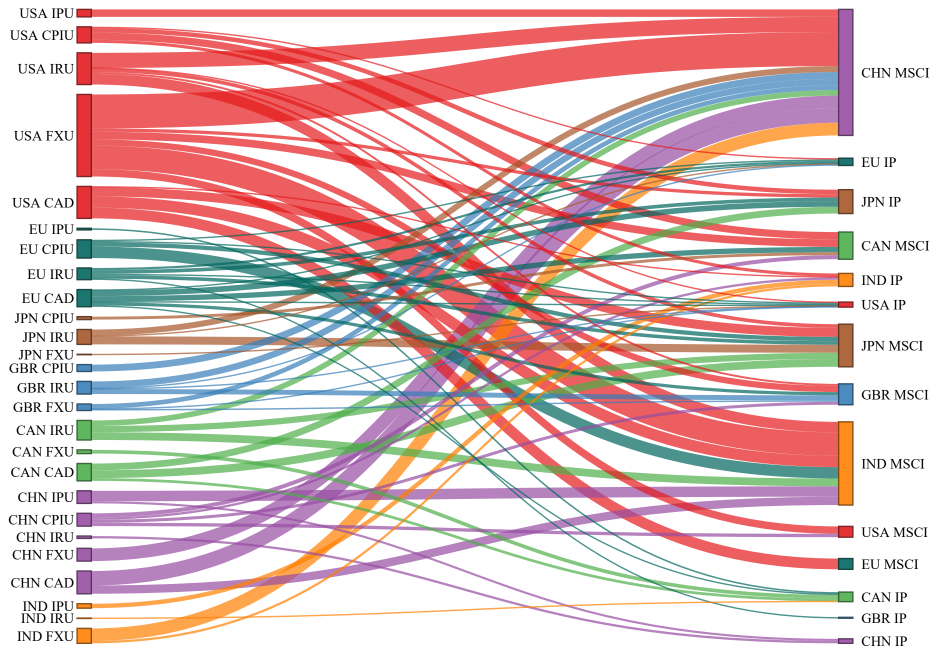
As in the previous section, we can see from Figure 4 that spillovers are more frequently observed for idiosyncratic uncertainty, however, when they do occur common uncertainty shocks can have larger effects. This mirrors the findings of Istrefi and Mouabbi (2018) and Ozturk and Sheng (2018). Additionally, we again find that while idiosyncratic and aggregate uncertainty spillovers appear similar the former overstates the role played by Japanese, British and Indian uncertainty. Moreover, we fail to detect the important role played by interest rate uncertainty across economies unless we account for common uncertainty. This again underscores the importance of also considering common uncertainty. As expected, these findings hold when we consider Sankey diagrams using the 68 percent credible interval but the lack of a dominant economy becomes even more pronounced.

Figure 4: Idiosyncratic and Common Uncertainty: Summary of Impulse Responses Showing Declines in Real and Financial Growth Following a Shock to an Uncertainty Component



Note: We report impulse response functions for industrial production growth (IP) and stock market (MSCI) growth where the uncertainty shock has a negative effect which is non-zero according to the 84 percent credible interval. Each line's width corresponds to the depth of the median impulse response function's trough.

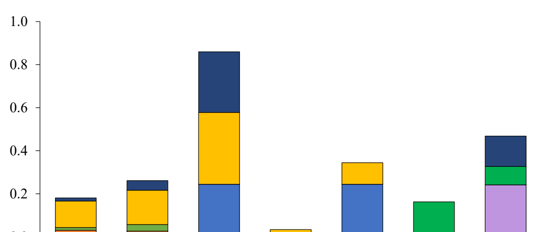
Figure 5: Aggregate Uncertainty: Summary of Impulse Responses Showing Declines in Real and Financial Growth Following a Shock to an Uncertainty Component



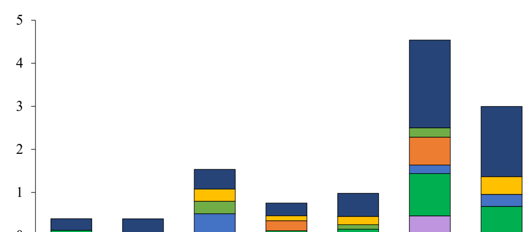
% Point Decline in GDP Growth

% Point Decline in Stock Price Growth

Uncertainty Shock



	USA	EU	JPN	GBR	CAN	CHN	IND
USA U	0.01	0.04	0.28	0.00	0.00	0.00	0.14
EU U	0.12	0.16	0.33	0.03	0.10	0.00	0.00
JPN U	0.01	0.03	0.00	0.00	0.00	0.00	0.00
GBR U	0.03	0.03	0.00	0.00	0.00	0.00	0.00
CAN U	0.00	0.00	0.24	0.00	0.23	0.00	0.00
CHN U	0.00	0.00	0.00	0.00	0.00	0.16	0.09
IND U	0.00	0.00	0.00	0.00	0.01	0.00	0.24



	USA	EU	JPN	GBR	CAN	CHN	IND
USA U	0.27	0.39	0.46	0.30	0.54	2.04	1.63
EU U	0.00	0.00	0.28	0.12	0.19	0.00	0.41
JPN U	0.00	0.00	0.29	0.00	0.11	0.22	0.00
GBR U	0.00	0.00	0.00	0.23	0.00	0.65	0.00
CAN U	0.00	0.00	0.51	0.00	0.00	0.20	0.28
CHN U	0.12	0.00	0.00	0.11	0.15	0.98	0.68
IND U	0.00	0.00	0.00	0.00	0.00	0.46	0.00

Note: In the top figure, we report impulse response functions for industrial production growth (IP) and stock market (MSCI) growth where the uncertainty shock has a negative effect which is non-zero according to the 84 percent credible interval. Each line's width corresponds to the depth of the median impulse response function's trough. In the bottom figures, we whether an adverse aggregate uncertainty shock has a negative effect on GDP growth or the change in the stock price in each economy.

If we now focus on Figure 5, we find that the US is a key source of aggregate uncertainty affecting the real sector of most economies and playing a critical role in financial markets. This tends to be driven by movements in idiosyncratic rather than common uncertainty (see Figure 4). Importantly, however, we find that other important trends uncovered in the previous subsection re-emerge. Specifically, every economy adversely affects the real or financial sectors of other economies with Eurozone uncertainty playing a particularly important role in affecting output growth in advanced economies. China and the UK are also notable transmitters in some cases. The regional China-India relationship also remains with Chinese as well as US uncertainty having a notable impact on the Indian economy.

In terms of vulnerability to foreign uncertainty we can clearly see that output growth in most countries is affected by spillovers. This is even more accentuated if we use a less conservative credible interval of 68 percent (see Appendix C). Somewhat differently from the previous subsection, though, we see more spillovers from domestic uncertainty to the domestic economy. In fact, China is only affected by domestic uncertainty using the more conservative 84 percent credible interval. If we consider financial markets, as expected, the US and Eurozone are least affected by foreign uncertainty compared to the smaller advanced economies of the UK, Canada and Japan. The emerging stock markets of China and India are most strongly affected and are affected by uncertainty shocks in multiple regions.

If we contrast the effects of uncertainty shocks on output growth and financial markets, it is evident that the financial sectors of different economies tend to be hit harder and by a larger number of uncertainty shocks relative to the real sector (Figure 5). This also holds across different uncertainty proxies (Figure 4). This aligns with Mumtaz and Musso (2019) who examine the contribution of variable-specific, country-specific, regional and global uncertainty to the volatility of different macro-financial variables. They find that, on average across countries, global uncertainty explains more than half of the volatility of stock price growth since the 1990s. In contrast, variable-specific uncertainty plays a larger role in explaining real economic activity. Our findings also coincide with the concept of a global financial cycle (see Miranda-Agrippino and Rey, 2020) with spillovers in foreign uncertainty playing a role in driving comovements in financial variables across countries.

If we continue to focus on Figure 5, we can also provide an initial assessment of the relative importance of different components of uncertainty. Common to most countries is the important role of interest rate uncertainty reflecting uncertainty around monetary policy, financial uncertainty and fundamentals (Istrefi and Mouabbi, 2018). In contrast, industrial production uncertainty, a common proxy for macroeconomic uncertainty, is least important. There are also, however, important differences across countries. Most notably, in terms of the US, the strongest effects are in terms of interest rate, exchange rate and current account uncertainty. This is expected given that these components of uncertainty are important transmission channels which link the US to the global economy and influence the global financial cycle (see Degasperi, Hong and Ricco, 2021 for a useful summary). We will explore the role played by these different components in further detail in the next subsection.

5.2.2 Connectedness Indices

Our findings so far demonstrate the complexity of uncertainty spillovers and show that a granular perspective can complement approaches which consider a single or aggregate global uncertainty shock. We have uncovered which economies tend to be important sources of uncertainty and which economies are most affected by spillovers. We have also considered the relative importance of different components of uncertainty. To shed further light on these issues and to further compare the magnitude of different spillovers, we present Diebold-Yilmaz (2014) connectedness indices based on our GFEVDs at a horizon of 12 months.[8] We consider the relative role played by different economies and components of uncertainty and how these

[8] For each 42 or 49 dimensional PVAR, the matrix of GFEVDs is very large and will not be presented here, but is available upon request.

change according to the uncertainty proxy used. We then return to our more specific question of how uncertainty spilllovers affect macro-financial variables.

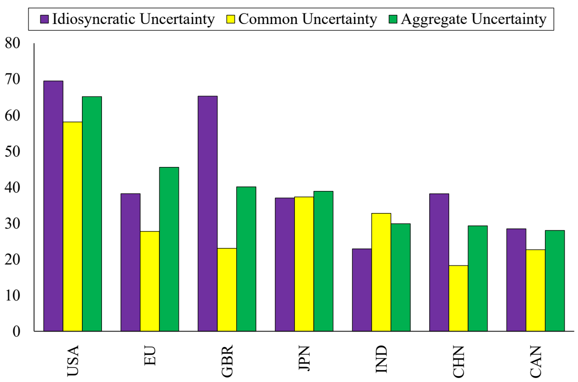
Our approach can be explained using Table 1 below. If we have $K = NG$ endogenous variables, the upper-left $K \times K$ matrix contains our GFEVDs. To examine foreign uncertainty spillovers "to" other variables in our PVAR we sum each uncertainty column, excluding domestic spillovers. Once we have obtained our column totals, to find foreign uncertainty spillovers originating from each economy, we take the average across each economy's uncertainty components (Figure 6, top left). To examine the role played by different components of uncertainty, we take the average across economies (Figure 6, top right). To analyze whether there is cross-country heterogeneity in terms of the relative importance of components of uncertainty, we focus in on foreign spillovers in aggregate uncertainty by economy and component (Figure 6, bottom left). Last, in order to re-examine spillovers received by macro-financial variables "from" foreign uncertainty we sum each macro-financial row, excluding contributions from macro-financial variables and domestic uncertainty (Figure 6, bottom right). Common current account uncertainty is not considered in these figures for reasons discussed previously.

