Econometric Modelling in a Changing, Globalised World

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Declaration

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Signed:

Date:

"We are all caught in an inescapable network of mutuality, tied in a single garment of destiny. Whatever affects one directly, affects all indirectly. We are made to live together because of the interrelated structure of reality. Did you ever stop to think that you can't leave for your job in the morning without being dependent on most of the world?"

Martin Luther King Jr.,

December 24 1967,

Massey Lecture Series,

Ebeneezer Baptist Church, Atlanta

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Abstract

This thesis takes the literature on multi-country Bayesian Panel Vector Autoregressions as its starting point. In three self-contained but related essays, we refine and apply the econometric methods and modelling assumptions necessary to objectively consider different aspects of globalisation.

The first essay analyses the Asia Pacific's possible decoupling from the US. We use Bayesian variable selection methods to model empirically relevant interdependencies between the US and eleven Asia Pacific countries. This allows us to capture regional interdependencies and bidirectional spillovers between the US and Asia Pacific. We show that shocks to US economic conditions, financial markets and uncertainty are important but regional shocks play a larger role in a typical Asia Pacific country. We also detect substantive spillovers from the Asia Pacific to US financial markets.

The second essay devises a novel econometric strategy to distinguish between: interdependence, contagion through interdependence and abrupt contagion. Appealing to multiple definitions of contagion, we allow the nature and magnitude of interdependencies and transmission channels selected for inclusion to change over time. Using our approach, we analyse crisis episodes in Latin America. We

only detect abrupt contagion during the global financial crisis from the US to Argentina and Brazil. During crises, results also show that macroeconomic and uncertainty channels play a role not just financial channels.

The third essay uses professional forecast data to analyse spillovers in five components of uncertainty across advanced and emerging economies. Uncertainty surrounding output growth, inflation, the interest rate, exchange rate and current account is considered. While the US affects other economies through interest rate, exchange rate and current account uncertainty, interest rate and inflation uncertainty spillovers are also seen from the Eurozone and UK. Uncertainty spillovers are more frequently observed, but smaller when forecaster disagreement rather than the variance of mean forecast errors is used to proxy uncertainty.

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Chapter 1

Introduction

1.1 Motivation

Over the past decade, deepening economic integration on a global and regional scale has come under intense scrutiny, presenting a major challenge to policy-makers and politicians. To quantitatively analyse our changing, globalised world, new econometric methods need to be developed and old modelling assumptions require reconsideration. When developing new methods, challenges facing the econometrician include: the large number of countries and variables under consideration; the need to allow for interdependencies between countries; the need to allow for abrupt and gradual economic change; and short time-series. Such issues are further compounded when we wish to also consider developing and emerging countries which, in the past, were excluded from analysis or assumed to be small open economies.

One popular class of models, first proposed by Sims (1980), and used by macroeconomists in central banks, government, the private sector and academia are Vector Autoregressions (VARs). These are time series models which are multivariate, involving many variables. They also have simple theoretical underpinnings, traditionally treating all economic variables as endogenous such that each variable depends upon its past, lagged values and lagged values of all other variables in the system. In the face of globalisation, regionalism and heightened interdependence, VARs have evolved with researchers using data from several countries instead of one country. This has led to the estimation of multi-country Panel VARs (PVARs).

PVARs can suffer from overparameterisation problems since the number of variables is large relative to the number of observations. Bayesian estimation methods are a popular means to overcome these problems (see Canova and Ciccarelli, 2013 for an overview of the literature and, among many others, Billio et al., 2016, Koop and Korobilis, 2016 and 2019, Korobilis, 2016 and Huber and Pfarrhofer, 2019 for recent extensions). However, with econometricians seeking to assess the efficacy of new algorithms and models, the US, Europe and other high income economies with long, rich time series data remain the focus.

Bayesian PVAR methods have not seen the same level of popularity in macroeconomic analyses of developing and emerging countries. This is despite the fact that the risk of overparameterisation is increased in such settings due to a lack of long, high frequency data. Perhaps paradoxically, low data availability, quality and comparability, has discouraged research considering developing and emerging countries. There may also be misconceptions surrounding what constitutes a Big Data problem. With Banbura et al. (2010) deploying a VAR with 130 dependent variables, recent studies emphasise the number of variables or countries used in analysis. However, it is the variable to observation *ratio* which characterises a Big Data problem rather than the PVAR size alone. This makes the frequency of the data and estimation strategy key with, for example, a ten country PVAR much more difficult to estimate than ten individually estimated country VARs, assuming the same number of variables per country in both pieces of analysis.

1.2 Contributions and Unifying Themes

Motivated by the concerns outlined above and taking the literature on large multi-country Bayesian Vector Autoregressions and Panel Vector Autoregressions as our starting point, this thesis seeks to refine, develop and apply the econometric methods and modelling assumptions necessary to objectively consider the often politicised policy challenges associated with globalisation. The contribution is provided in three self-contained but related essays.

Chapter 2 is titled "*The Asia Pacific's Decoupling from the US: Modelling Regional Interdependencies and Bidirectionality Matters*". Policymakers have debated whether Asia is decoupling from the US for over a decade. This chapter uses Bayesian variable selection methods to model empirically relevant interdependencies between the US and eleven Asia Pacific countries. Unlike previous studies, our 52 variable Panel VAR allows all twelve countries to affect one another through different transmission channels. This means we can capture regional interdependencies and bidirectional spillovers between the US and Asia Pacific. We show that shocks to US economic conditions, financial markets and uncertainty are important but regional shocks play a larger role in a typical Asia Pacific country. Regional shocks to financial markets and economic conditions have more pronounced effects than shocks to international competitiveness. US and regional monetary policy shocks are both relatively less important. We also detect substantive spillovers from the Asia Pacific to US financial markets indicating a bidirectional not unidirectional relationship.

Chapter 3 is titled "*Interdependence or Contagion: A Model Switching Approach with a Focus on Latin America*". Empirical research analysing contagion has become increasingly fragmented. Different definitions of contagion have resulted in different methods being deployed to analyse financial transmission channels. This chapter devises a novel econometric strategy where the nature of interdependencies, magnitude of interdependencies and transmission channels selected for inclusion can change over time. We thus appeal to multiple definitions of contagion, distinguishing between: interdependence, contagion through interdependence and abrupt contagion through changing linkages. Using our approach we analyse different crisis episodes in Latin America. Results generally indicate interdependence not contagion during the currency crises of the 1990s and Argentine crisis of 1998 - 2002. During the global financial crisis, results indicate abrupt contagion from the US to Argentina and Brazil. Mexico, however, experiences contagion through existing interdependencies with the US. Results also show that macroeconomic and uncertainty channels play a role during different crises not just financial channels. By establishing whether or not different interdependencies and transmission channels are present during different crises our model switching approach provides new insights.

Chapter 4 is titled "*Measuring International Uncertainty Spillovers and their Impact on the Economy*". We use a large professional forecasts data set to analyse spillovers in five components of uncertainty across seven advanced and emerging economies. Uncertainty surrounding output growth, inflation, the interest rate, exchange rate and current account is considered. We also examine how our results vary depending on whether we proxy each component of uncertainty using disagreement among forecasters, the variance of their mean forecast errors or a combination of these two measures. These issues are investigated by estimating three multi-country Bayesian Panel VARs arising from our three uncertainty proxies reflecting idiosyncratic, common and aggregate uncertainty. We find that the US affects other economies through interest rate, exchange rate and current account uncertainty but spillovers in interest rate and inflation uncertainty are also seen from the Eurozone and UK. Across economies, the financial sector is hit harder by foreign uncertainty than the real sector with China, India and Japan being most affected. Idiosyncratic uncertainty spillovers are more frequently observed than spillovers in common uncertainty. However, when they do occur, foreign common uncertainty shocks produce larger negative responses.

There are several important themes which span all three essays. First, rather than developing new econometric methods and illustrating their efficacy by applying them we do the reverse. With a specific issue in mind, we tailor and extend existing methods to thoroughly and sympathetically shed light on the problem of interest. Second, at the heart of each piece of analysis, lies an attempt to further our understanding of the complex nature of interdependencies between countries. Third, emerging economies play an important role in all three essays. While economists have typically focused on North-North interdependencies between high income countries, we also model and uncover the importance of South-South interdependencies between developing or emerging countries in a given region.

This is a particularly important theme in Chapters 2 and 3. Fourth, while the small open economy assumption (also referred to as block exogeneity) remains popular, we also allow for the possibility that developing or emerging countries can influence high-income countries in Chapters 2 and 4. Put differently we allow for bidirectionality in North-South linkages. Again, the evidence we uncover suggests that allowing for bidirectionality is important and that even the US can be influenced by emerging markets. Fifth, we challenge the assumption that the US is always the dominant source of external shocks, instead disentangling the role played by different economies.

As of July 2020, a working paper version of Chapter 3 has been published as: Davidson, S.N., 2020., Interdependence or Contagion: A Model Switching Approach with a Focus on Latin America, *Economic Modelling*, 85, pp. 166 - 197. A working paper version of Chapter 2 has been submitted for possible publication. Chapter 4 is co-authored work with Joscha Beckmann, Gary Koop and Rainer Schüssler and a working paper version has been submitted for possible publication. All empirical work in this joint research was undertaken by myself as well as the writing of the second draft of the paper.

Chapter 2

The Asia Pacific's Decoupling from the US: Modelling Regional Interdependencies and Bidirectionality Matters

2.1 Introduction

Deepening economic integration arising from globalisation and regionalism has come under intense scrutiny. For over a decade, policy institutions in Asia (see He et al., 2007, Athukorala and Kohpaiboon, 2009, Park and Shin, 2009, He and Liao, 2012, Kim et al., 2011, Park, 2011, 2017), the US (Leduc and Spiegel, 2013) and Europe (Lam and Yetman, 2013) have provided a platform for research debating whether Asia is decoupling from the US.

In this chapter, we explore interdependencies between the US and eleven Asia

Pacific (AP) countries: Indonesia, Thailand, the Philippines, Malaysia, Singapore, China, Japan, South Korea, India, Australia and New Zealand. For each AP country, we quantify the relative importance of: extra-regional shocks primarily originating from the US[1], regional shocks originating from other AP countries and domestic shocks. We also consider whether spillovers are solely seen from the US to AP countries or whether bidirectionality is present with AP shocks spilling over to the US.