Table 1: Connectedness Table Representation

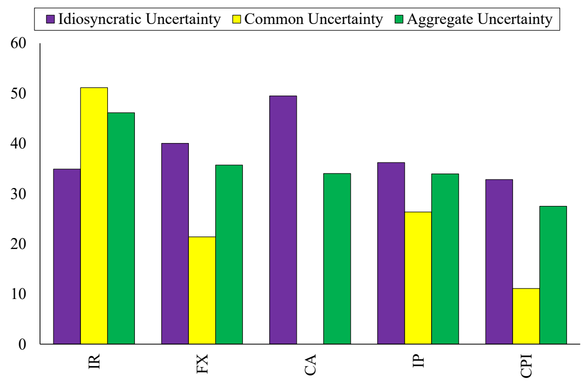
	x_1	x_2	$\cdots$	x_K	**From Others**
x_1	d_{11}	d_{12}	$\cdots$	d_{1K}	$\sum d_{1w,w \neq selected\ terms}$
x_2	d_{21}	d_{22}	$\cdots$	d_{2K}	$\sum d_{2w,w \neq selected\ terms}$
$\vdots$	$\vdots$	$\vdots$	$\ddots$	$\vdots$	$\vdots$
x_K	d_{K1}	d_{K2}	$\cdots$	d_{KK}	$\sum d_{Kw,w \neq selected\ terms}$
To Others	$\sum d_{v1,v \neq domestic\ terms}$	$\sum d_{v2,v \neq dom.\ terms}$	$\cdots$	$\sum d_{vN,v \neq dom.\ terms}$	

Figure 6: Connectedness Estimates

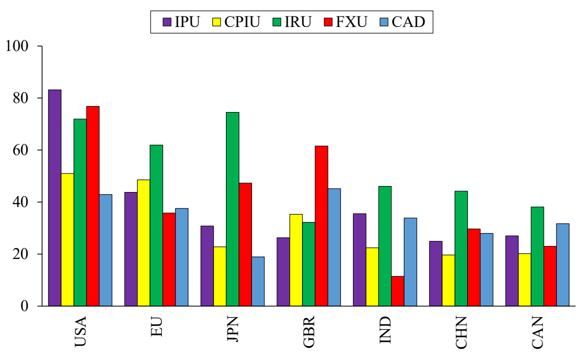
Foreign Uncertainty Spillovers to Other Variables: Averaged Across Components



Foreign Uncertainty Spillovers to Other Variables: Averaged Across Economies



Foreign Aggregate Uncertainty Spillovers to Other Variables: By Economy and Component



Spillovers Received by Macro-financial Variables From Foreign Uncertainty

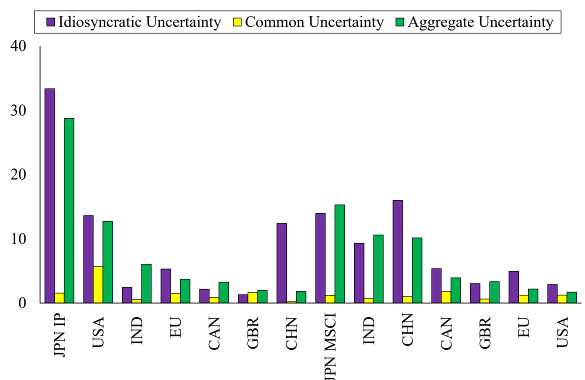


Figure 6 reinforces several important insights. In terms of economies, the findings confirm that spillovers from US and Eurozone uncertainty are largest with Canada having the smallest impact on other countries. We also find that, on average, macroeconomic uncertainty arising from industrial production growth uncertainty and inflation uncertainty is less important with interest rate and exchange rate uncertainty playing a larger role. This, together with the findings from the previous subsection, reflects recent studies which find that in a domestic context, financial uncertainty has a more adverse effect on the economy than macroeconomic uncertainty (Ludvigson et al., 2021, Davidson et al., 2022).

If we focus in on aggregate uncertainty, however, we can see that the most prominent component of uncertainty (in terms of spillovers to other variables) varies across economies. As in our previous subsection, interest rate uncertainty again emerges as an important component. Exchange rate uncertainty remains important for five out of seven countries. The muted role of industrial production and inflation uncertainty typically holds across countries with the exception of the Eurozone and US industrial production uncertainty.

From Figure 6 we can also see that uncertainty explains the largest fraction of variation in Japanese stock prices and industrial production, followed by Chinese and Indian stock prices confirming our earlier findings. We can also see that idiosyncratic has much larger effects on the real and financial sectors compared to common uncertainty. This finding holds across all macro-financial variables.

Using forecaster disagreement as a survey-based measure of uncertainty has been debated in the literature. However, if a good proxy is one which has stronger effects on the real or financial sectors, then our findings indicate that idiosyncratic uncertainty plays a much larger role. Furthermore, in Section 3 we discussed a criticism of common uncertainty V and aggregate uncertainty U (where y_{t+h} was used both in constructing forecast errors and as a variable in the VAR). Idiosyncratic uncertainty does not suffer from this criticism. Nonetheless, failing to account for common uncertainty can distort findings. For instance, it is important to account for common uncertainty in order to determine the relative importance of the Eurozone and UK.

6 Conclusion

This paper contributes to the literature on international uncertainty spillovers. By using data from surveys of professional forecasters we can construct comparable measures of uncertainty across seven key advanced and emerging economies. Specifically, we can analyze cross country spillovers in uncertainty regarding: output growth, inflation, the current account, the short-term interest rate and the exchange rate. Importantly, we construct three survey-based proxies for each component of uncertainty: disagreement among forecasters, the conditional variance of their forecast errors and a measure combining both aspects. Our proxies reflect idiosyncratic, common and aggregate uncertainty respectively. By estimating three panel VARs, we can take a disaggregated approach. We can therefore disentangle which economies are the source of uncertainty shocks, which components of uncertainty are important and how our findings change depending on which proxy is used.

Our results clearly demonstrate that cross-country uncertainty spillovers exist and are important. In particular, we have three sets of findings which require further exploration in future studies. First, while the US is an important source of uncertainty, it does not dominate. Instead, uncertainty shocks originate from all economies with the Eurozone followed by the UK and China, also acting as important transmitters of uncertainty. These dynamics are not captured by approaches which assess the effects of a single global uncertainty shock, emphasizing the advantages of our VAR-based approach.

Second, on average across economies, we find that foreign output growth uncertainty plays the smallest role. Instead, foreign interest rate and exchange rate uncertainty are of greater importance. This suggests that foreign spillovers in financial uncertainty are more important than spillovers in macroeconomic uncertainty. This aligns with the literature on domestic uncertainty shocks (see, for example, Ludvigson et al., 2021 and Davidson et al., 2022).

Third, we show that different empirical survey-based proxies for uncertainty have different effects. Disagreement seems to be a useful uncertainty proxy from an empirical point of view since it is easily obtained and generates substantial spillovers which affect real and financial variables. However, when they do occur, common uncertainty shocks produce large negative responses. Additionally, failing to account for common uncertainty leads to the effects of smaller countries being overestimated.

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Appendix A: Data

For the UK, survey data from *Consensus Economics* on PPI inflation rather than CPI inflation is used. Similarly for China, since survey data on short-term interest rates is limited, the monetary aggregate M2 is used. Since all exchange rate forecasts are relative to the dollar, we use options-based foreign exchange rate volatility for the G7, collected from Datastream, to proxy US idiosyncratic, common and aggregate exchange rate uncertainty. For the remaining exchange rates, it is not always possible to calculate disagreement according to (2) in the early part of the sample due to unavailability of disagreement across forecasters. Where this is the case, we use the absolute value of the difference between the highest and lowest forecast to measure disagreement following Cavusoglu and Neveu (2015).

All data on industrial production, MSCI stock prices and exogenous variables is obtained from Datastream with the following exceptions. Monthly data on industrial production is unavailable for China so we use monthly Chinese GDP growth obtained from Chang et al. (2015) to construct forecast errors and therefore common uncertainty for Chinese industrial production growth. This allows us to retain common industrial production uncertainty across economies in the models. Our measure of global oil price uncertainty is constructed using *Consensus Economics* forecasts and our global economic policy uncertainty measure is taken from Baker et al. (2016).

Fixed event forecasts correspond to a given point in time, for example the current year. Naturally, disagreement decreases with time evolving. Disagreement about the future stance of the economy over the full year is for example higher in December compared to January. Using the weights suggested by Patton and Timmerman (2011), we create a weighted average of fixed event forecasts for the current and following year with the weight on the former (latter) decreasing (increasing) as time evolves. This allows us to generate fixed-horizon forecasts which always correspond to the next 12 months.

Appendix B: Technical Appendix

Bayesian methods require a prior and this is provided by the stochastic search specification selection (S^4) methods we use. This prior is not a conventional subjective prior, but a more objective prior based on one of the automatic variable selection priors. This type of prior is popular in the machine learning literature and increasingly used in econometrics, particularly in cases such as ours where the number of coefficients to be estimated is large relative to the number of observations.

S^4 methods are an extension of stochastic search variables selection (SSVS) methods. These were developed for use in VARs by George, Sun and Ni (2008). To provide the basic idea behind SSVS, consider a single VAR coefficient which we shall simply call α. A conventional Normal prior takes the form:

$$\alpha \sim N\left(\alpha_0, v_0^2\right). \tag{5}$$

The choice of prior variance, v_0^2, determines the strength of the prior shrinkage. If the prior mean, α_0, is zero then a small value for v_0^2 implies prior shrinkage of the coefficient to be near zero. The SSVS prior is a mixture of two Normal priors, one of which has a very tiny prior variance and the other a large prior variance. The SSVS algorithm lets the data decide which prior to choose. If the tiny variance prior is chosen, the coefficient is estimated to be very close to zero. To be precise, the SSVS prior takes the form:

$$\alpha|\gamma \sim (1-\gamma)\, N\left(0, \tau_1^2\right) + \gamma N\left(0, \tau_2^2\right) \tag{6}$$

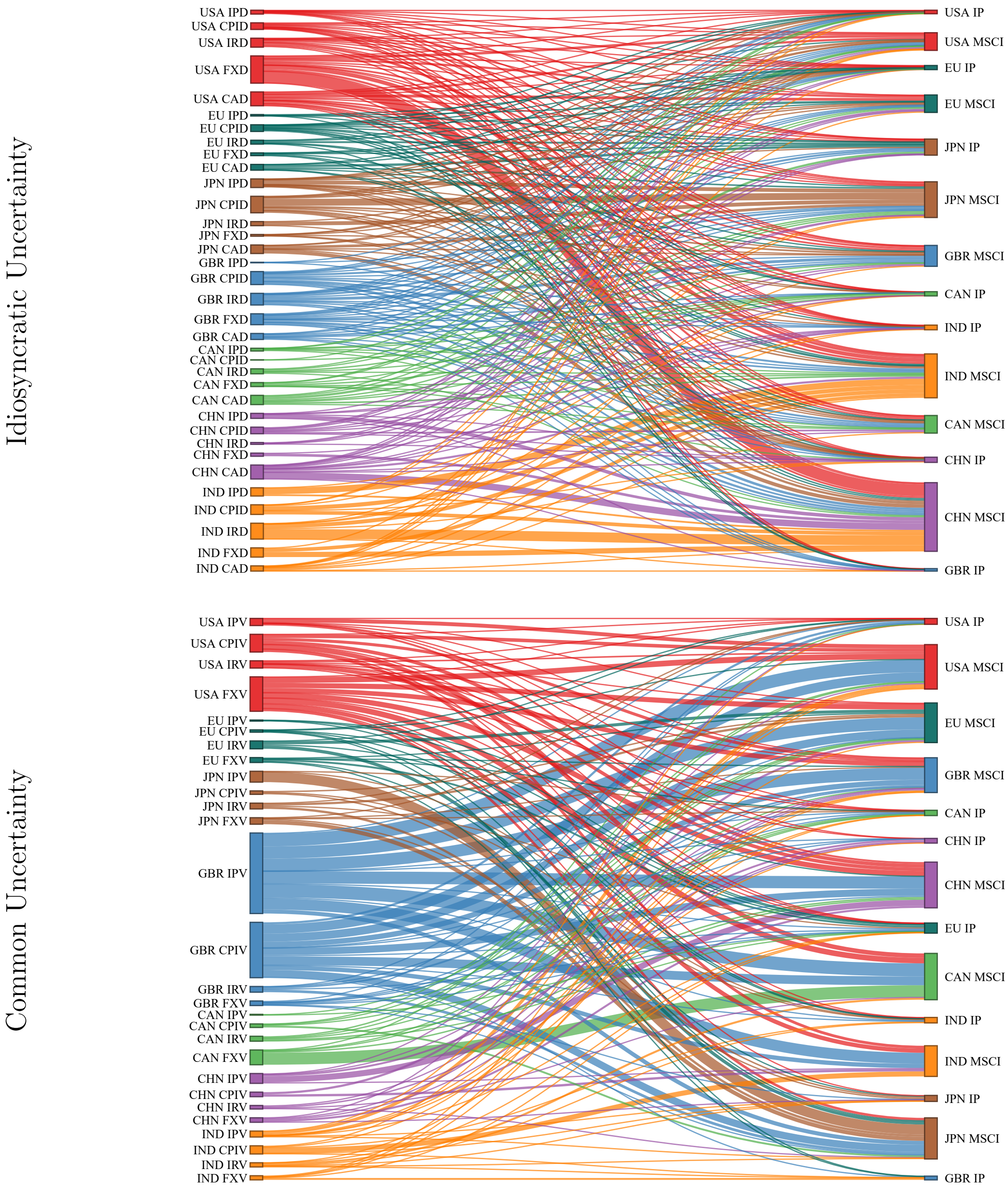
with τ_1 being tiny and τ_2 being large and $\gamma \in \{0, 1\}$ is an unknown parameter which is estimated in the algorithm. The probability that $\gamma = 1$ is known as the PIP.