Three features distinguish our high-dimensional approach from past research. First, we account for regional interdependencies. While the effects of shocks originating from the US are the main focus of the existing literature, we reclassify these "external" structural shocks as extra-regional shocks. We then account for a further set of regional shocks originating from other AP countries. For example, we can consider the effect of a shock to Indonesian GDP growth on Malaysian variables. This is an important feature, allowing us to circumvent distortions which can occur when using bilateral or trilateral Panel VARs (see Canova and Cicarelli, 2013 and Georgiadis, 2017). Second, we account for global interdependencies. Recognising that the small open economy assumption does not apply to all AP variables, we allow for spillovers from the AP to the US as well as vice versa. This means, for instance, that GDP growth in China can affect US variables. Third, we include a comprehensive set of variables for each economy, allowing us to distinguish between interdependencies driven by financial linkages as well as trade linkages. For the US, we include variables which reflect economic conditions, monetary policy, financial conditions and economic uncertainty. For each AP country, we include variables reflecting economic conditions, monetary policy

[1]We also account for oil and non-fuel commodity price shocks but find that they play a relatively small role compared to most US shocks.

and financial markets. We also include the real effective exchange rate (REER) which reflects countries' relative international competitiveness.

To jointly model variables in the US and our AP countries, we estimate a 52 variable Bayesian Panel Vector Autoregressive (PVAR) model. Our PVAR allows us to explore interdependencies between all twelve countries, producing country-specific impulse response functions and forecast error variance decompositions. However, this enhanced flexibility comes at a cost. It can be difficult to detect which interdependencies are non-zero and the model may become overparameterised. We address these issues by exploiting Bayesian variable selection. Specifically, we deploy the Stochastic Search Specification Selection (S^4) approach of Koop and Korobilis (2016). This allows us to consider different restricted versions of the PVAR, estimating interdependencies between countries which are supported by the data and setting unimportant interdependencies to zero. The latter leads to a parisimonious model overcoming overparameterisation concerns.

Our main findings are as follows. We show that shocks to US economic conditions, financial markets and uncertainty are important but regional shocks play a larger role in a typical Asia Pacific country. Regional shocks to financial markets and economic conditions have more widespread effects relative to regional shocks in international competitiveness. Foreign monetary policy shocks originating from the US and other AP countries are relatively less important. There is, however, considerable cross-country heterogeneity. In Australia, New Zealand, India, China and Japan, domestic shocks dominate. US shocks explaining a sizable fraction of the remaining variation in the former two countries while regional shocks explain more of the remaining variation in the latter three. In Singapore, US shocks also play a more prominent role. In Korea and Southeast

Asian countries (Indonesia, Thailand, the Philippines and Malaysia) shocks from other Southeast Asian countries play the most prominent role. Indonesia is particularly vulnerable to foreign shocks and is also affected by shocks in East Asian countries (Japan, China and Korea). We also detect substantive spillovers from the Asia Pacific to the US stock market. These tend to be driven by movements in regional financial markets. Smaller spillovers are also seen to the US excess bond premium and US GDP growth. Overall, this indicates a bidirectional rather than unidirectional relationship between the Asia Pacific and US.

The rest of this chapter is structured as follows. In section 2.2, we briefly review related multi-country PVAR studies. In section 2.3, we discuss our empirical strategy. Section 2.4 presents our results on the relative importance of extra-regional and regional shocks for each AP economy and bidirectional spillovers between the US and Asia. Section 2.5 summarises conclusions. The Chapter 2 appendix includes a data appendix (Appendix A.1), technical appendix (Appendix A.2) and supplementary figures (Appendix A.3).

2.2 Related Multi-country PVAR Studies

In this section, we will discuss two strands of the literature relevant to our work. First, we will consider studies examining the effects of external shocks on developing and emerging economies, focusing on the empirical framework typically used. Second, we will consider how this framework has been used to investigate whether Asia is decoupling from the US.

External shocks are considered an important source of macroeconomic volatility in developing and emerging economies (see Loayza et al., 2007 and Kose et al., 2005 for an overview). The literature investigating the effects of external shocks on these economies focuses on two questions. What types of external shocks may occur? What is the relative contribution of external and domestic shocks to the volatility of different macroeconomic indicators? In terms of the former question, studies tend to focus on a limited set of external shocks which are macroeconomic in nature. This is, in part, due to short time series which limit the number of possible variables which can be included in analysis. For instance, Raddatz (2007) uses a recursive identification scheme to consider the effects of shocks to aid flows, high-income countries' GDP, terms of trade, the international interest rate and natural disasters on low income countries. Using short-run and long-run restrictions, Allegret et al. (2012) consider the effects of shocks to US GDP, US monetary policy, the world MSCI index and oil prices on East Asian economies. When considering the determinants of external vulnerability, Loayza and Raddatz (2007) limit the need for identifying assumptions, focusing on how the effects of terms of trade shocks vary according to country characteristics.