Note that SSVS applies to individual coefficients. Koop and Korobilis (2016) extend this, developing the S^4 algorithm which applies to blocks of parameters corresponding to SIs and DIs. In the present paper, we further extend the S^4 algorithm so that it restricts blocks of parameters inspired by our research question. The blocks we consider depend on our two types of variables (i.e. uncertainty variables and macro-financial variables). The blocks capture whether one group (e.g. uncertainty variables) in economy i affects other groups (e.g. macro-financial variables) in economy j for $i, j = 1, ..., 7$.

The final detail in the S^4 prior is the choice of τ_1 and τ_2. Koop and Korobilis (2016) extend the standard approach and use hierarchical priors for τ_1 and τ_2. We take this one step further, estimating the hyperparameters in our hierarchical priors so that they minimize the marginal likelihood.

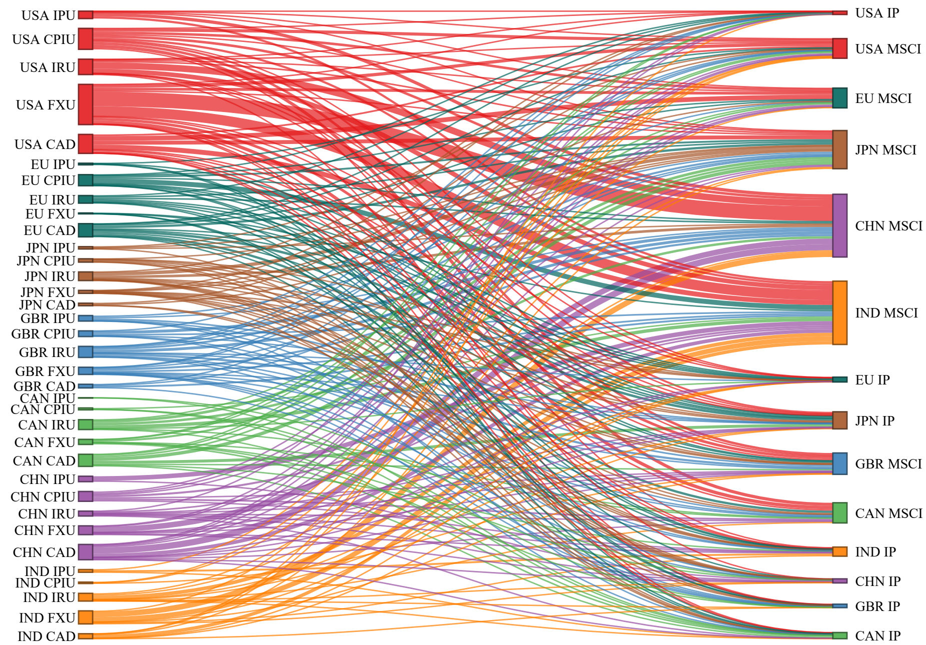
Appendix C: Supplementary Figures

Figure 7: Idiosyncratic and Common Uncertainty: Summary of Impulse Responses Showing Declines in Real and Financial Growth Following a Shock to an Uncertainty Component



Note: We report impulse response functions for industrial production growth (IP) and stock market (MSCI) growth where the uncertainty shock has a negative effect which is non-zero according to the 68 percent credible interval. Each line's width corresponds to the depth of the median impulse response function's trough.

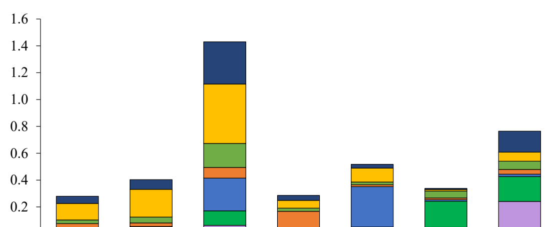
Figure 8: Aggregate Uncertainty: Summary of Impulse Responses Showing Declines in Real and Financial Growth Following a Shock to an Uncertainty Component



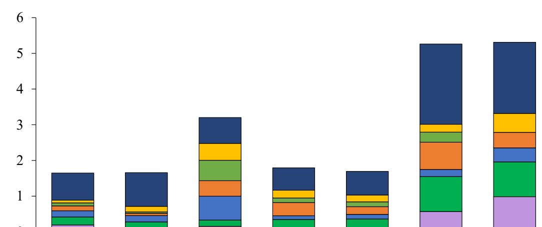
% Point Decline in GDP Growth

% Point Decline in Stock Price Growth

Uncertainty Shock



	USA	EU	JPN	GBR	CAN	CHN	IND
USA	0.05	0.07	0.31	0.04	0.03	0.01	0.16
EU	0.12	0.21	0.44	0.06	0.10	0.01	0.07
JPN	0.03	0.04	0.18	0.02	0.02	0.05	0.06
GBR	0.04	0.03	0.08	0.15	0.01	0.01	0.03
CAN	0.01	0.01	0.24	0.01	0.30	0.01	0.02
CHN	0.01	0.01	0.11	0.00	0.02	0.19	0.18
IND	0.01	0.03	0.06	0.01	0.03	0.05	0.24

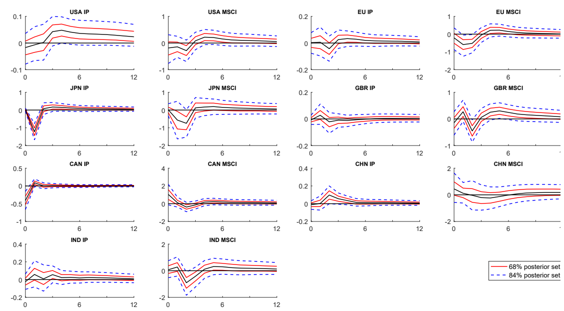


	USA	EU	JPN	GBR	CAN	CHN	IND
USA	0.76	0.94	0.72	0.63	0.66	2.25	1.99
EU	0.07	0.16	0.47	0.22	0.19	0.22	0.53
JPN	0.08	0.04	0.58	0.13	0.14	0.28	0.00
GBR	0.14	0.06	0.43	0.37	0.21	0.76	0.44
CAN	0.17	0.18	0.67	0.10	0.13	0.20	0.39
CHN	0.22	0.25	0.18	0.27	0.30	0.98	0.98
IND	0.19	0.03	0.15	0.08	0.06	0.57	0.98

Note: In the top figure, we report impulse response functions for industrial production growth (IP) and stock market (MSCI) growth where the uncertainty shock has a negative effect which is non-zero according to the 68 percent credible interval. Each line's width corresponds to the depth of the median impulse response function's trough. In the bottom figures, we whether an adverse aggregate uncertainty shock has a negative effect on GDP growth or the change in the stock price in each economy.

Online Only Appendix: Additional Figures

Figure 9: Responses to Canada Disagreement Shocks



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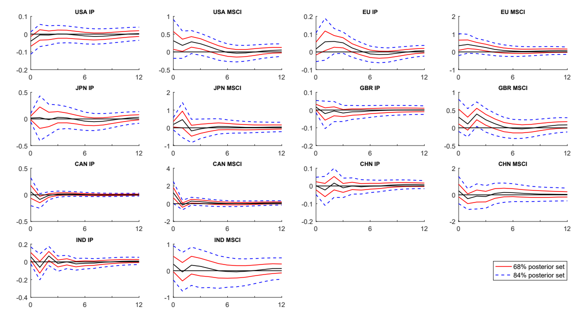
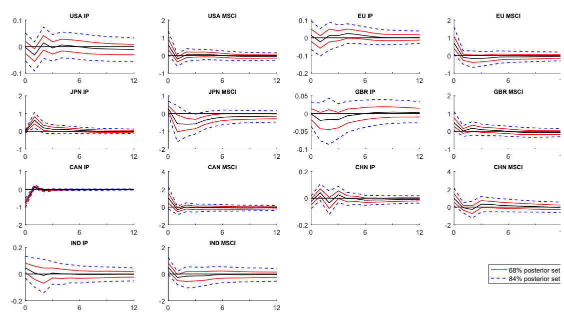
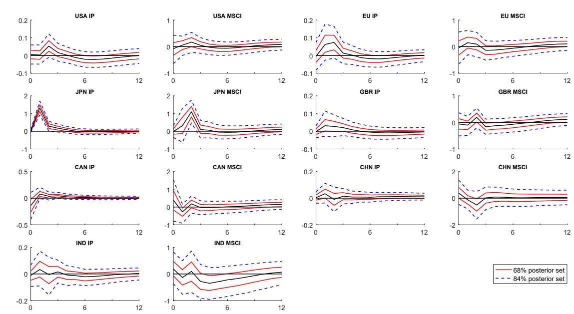


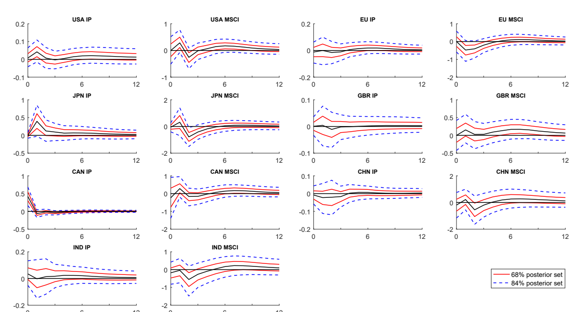
CPID



FXD



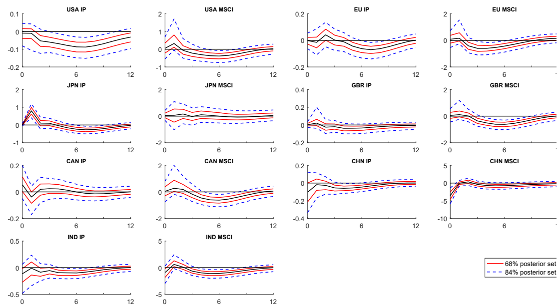
IPD



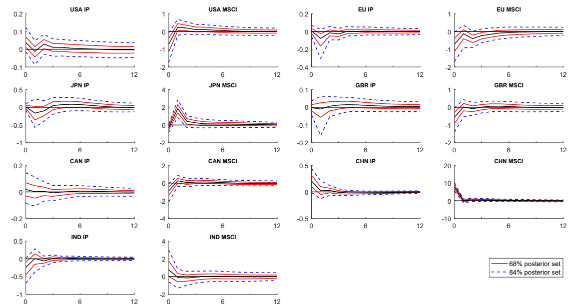
IRD

[†]Note: The figure shows the response of each macro-financial variable to a shock in Canadian disagreement regarding the current account (CAD), inflation (CPID), the exchange rate (FXD), industrial production (IPD) and short-term interest rate (IRD). 68 and 84 percent credible intervals are provided.