Other studies examining the transmission of shocks to Latin America (Canova, 2005) and low income countries (Barrot et al., 2018) take a different approach. They argue that a small number of 'primitive' shocks to global supply, demand, monetary policy and commodity prices drive movements in global variables and can be identified using sign restrictions. However, a number of issues remain. First, the primitive shocks identified fail to fully capture global financial conditions and uncertainty. Following the financial crisis, both aspects have been deemed important drivers of domestic and international business cycles (see e.g. Beckmann et al., 2020, Bloom, 2009, Ludvigson et al., forthcoming and Ha et al., 2020). Second, when constructing proxies for global variables attention is restricted to the US or G7 despite a lessening of their global economic dominance. This becomes problematic in cases where the post-1990s make up a sizeable part of the sample since the global shocks may not be truly global in nature. Focus on the G7 also fails to acknowledge that the US, Europe and Japan have very different ties with different regions. Barrot et al. (2018) address these issues by accounting for China as well as the G7 when constructing global shocks.

Studies have also attempted to discern whether external shocks dominate domestic shocks. Raddatz (2007) finds that external shocks account for only a small proportion of output volatility in low income countries. These findings are reaffirmed by Barrot et al. (2018) using a larger sample of countries and longer time series. However, they find that the role played by external shocks increases if the sample starts in 1990. In contrast, Canova (2005) finds that global supply, demand and monetary shocks originating from the US, on average, account for more than half of output volatility among Latin American economies. Allegret et al. (2012) also show that, on average, nearly 40% of variation in East Asian economies GDP is explained by external shocks. However, considerable cross-country heterogeneity is also uncovered in both studies.

These findings are not surprising given that Canova (2005) and Allegret et al. (2012) use quarterly data starting in the 1990s rather than annual data starting in the 1960s or 1970s. We would also expect Latin American and Asian countries be more responsive to US shocks. However, regional shocks arising from neighbouring countries are not accounted for. Failing to account for regional shocks may lead to distortions arising from omitted variables bias. Canova and Cicarelli (2013) confirm that using bilateral or trilateral PVARs when the data generating process is more complex can significantly distort the estimated structural shocks. Similarly, Georgiadis (2017) shows that spillover estimates from bilateral VARs are less accurate than those obtained from multilateral VARs, particularly when the spillover-recipient has a high level of global integration overall. Regional shocks may explain a considerable proportion of variability especially when regional economic and financial integration is high. This is potentially less problematic when considering low income countries and perhaps even Latin America. But regional shocks cannot be ignored when examining the Asia Pacific where trade and financial openness is high among several economies.

The small open economy assumption remains widespread in the literature examining the effects of external shocks. When appropriately applied, the assumption that global variables are uninfluenced by domestic variables brings advantages including a reduction in the number of parameters to be estimated, increased precision and a reduction in spurious results (see Cushman and Zha, 1997 and Zha, 1999). However, with the rapid growth in the Asia Pacific, it is increasingly difficult to claim that the small open economy assumption holds across all developing and emerging nations even with respect to the US.

Turning to the second relevant strand of the literature, several facts point towards Asia decoupling from the US. Since 1990, Asia has seen rising intra-regional trade as export markets become more diversified and the US export share falls (Park and Shin, 2009, Park, 2017). A lack of synchronicity has also been observed between US and Asian output before the global financial crisis and during the subsequent recovery (Leduc and Spiegel, 2013). Using a structural factor model, He and Liao (2012) find that while a global factor has played an increasing role over time in driving output in industrialised countries, it remains less synchronised with output in Asia. Nonetheless, intra-regional trade shares should be interpreted with caution given the vertical integration of production chains where the final good is exported outwith the region (Athukorala and Kohpaiboon, 2009).

To our knowledge, only two studies use VARs to examine Asia's possible decoupling. For nine East Asian economies, Kim et al. (2011) construct nine VARs consisting of G7 aggregate output, aggregate regional output and individual output. Using a recursive identification scheme, they show that in the 2000s G7 shocks explain about 20% of aggregate Asian output and, on average, over 10% of individual output. East Asian aggregate shocks explain 50% of G7 output and over 20% of individual output. Bidirectionality is also present in Cuadro-Sáez et al. (2009) who find that emerging economies influence global equity markets most strongly during "bad" times but also during "good" times. While Latin American economies affect US equity markets more than Asian or Eastern European economies, the dataset only spans 2000 - 2004 and does not capture the subsequent rapid growth of the Asia Pacific. Turning to our second VAR based study, in Park (2017) US financial shocks are also considered. Again, for each East Asian economy, a VAR is constructed consisting of US output, the Chicago Board Options Exchange Volatility Index (VIX), global trade volume growth, Chinese output and individual output. Using a recursive identification scheme, it is shown that US output shocks explain a quarter of output volatility whereas China output shocks explain a fifth.

Together Kim et al. (2011) and Park (2017) highlight the importance of investigating regional interdependencies and bidirectional spillovers in greater detail. We discuss how we can disentangle global and regional spillovers originating from different countries and different transmission channels in the next section.