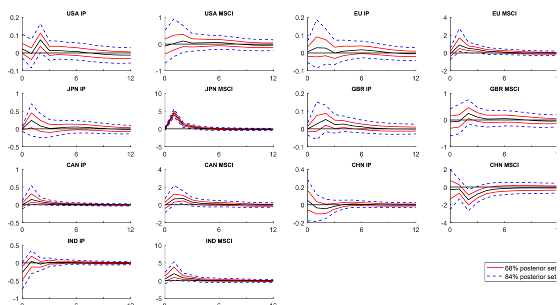
Figure 10: Responses to China Disagreement Shocks



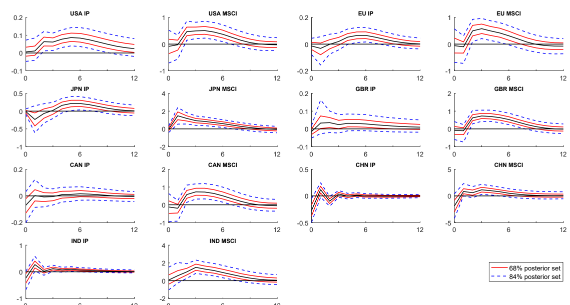
CAD



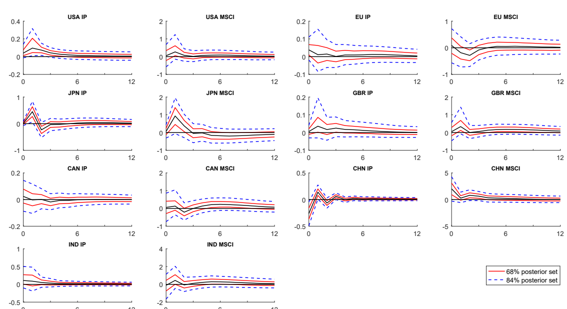
CPID



FXD



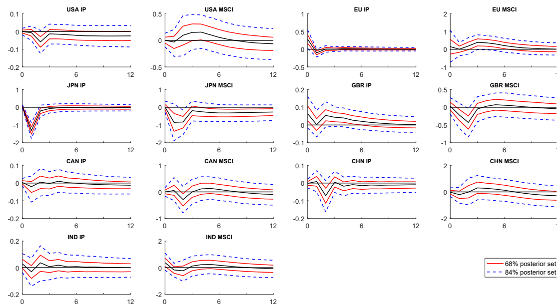
IPD



IRD

[†]Note: The figure shows the response of each macro-financial variable to a shock in Chinese disagreement regarding the current account (CAD), inflation (CPID), the exchange rate (FXD), industrial production (IPD) and short-term interest rate (IRD). 68 and 84 percent credible intervals are provided.

Figure 11: Responses to Eurozone Disagreement Shocks



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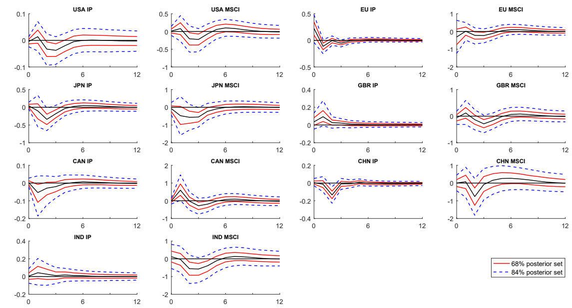
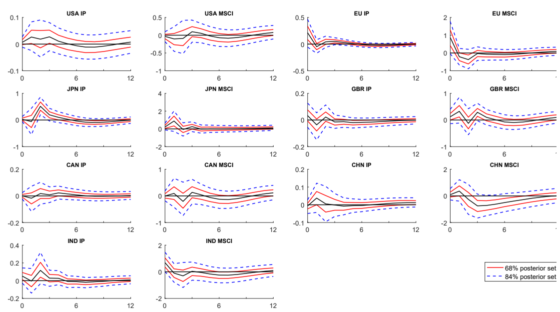
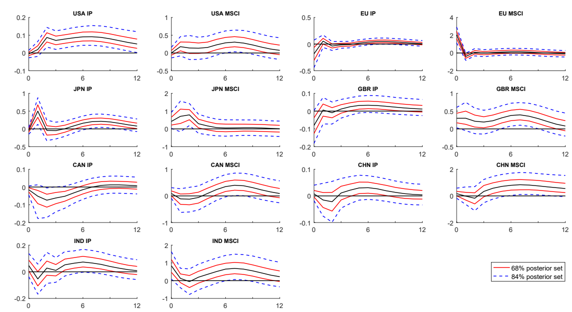


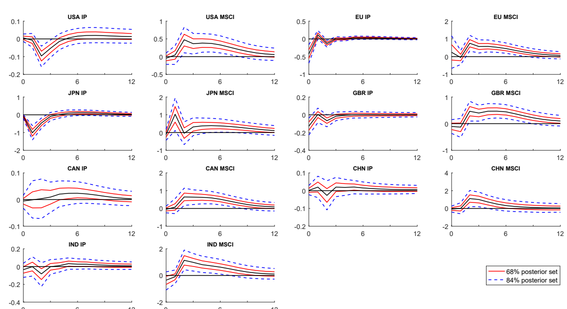
CPID



FXD



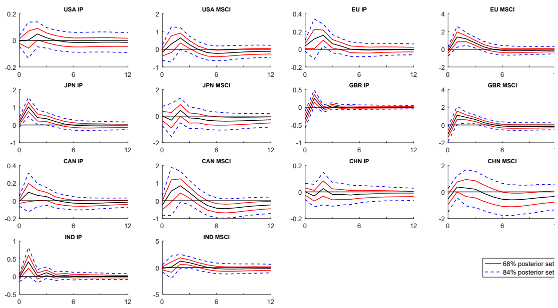
IPD



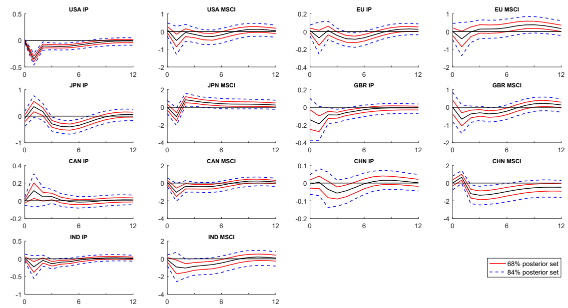
IRD

†Note: TThe figure shows the response of each macro-financial variable to a shock in Eurozone disagreement regarding the current account (CAD), inflation (CPID), the exchange rate (FXD), industrial production (IPD) and short-term interest rate (IRD). 68 and 84 percent credible intervals are provided.

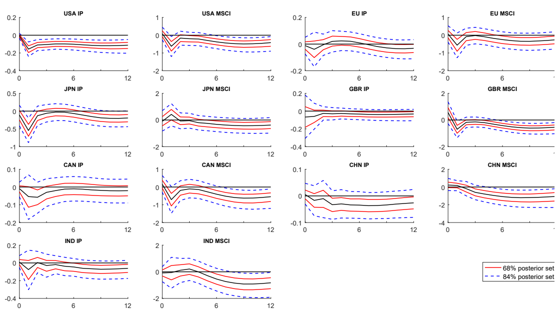
Figure 12: Responses to UK Disagreement Shocks



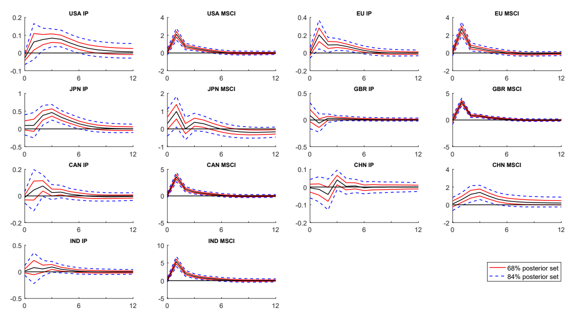
CAD



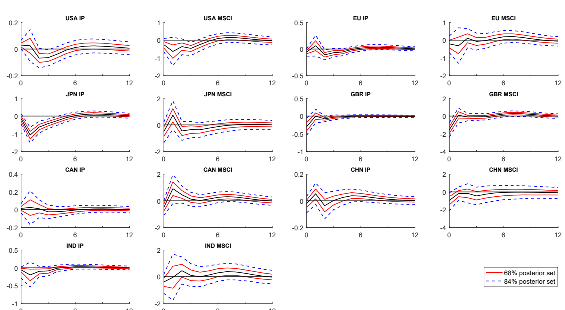
CPID



FXD



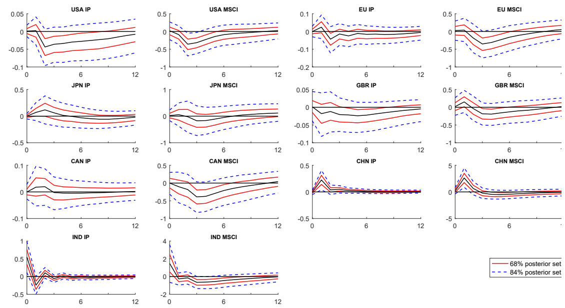
IPD



IRD

†Note: The figure shows the response of each macro-financial variable to a shock in UK disagreement regarding the current account (CAD), inflation (CPID), the exchange rate (FXD), industrial production (IPD) and short-term interest rate (IRD). 68 and 84 percent credible intervals are provided.

Figure 13: Responses to India Disagreement Shocks



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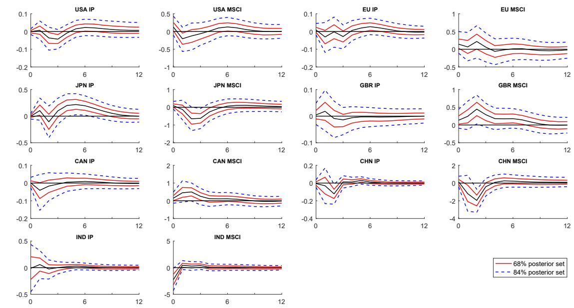
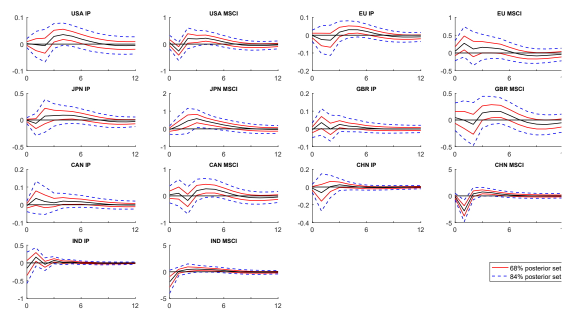
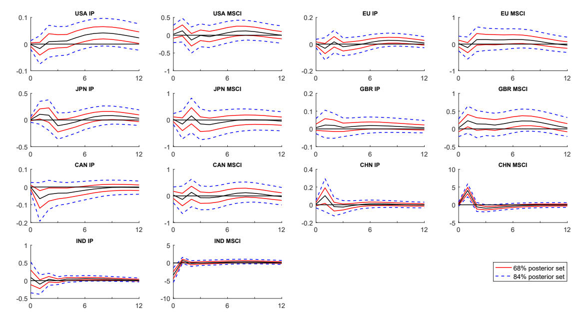


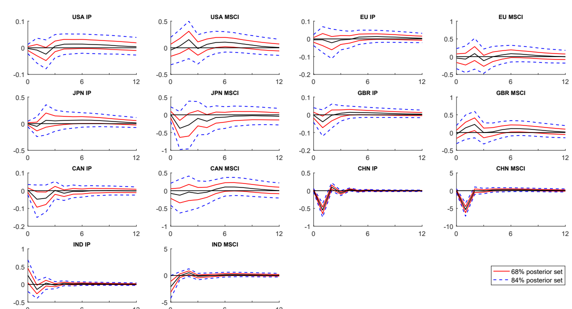
CPID



FXD



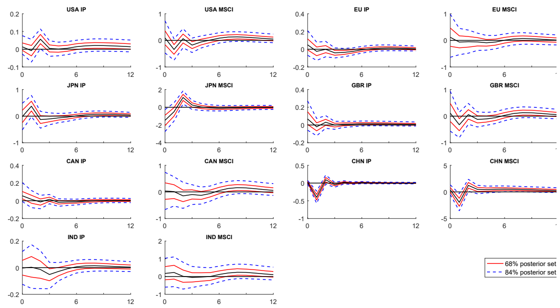
IPD



IRD

[†]Note: The figure shows the response of each macro-financial variable to a shock in Indian disagreement regarding the current account (CAD), inflation (CPID), the exchange rate (FXD), industrial production (IPD) and short-term interest rate (IRD). 68 and 84 percent credible intervals are provided.

Figure 14: Responses to Japanese Disagreement Shocks



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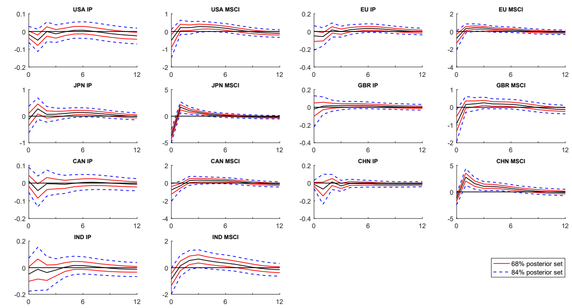
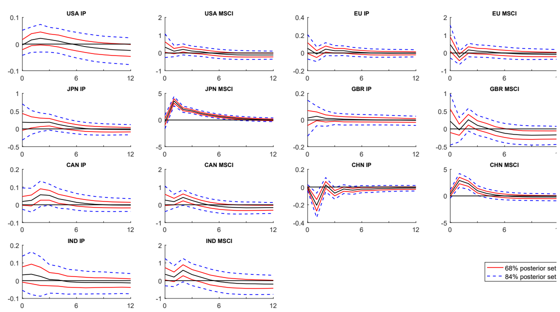
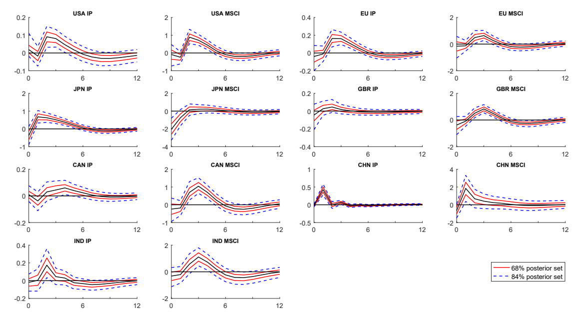


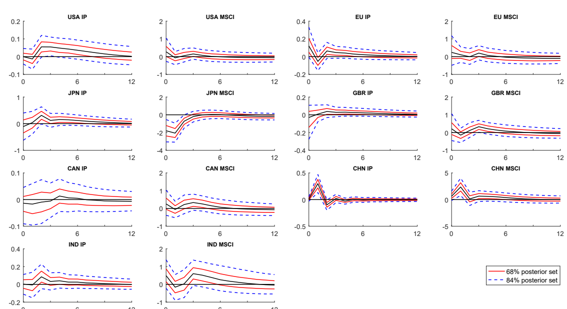
CPID



FXD



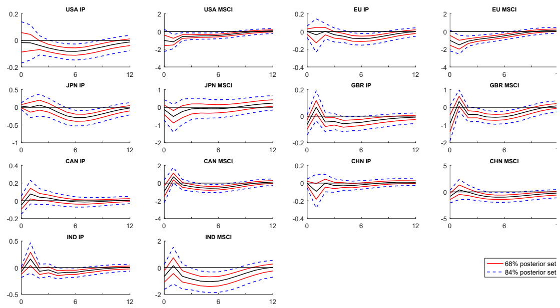
IPD



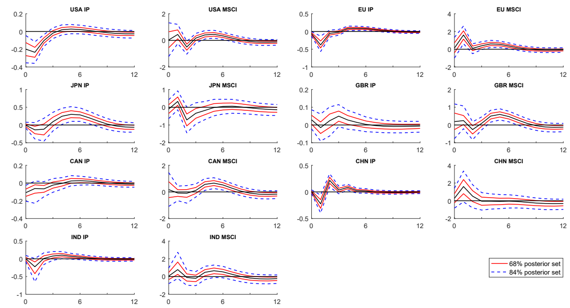
IRD

†Note: The figure shows the response of each macro-financial variable to a shock in Japanese disagreement regarding the current account (CAD), inflation (CPID), the exchange rate (FXD), industrial production (IPD) and short-term interest rate (IRD). 68 and 84 percent credible intervals are provided.

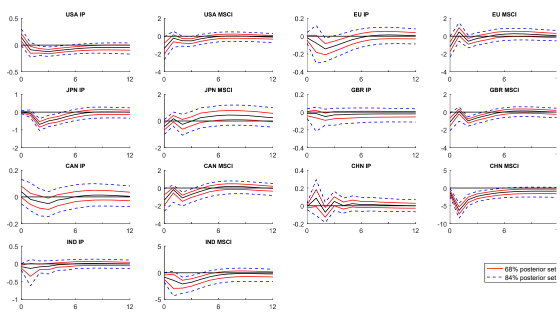
Figure 15: Responses to US Disagreement Shocks



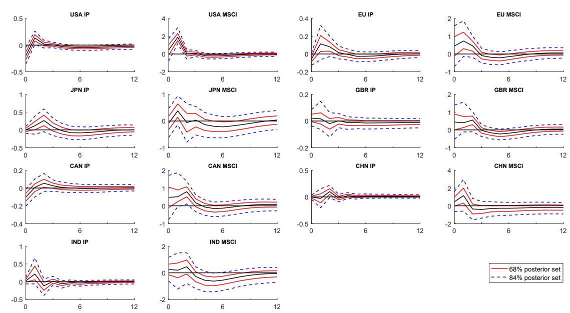
CAD



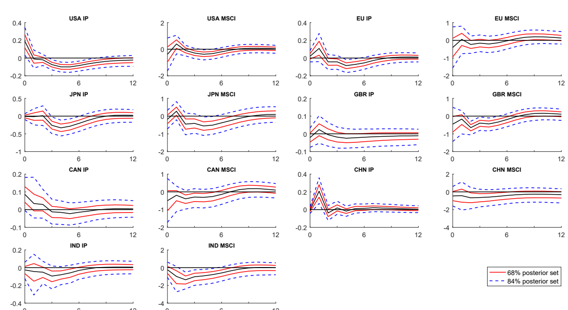
CPID



FXD



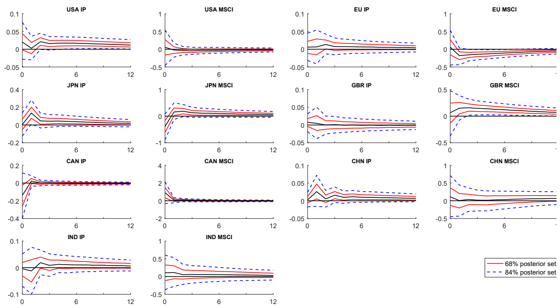
IPD



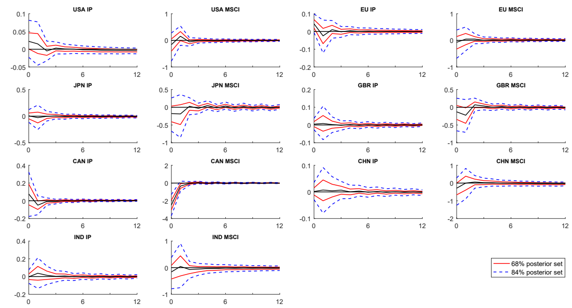
IRD

†Note: The figure shows the response of each macro-financial variable to a shock in US disagreement regarding the current account (CAD), inflation (CPID), the exchange rate (FXD), industrial production (IPD) and short-term interest rate (IRD). 68 and 84 percent credible intervals are provided.

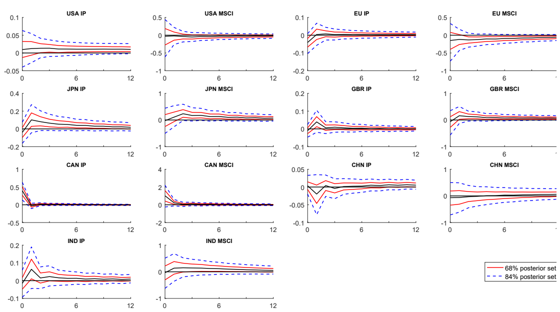
Figure 16: Responses to Canada Forecast Error Variance Shocks



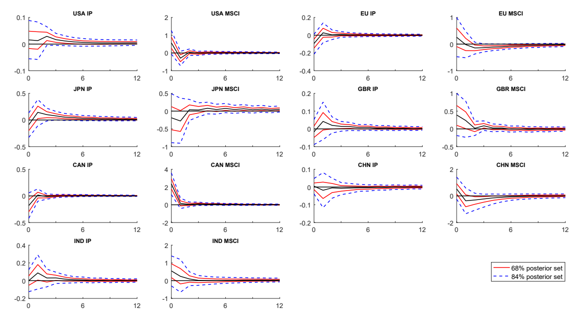
CPIV



FXV



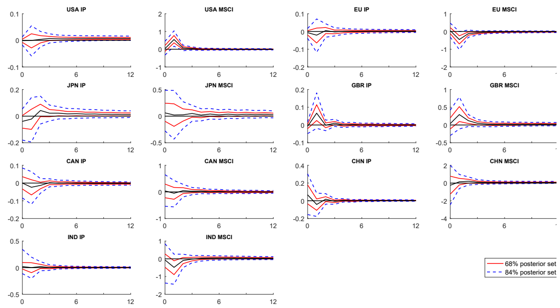
IPV



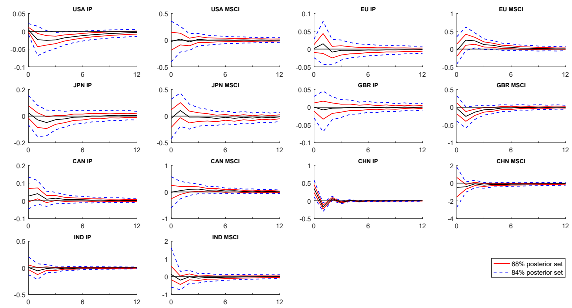
IRV

†Note: The figure shows the response of each macro-financial variable to a shock in Canadian forecast error variances regarding inflation (CPIV), the exchange rate (FXV), industrial production (IPV) and short-term interest rate (IRV). 68 and 84 percent credible intervals are provided.

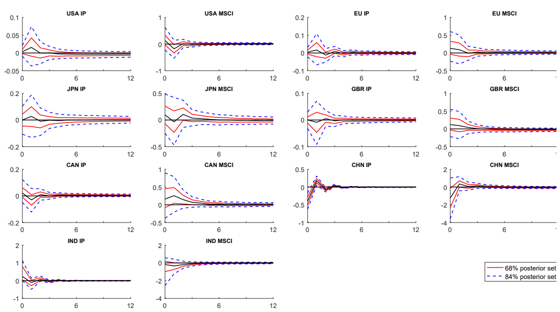
Figure 17: Responses to China Forecast Error Variance Shocks



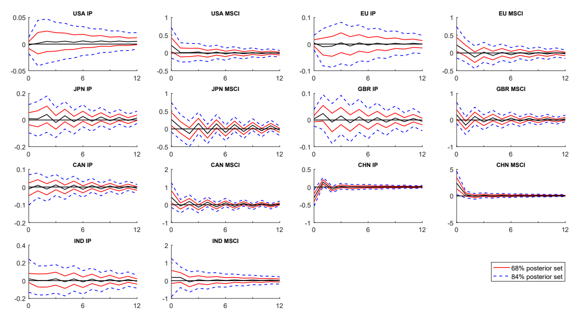
CPIV



FXV



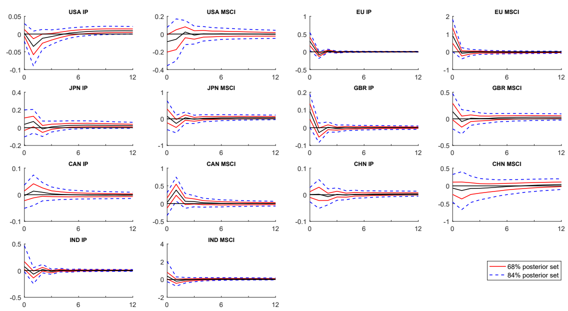
IPV



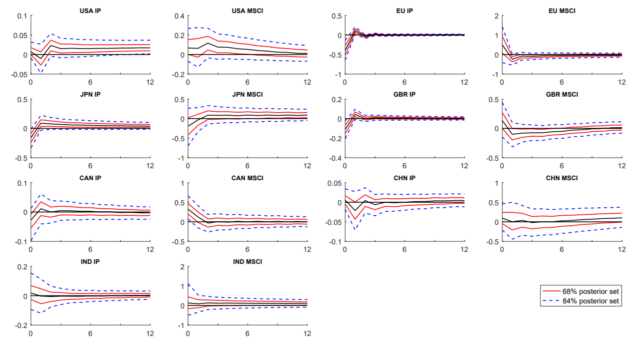
IRV

†Note: The figure shows the response of each macro-financial variable to a shock in Chinese forecast error variances regarding inflation (CPIV), the exchange rate (FXV), industrial production (IPV) and short-term interest rate (IRV). 68 and 84 percent credible intervals are provided.