2.3 Empirical Strategy

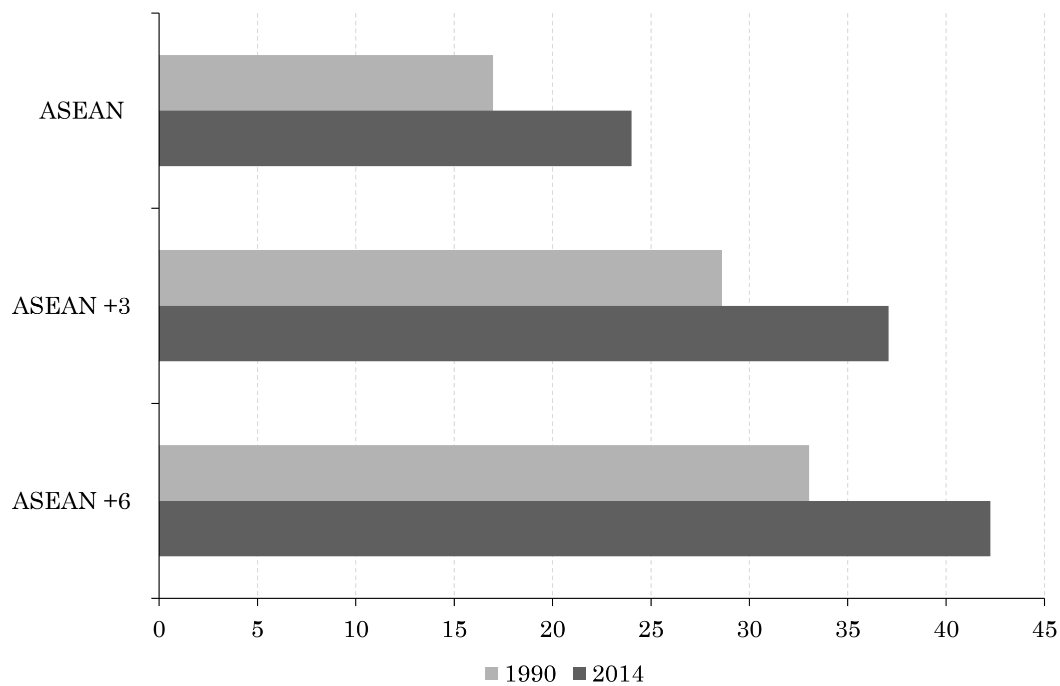
Here, we outline our empirical strategy. We begin by giving an overview of the data used before discussing our econometric methods.

2.3.1 Data

We first select which AP countries to include in our PVAR. We use the Association of Southeast Asian Nations (ASEAN) as our starting point, a political and economic grouping founded in 1967 by Indonesia (IDN), Malaysia (MYS), the Philippines (PHL), Singapore (SGP) and Thailand (THA). By the late 1990s, ASEAN had established a free trade area and grown to include: Brunei, Myanmar, Cambodia, Laos and Vietnam. Following the Asian financial crisis and subsequent controversy surrounding the IMF's use of loan conditionality (see Ito, 2012), the ASEAN +3 was formed to strengthen cooperation between ASEAN and its East Asian neighbours: China (CHN), Japan (JPN) and South Korea (KOR). The group oversaw the launch of the Chiang Mai Initiative, a multilateral currency swap arrangement to alleviate short-term liquidity crises. With the creation of the annual East Asia Summit forum, a new group has arisen known as the ASEAN +6, extending the ASEAN +3 to include other Asia Pacific countries: Australia (AUS), India (IND) and New Zealand (NZL). In 2012, the ASEAN +6 began free trade negotiations under the regional comprehensive economic partnership (RCEP) with India opting out in late 2019.

Given the availability of quarterly data, in our PVAR we include the five founding members of ASEAN and the +6 countries. This comprises a heterogeneous group of developing and emerging nations with the exception of Japan, until recently the major regional power, Australia and New Zealand. Singapore only achieved high income status at the end of the 1980s while Korea later joined this category in the mid 1990s. Taking intra-regional trade as one indicator of regional integration, the intuition behind the gradual expansion of the PVAR is shown in Figure 2.1.

Figure 2.1: Intraregional Trade Share across the Asia Pacific (%): 1990 vs 2014



Adapted from: OECD (2016) whose source is the IMF, Direction of Trade Statistics.
Note: Total within group trade as a share of groups' total world trade.

For each AP country, we include quarterly data on: GDP growth (G), the short-term interest rate (R) and the real effective exchange rate (E). Unlike previous studies, we also include stock price growth (S) so that we can consider financial interdependencies at the global and regional level. These variables serve two purposes. First, they are important in determining the impact of extra-regional shocks. Second, they allow us to consider regional shocks to economic conditions, monetary policy, international competitiveness and financial markets. With eleven countries with four variables each, our model is already huge even before considering which extra-regional variables to include.