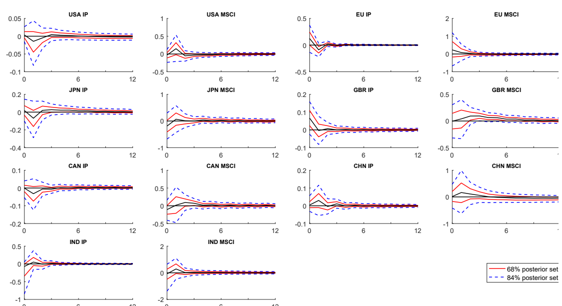
Figure 18: Responses to Eurozone Forecast Error Variance Shocks



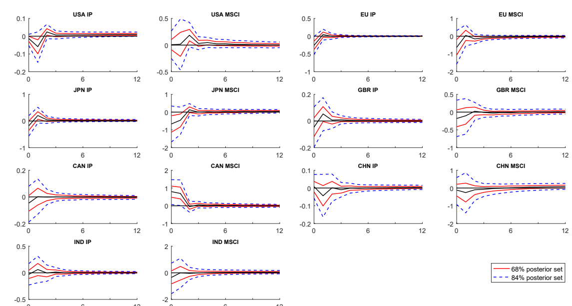
CPIV



FXV



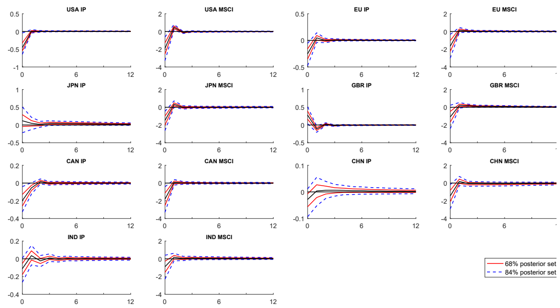
IPV



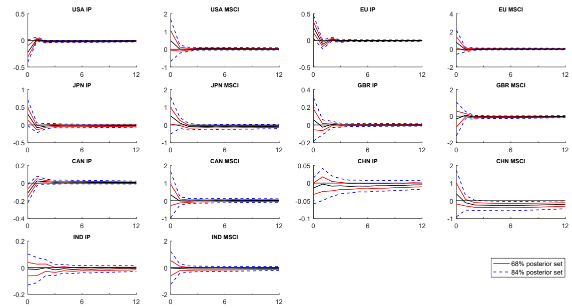
IRV

†Note: The figure shows the response of each macro-financial variable to a shock in Eurozone forecast error variances regarding inflation (CPIV), the exchange rate (FXV), industrial production (IPV) and short-term interest rate (IRV). 68 and 84 percent credible intervals are provided.

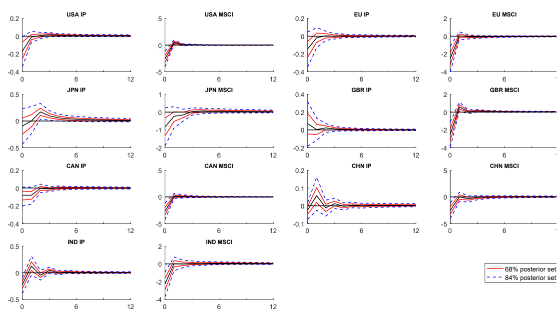
Figure 19: Responses to UK Forecast Error Variance Shocks



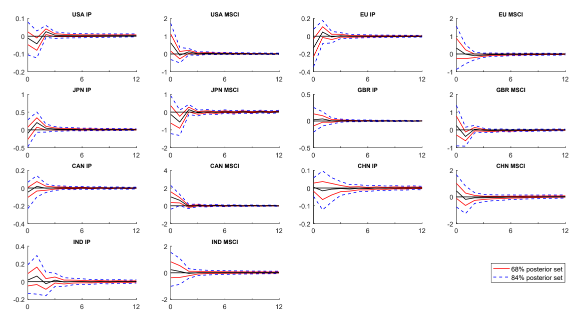
CPIV



FXV



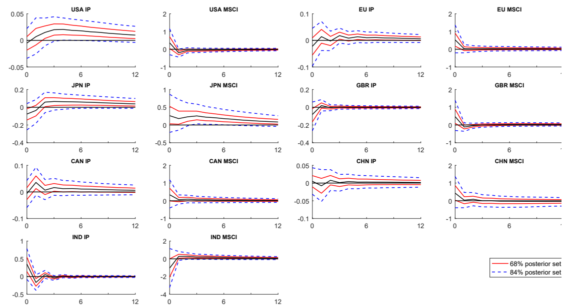
IPV



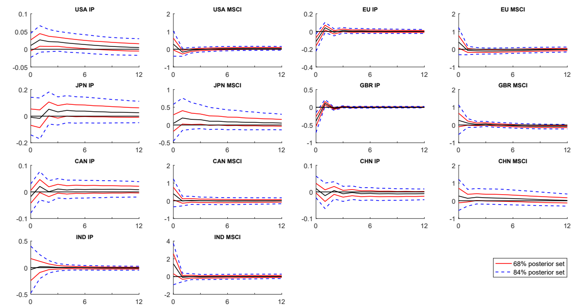
IRV

†Note: The figure shows the response of each macro-financial variable to a shock in UK forecast error variances regarding inflation (CPIV), the exchange rate (FXV), industrial production (IPV) and short-term interest rate (IRV). 68 and 84 percent credible intervals are provided.

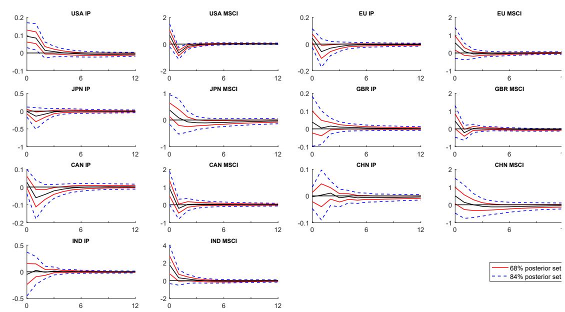
Figure 20: Responses to India Forecast Error Variance Shocks



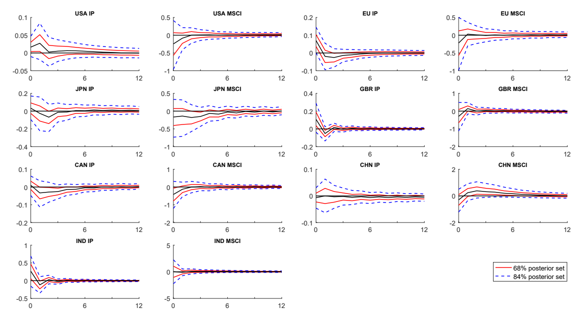
CPIV



FXV



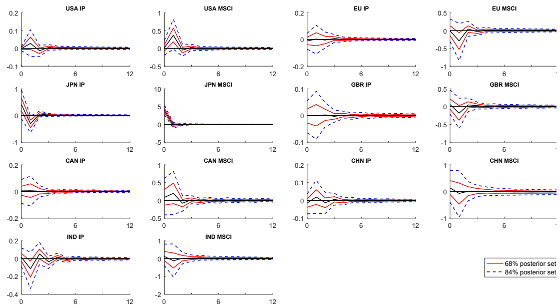
IPV



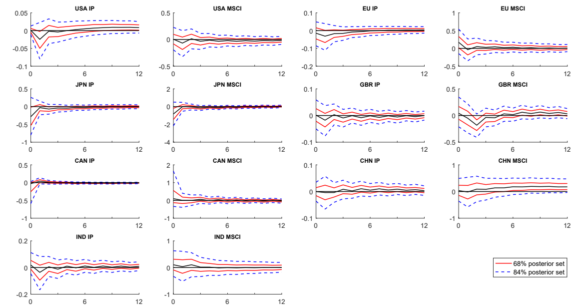
IRV

†Note: The figure shows the response of each macro-financial variable to a shock in Indian forecast error variances regarding inflation (CPIV), the exchange rate (FXV), industrial production (IPV) and short-term interest rate (IRV). 68 and 84 percent credible intervals are provided.

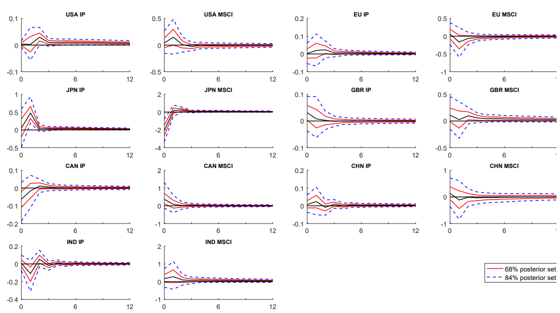
Figure 21: Responses to Japan Forecast Error Variance Shocks



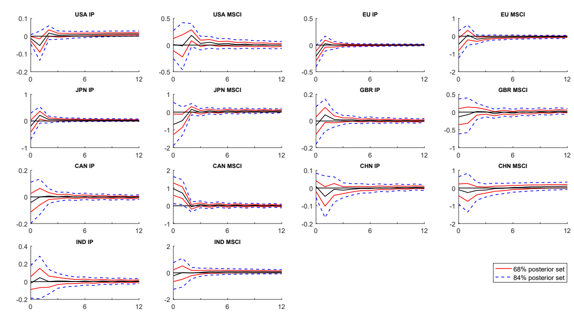
CPIV



FXV



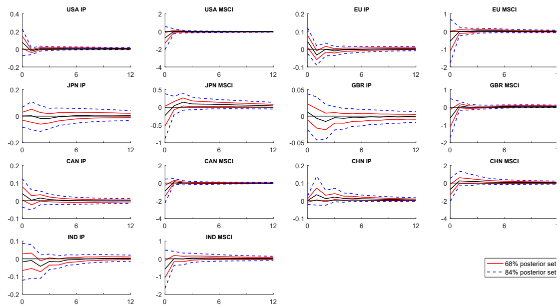
IPV

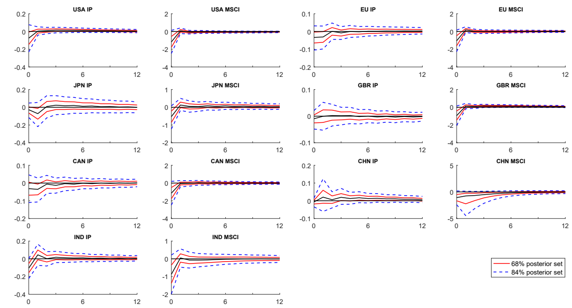


IRV

†Note: The figure shows the response of each macro-financial variable to a shock in Japanese forecast error variances regarding inflation (CPIV), the exchange rate (FXV), industrial production (IPV) and short-term interest rate (IRV). 68 and 84 percent credible intervals are provided.

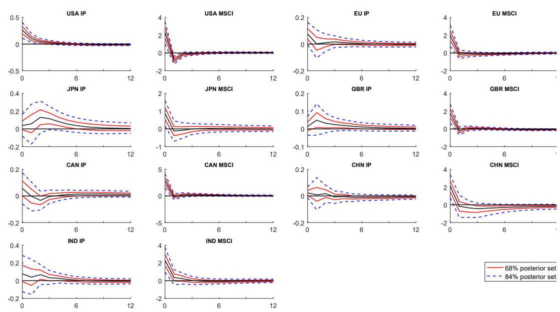
Figure 22: Responses to US Forecast Error Variance Shocks

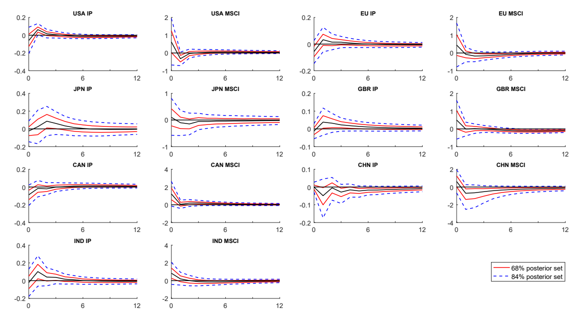




CPIV

FXV



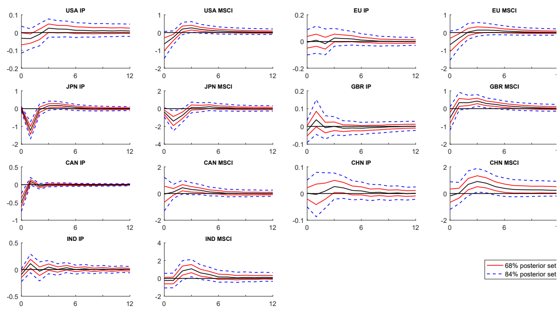


IPV

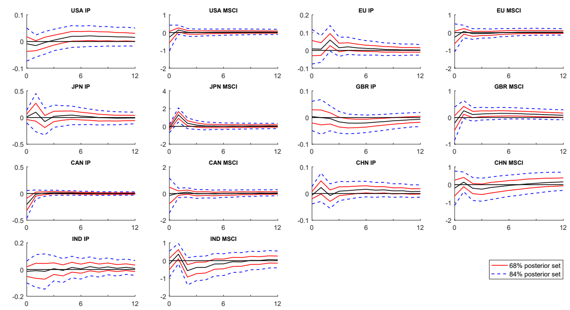
IRV

†Note: The figure shows the response of each macro-financial variable to a shock in US forecast error variances regarding inflation (CPIV), the exchange rate (FXV), industrial production (IPV) and short-term interest rate (IRV). 68 and 84 percent credible intervals are provided.

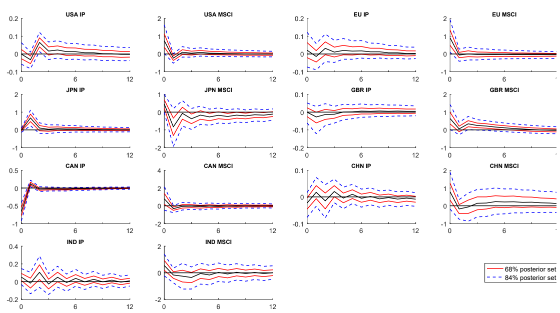
Figure 23: Responses to Canada Combined Uncertainty Shocks



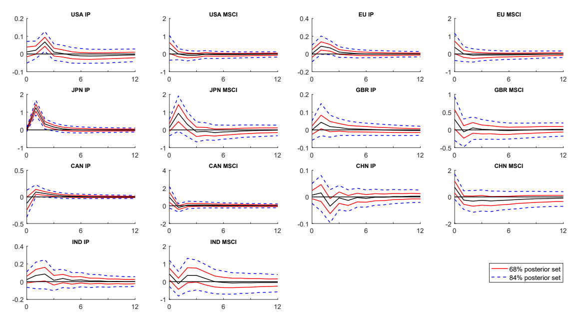
CAD



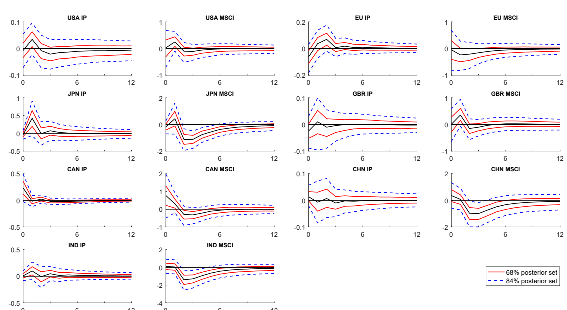
CPIU



FXU



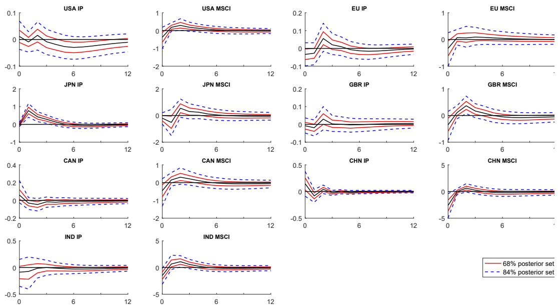
IPU



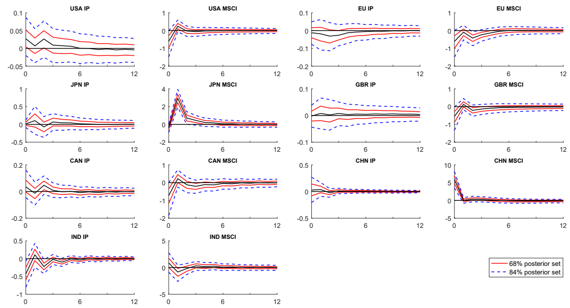
IRU

†Note: The figure shows the response of each macro-financial variable to a shock in Canadian combined uncertainty regarding the current account (CAU), inflation (CPIU), the exchange rate (FXU), industrial production (IPU) and short-term interest rate (IRU). 68 and 84 percent credible intervals are provided.

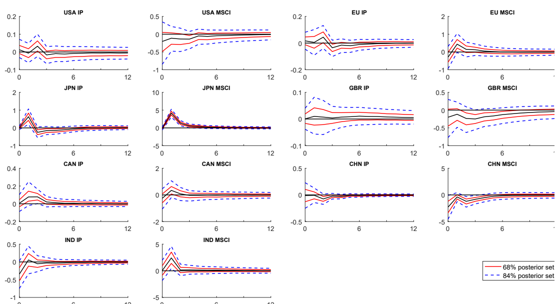
Figure 24: Responses to China Combined Uncertainty Shocks



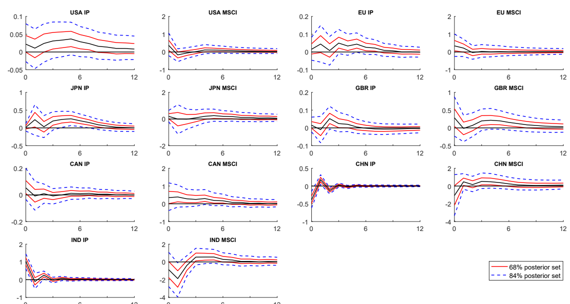
CAD



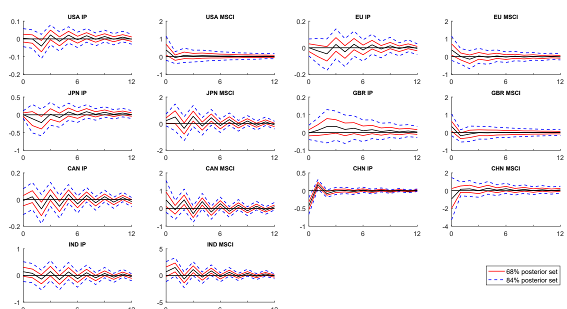
CPIU



FXU



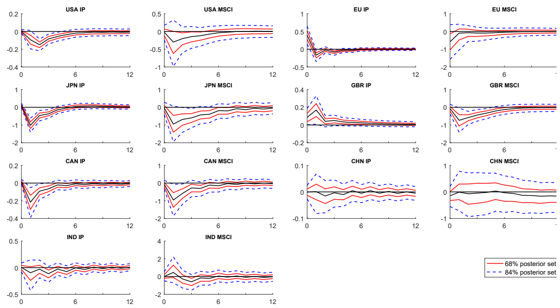
IPU



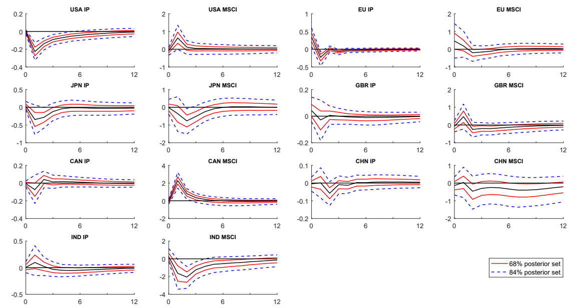
IRU

†Note: The figure shows the response of each macro-financial variable to a shock in Chinese combined uncertainty regarding the current account (CAD), inflation (CPIU), the exchange rate (FXU), industrial production (IPU) and short-term interest rate (IRU). 68 and 84 percent credible intervals are provided.

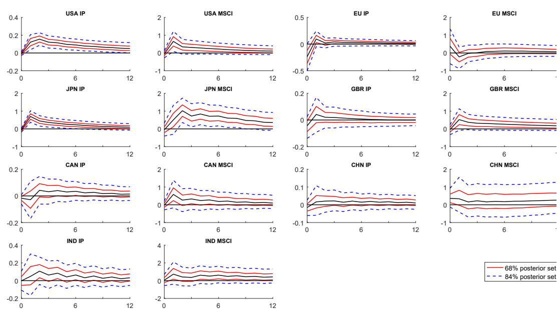
Figure 25: Responses to Eurozone Combined Uncertainty Shocks



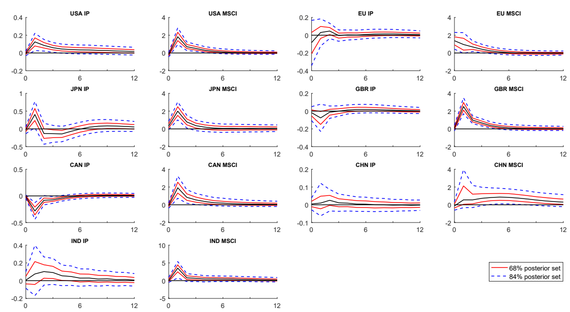
CAD



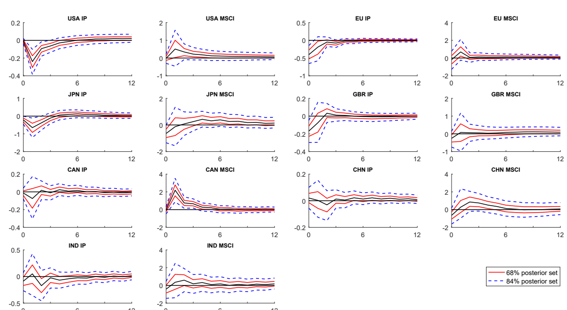
CPIU



FXU



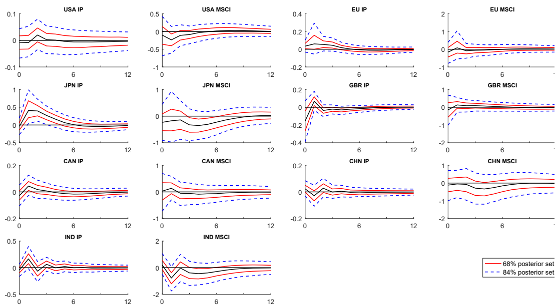
IPU



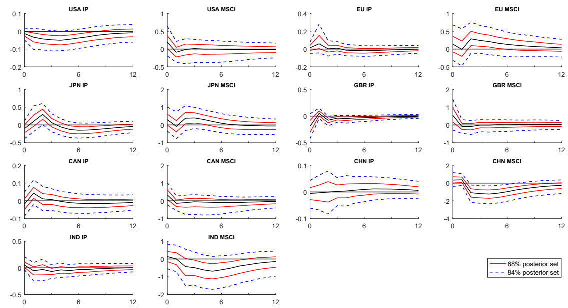
IRU

†Note: The figure shows the response of each macro-financial variable to a shock in Eurozone combined uncertainty regarding the current account (CAD), inflation (CPIU), the exchange rate (FXU), industrial production (IPU) and short-term interest rate (IRU). 68 and 84 percent credible intervals are provided.