In terms of extra-regional variables, we focus on the US which has historically been the Asia Pacific's main extra-regional trading partner and a significant political actor in the region. Additionally, prior to the Asian financial crisis many countries in the region adopted a dollar-peg exchange rate regime. We include US GDP growth (USA G) and the US treasury bill rate, the short-term interest rate (USA R). This allows us to consider the effects of extra-regional shocks to US economic conditions and monetary policy. Unlike previous studies, we also consider the effects of a broader array of financial and uncertainty shocks. We include US stock price growth (USA S) and the excess bond premium (EBP) developed by Gilchrist and Zakrajšek (2012), a measure of financial distress, charting US investors' changing attitudes in the corporate bond market. We also include measures of US real and financial uncertainty (USA RU and USA FU) developed by Jurado et al. (2015) and Ludvigson et al. (forthcoming). We also include a non-fuel commodity price index (COM) and oil price index (OIL) to capture commodity and oil price shocks.

We have 52 endogenous variables in our PVAR with data sources and transformations summarised in the data appendix (Appendix A.1). All variables are also standardised. We estimate our model over 1993:1 - 2016:4. In addition to excluding data from the 1980s, we also include three exogenous variables to control for time-variation: a time trend, asian financial crisis dummy and global financial crisis dummy.

2.3.2 Econometric Methods

In our multi-country PVAR[2] we move away from considering extra-regional and regional variables separately. Instead, treating all variables as endogenous, we can write our model as follows:

$$\begin{bmatrix} Y_t \\ z_t \end{bmatrix} = \underbrace{\begin{bmatrix} A_{11} & A_{12} \\ A_{21} & A_{22} \end{bmatrix}}_{\text{A}} \begin{bmatrix} Y_{t-1} \\ z_{t-1} \end{bmatrix} + \begin{bmatrix} \varepsilon_t \\ \epsilon_t \end{bmatrix} \quad (\varepsilon_t,\ \epsilon_t)' \sim N(0, \Sigma_u) \tag{2.1}$$

such that $z_t^{'} = (OIL_t, USA\ FU_t, USA\ G_t, USA\ RU_t, EBP_t, USA\ S_t, COM_t, USA\ R_t)$ and $y_{it} = (G_{it}, R_{it}, E_{it}, S_{it})$ correspond to the extra-regional and regional variables described in the previous subsection and the data appendix (Appendix A.1). Since we allow for interdependencies we have $Y_t^{'} = (y_{1t}, ..., y_{11,t})$. Due to having short time-series, we follow Canova (2005) and only allow for one lag rather than choosing the lag length based on information criteria or maximising the marginal likelihood.

Our PVAR allows for different types of what Canova and Ciccarelli (2013) term dynamic interdependencies (DIs) and static interdependencies (SIs). DIs occur if a lagged variable of AP country j affects a variable in another AP country ($A_{11} \neq diag(A_{11})$) or the US ($A_{21} \neq 0$). For instance, interest rate movements in China may affect Indonesian GDP growth or the US interest rate with a lag. DIs also occur if a US variable affects a variable in another AP country ($A_{12} \neq 0$). For example, a change in US GDP growth may affect Singaporean exchange rates

[2] 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 standardised so we do not include an intercept.

with a delay. SIs occur if there are contemperanous linkages between a variable of AP country j and a variable in AP country i ($\Sigma_{ij} \neq 0$) or the US ($\Sigma_u \neq diag(\Sigma_\varepsilon, \Sigma_\epsilon)$ where $diag(\Sigma_\varepsilon, \Sigma_\epsilon)$ is a blockdiagonal matrix). For instance there may be a contemperanous spillovers between Singaporean and Malaysian stock markets or between US financial conditions and Australian stock markets. Importantly, these DIs and SIs encompass block exogeneity assumptions.

With 52 endogenous variables, the number of possible interdependencies in our PVAR is huge. Bayesian methods are an increasingly popular means to address the overparameterisation problems associated with estimating multi-country VARs (see Canova and Ciccarelli, 2013 for an overview of the literature and Koop and Korobilis, 2016 and 2019 and Korobilis, 2016 for recent extensions). To estimate our PVAR, we use the Stochastic Search Specification Selection (S^4) MCMC algorithm of Koop and Korobilis (2016) which is designed to explicitly consider the DI and SI restrictions above. Specifically, they extend the Stochastic Search Variable Selection (SSVS) algorithm of George et al. (2008) to a multi-country setting. Denoting the jth element of $vec(A) = \alpha$ as α_j the principles underlying S^4 can be captured as follows:

$$\alpha_j|\gamma_j \sim (1-\gamma_j)N(0, \underline{c} \times \tau_j^2) + \gamma_j N(0, \tau_j^2) \tag{2.2}$$

where the binary parameter $\gamma_j \in \{0,1\}$ is estimated in the algorithm, $\underline{c}$ is a relatively small value chosen by the researcher and $\underline{\tau}_j$ is also estimated. If $\gamma_j = 1$, the first term in (2) disappears, we select the noninformative prior with high prior variance and α_j undergoes relatively little shrinkage. In other words, the DI or SI under consideration is included in the model. Conversely, if $\gamma_j = 0$, the second term in (2) disappears, we select the informative prior with low prior variance and α_j is shrunk towards zero. Put differently, the DI or SI under consideration is excluded from the model and interdependencies are included or excluded from the model in a data-driven manner.

In practice, rather than considering individual parameters, S^4 considers blocks of coefficients (or covariance terms) which correspond to bilateral relationships between countries. We modify this approach instead restricting single elements as described. Further details are in the technical appendix (Appendix A.2). We then calculate generalised impulse response functions (GIRFs) and generalised forecast error variance decompositions (GFEVDs) as in Koop et al. (1996), Pesaran and Shin (1998) and Lanne and Nyberg (2016). GIRFs and GFEVDs are invariant to the way the variables in the PVAR are ordered. This is an attractive feature since we have a large number of variables and do not wish to impose a specific ordering.

2.4 Results

For brevity, we focus on results obtained from the structural PVAR. We first consider the relative effects of extra-regional, regional and domestic shocks on each Asia Pacific economy. We then examine whether the relationship between the US and Asia Pacific is bidirectional with shocks originating in the Asia Pacific affecting the US.

In all figures, extra-regional variables (US, oil and non-fuel commodity prices) are in red, Southeast Asian variables (Indonesia, Malaysia, Singapore, Thailand, Philippines) are in green, East Asian variables are in purple (China, Japan, Korea) and other Asia Pacific variables (India, Australia, New Zealand) are in blue.

2.4.1 The Relative Effects of Different Shocks on Asia Pacific Countries

2.4.1.1 Impulse Response Functions

With 52 endogenous variables in our PVAR, we could discuss up to 52^2 GIRFs. Instead, we summarise GDP growth (G) and stock market growth (S) GIRFs[3] using Sankey diagrams. A link is shown if an adverse shock has a negative effect which is non-zero according to the 84 percent credible interval. The width of the link reflects the depth of the median GIRF's trough. In terms of the REER, we focus on the effects of a sudden depreciation which is likely to have an adverse affect on neighbouring export-oriented economies. For oil price and commodity price shocks, we also consider a decline in these variables for reasons described below. The full GIRFs (Figures A.1 - A.52) are provided in supplementary figure appendices (Appendix A.3.1 and A.3.2).

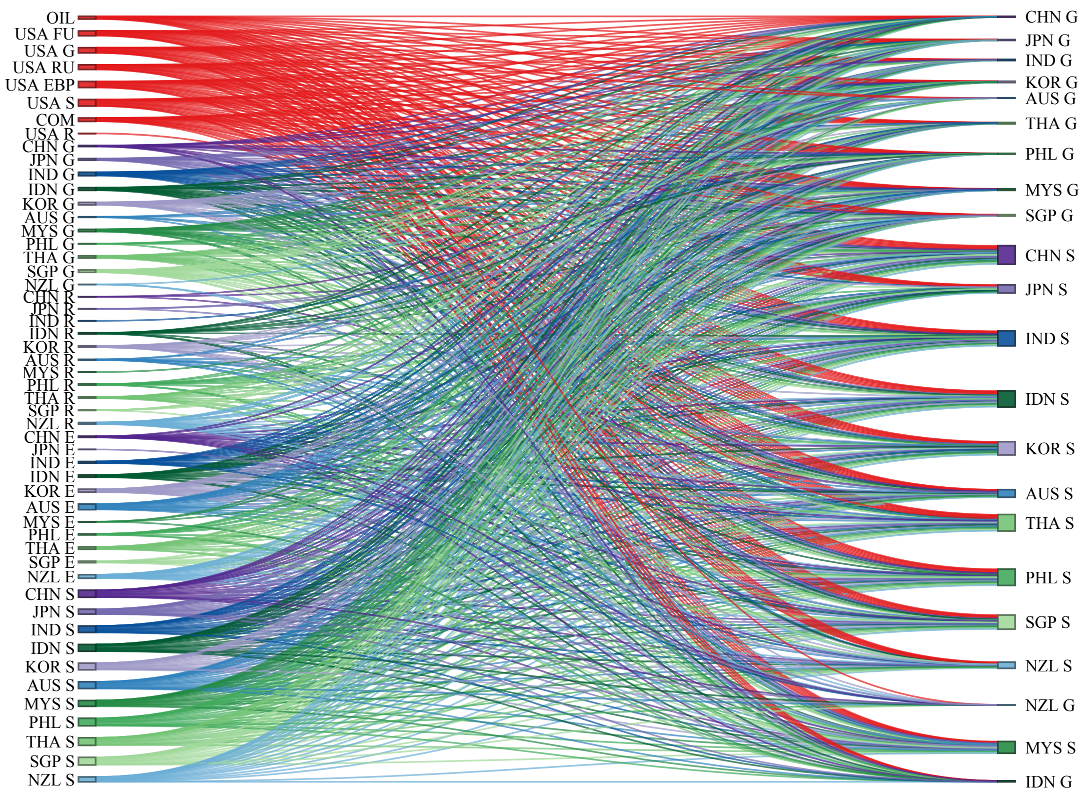
In order to compare the role played by extra-regional and regional shocks variables (the link width is comparable within figures but not across figures), we consider Figure 2.2. This together with our GIRFs, many of which have credible intervals containing zero at all horizons, shows that our flexible modelling approach and S^4 algorithm can effectively sort through the large number of potential linkages, selecting important ones for inclusion and shrinking unimportant ones to

[3]These have been rescaled to reverse standardisation of the raw data.

zero. Given our high-dimensional dataset and model, this is reassuring. Our results confirm that there are important regional interdependencies within the Asia Pacific as well as global interdependencies between the US and Asia Pacific. We also find that while the US is an important source of adverse shocks it does not play a dominant role. Rather, spillovers originating from each country affect other countries in the region with the financial sector being hit harder than the real sector. Negative affects arising from shocks to different countries' financial markets and, to a lesser extent, economic conditions occur more frequently (indicated by the number of links) and are sizable (indicated by the width of links). Adverse effects resulting from shocks to different countries' international competitiveness are less frequently observed and less pronounced. The least important shocks are monetary policy shocks which are least frequently observed and have the smallest impact.