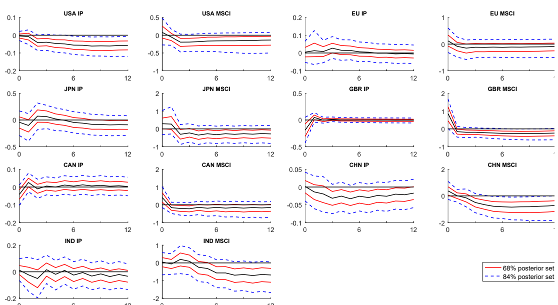
Figure 26: Responses to UK Combined Uncertainty Shocks



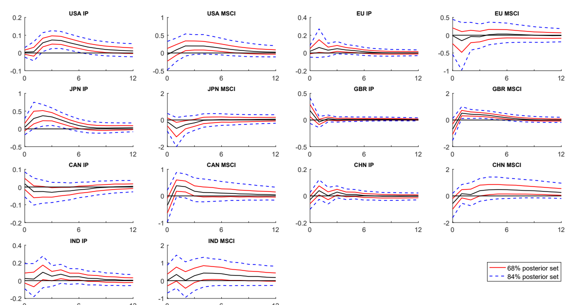
CAD



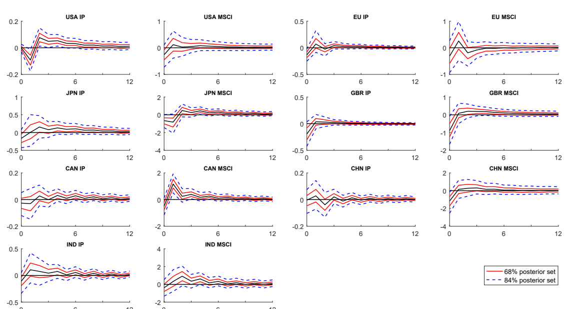
CPIU



FXU



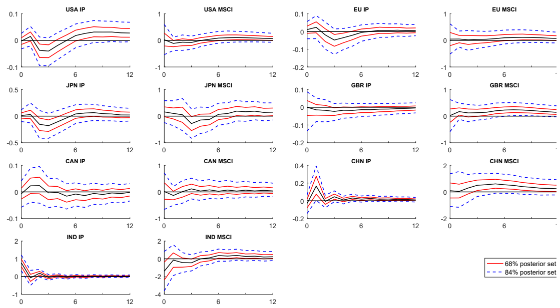
IPU



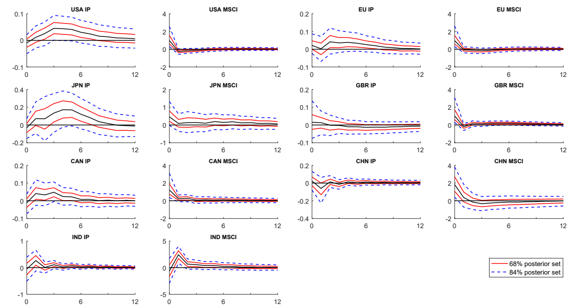
IRU

†Note: The figure shows the response of each macro-financial variable to a shock in UK combined uncertainty regarding the current account (CAD), inflation (CPIU), the exchange rate (FXU), industrial production (IPU) and short-term interest rate (IRU). 68 and 84 percent credible intervals are provided.

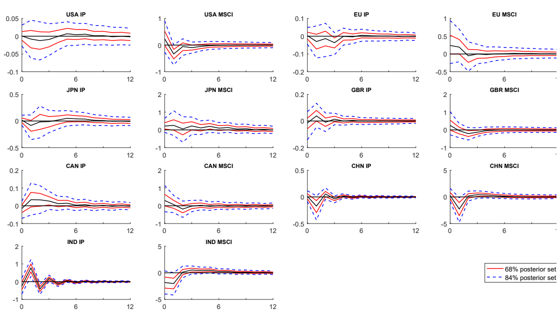
Figure 27: Responses to India Combined Uncertainty Shocks



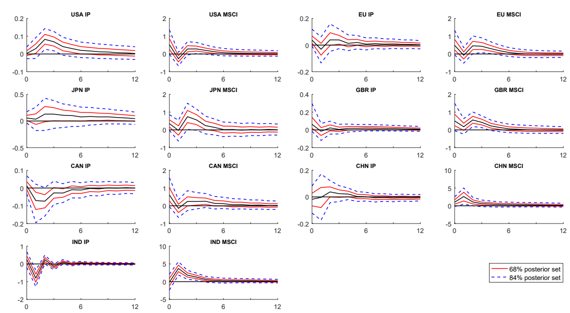
CAD



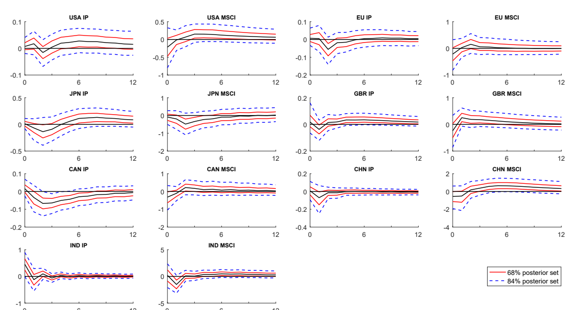
CPIU



FXU



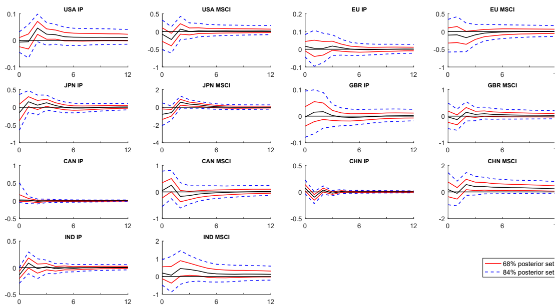
IPU



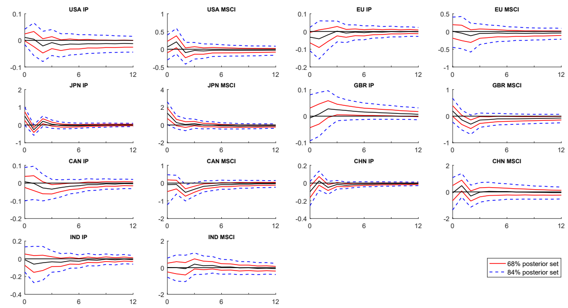
IRU

†Note: The figure shows the response of each macro-financial variable to a shock in Indian combined uncertainty regarding the current account (CAD), inflation (CPIU), the exchange rate (FXU), industrial production (IPU) and short-term interest rate (IRU). 68 and 84 percent credible intervals are provided.

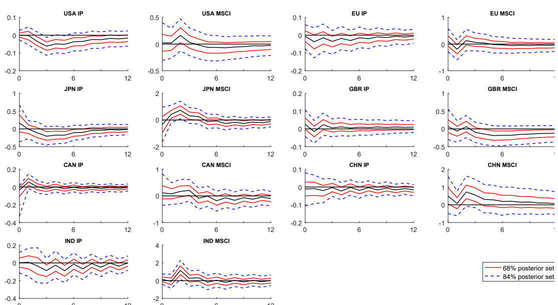
Figure 28: Responses to Japan Combined Uncertainty Shocks



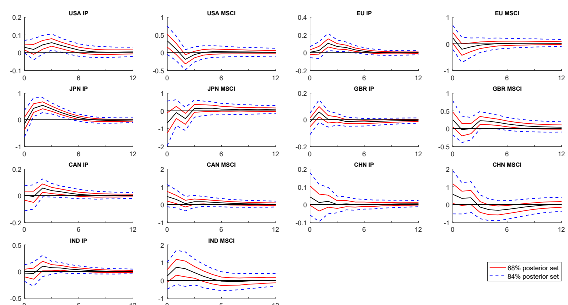
CAD



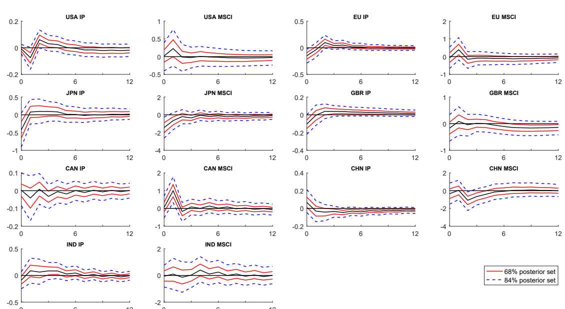
CPIU



FXU



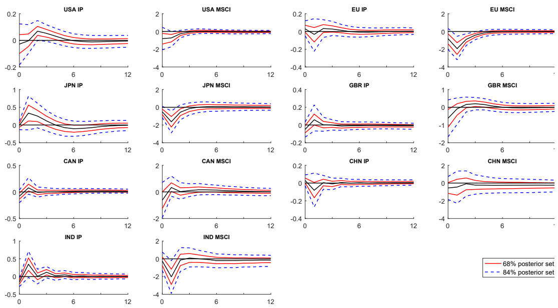
IPU



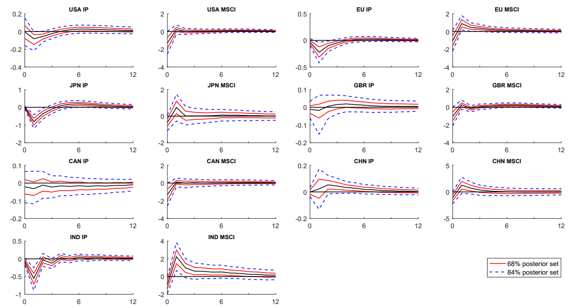
IRU

†Note: The figure shows the response of each macro-financial variable to a shock in Japanese combined uncertainty regarding the current account (CAD), inflation (CPIU), the exchange rate (FXU), industrial production (IPU) and short-term interest rate (IRU). 68 and 84 percent credible intervals are provided.

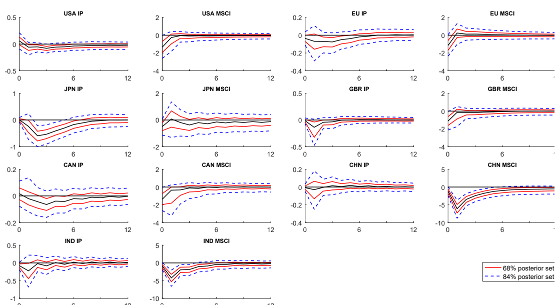
Figure 29: Responses to US Combined Uncertainty Shocks



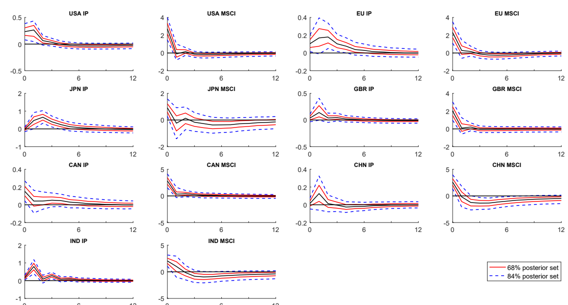
CAD



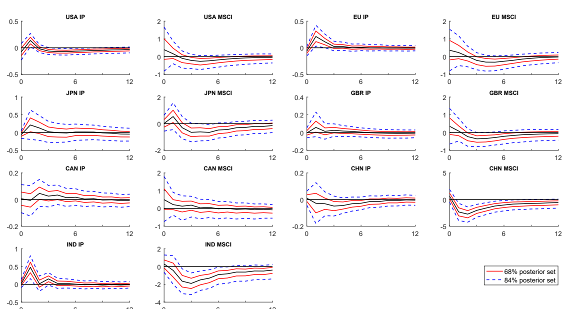
CPIU



FXU



IPU



IRU

†Note: The figure shows the response of each macro-financial variable to a shock in US combined uncertainty regarding the current account (CAD), inflation (CPIU), the exchange rate (FXU), industrial production (IPU) and short-term interest rate (IRU). 68 and 84 percent credible intervals are provided.