Turning to the effects of extra-regional shocks in Figure 2.3, we find that adverse shocks to US financial conditions captured through stock price growth and the excess bond premium have widespread negative affects on stock markets and GDP growth across AP countries. The exception is Australian and New Zealand GDP growth. Adverse shocks to US GDP growth, financial uncertainty and real uncertainty also negatively affect the majority of economies but unsurprisingly the effect on stock markets is not as pronounced. Again, New Zealand GDP growth is not affected by these shocks while Australian GDP growth is only affected by a decline in US GDP growth. Most starkly, at the 84% credible level a US monetary policy shock only affects Thailand. This coincides with Maćkowiak (2007) who finds that US monetary policy shocks are unimportant relative to other external shocks. Declines in the oil price and non-fuel commodities have smaller adverse affects as exporters are hit. The negative responses of non-exporters may result from oil price shocks driven by aggregate demand. In these instances, the gains in export revenue may have exceeded the losses incurred through oil price rises (Allegret et al., 2012).

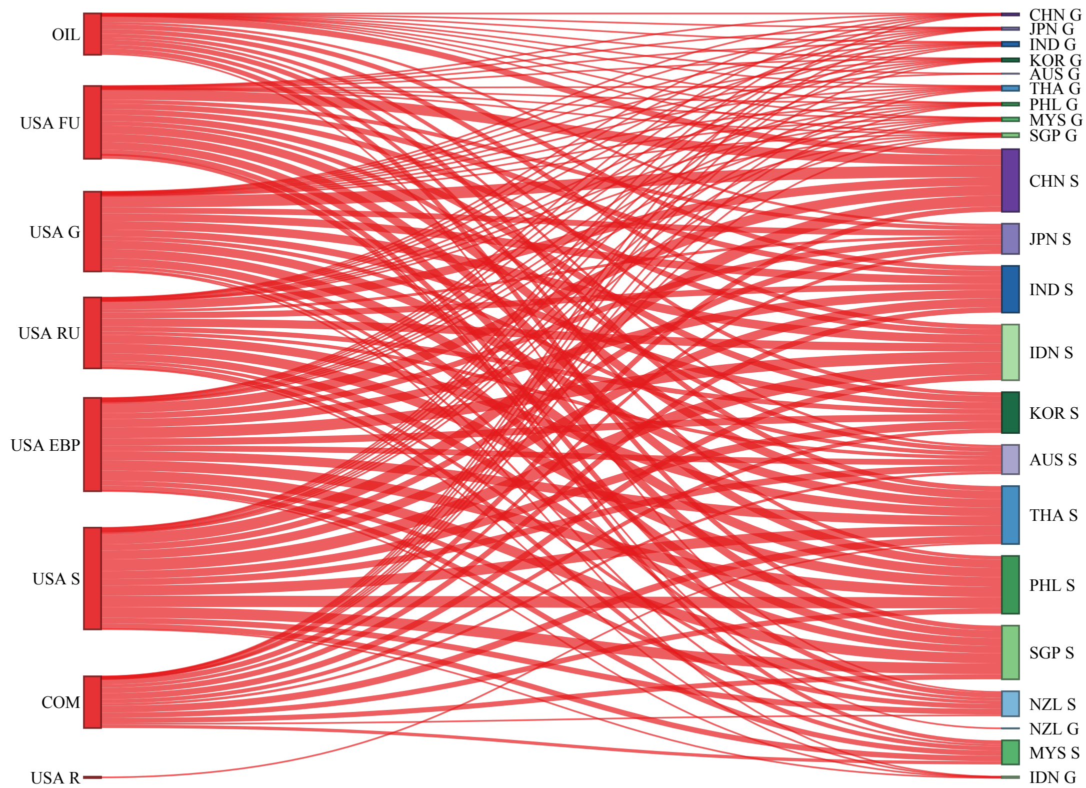
Figure 2.2: Summary of Impulse Responses Showing Important Declines in Real and Financial AP Growth Following Negative Shocks



Note: We report impulse response functions for GDP growth (G) and stock market (S) growth where there is an adverse 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.

Turning to the effects of regional shocks in Figure 2.4, shocks to US GDP growth have more sizable effects than shocks to any AP countries' GDP growth (top left). Shocks to GDP growth in New Zealand, the Philippines and Australia play a limited role. Shocks originating from other countries have widespread and sizable impacts with India and Indonesia, our third and fourth largest AP economies, being a major source of shocks. Their effects on stocks markets are more sizable with their largest adverse real effects being domestic. The countries least affected are New Zealand and Australia followed by Japan.

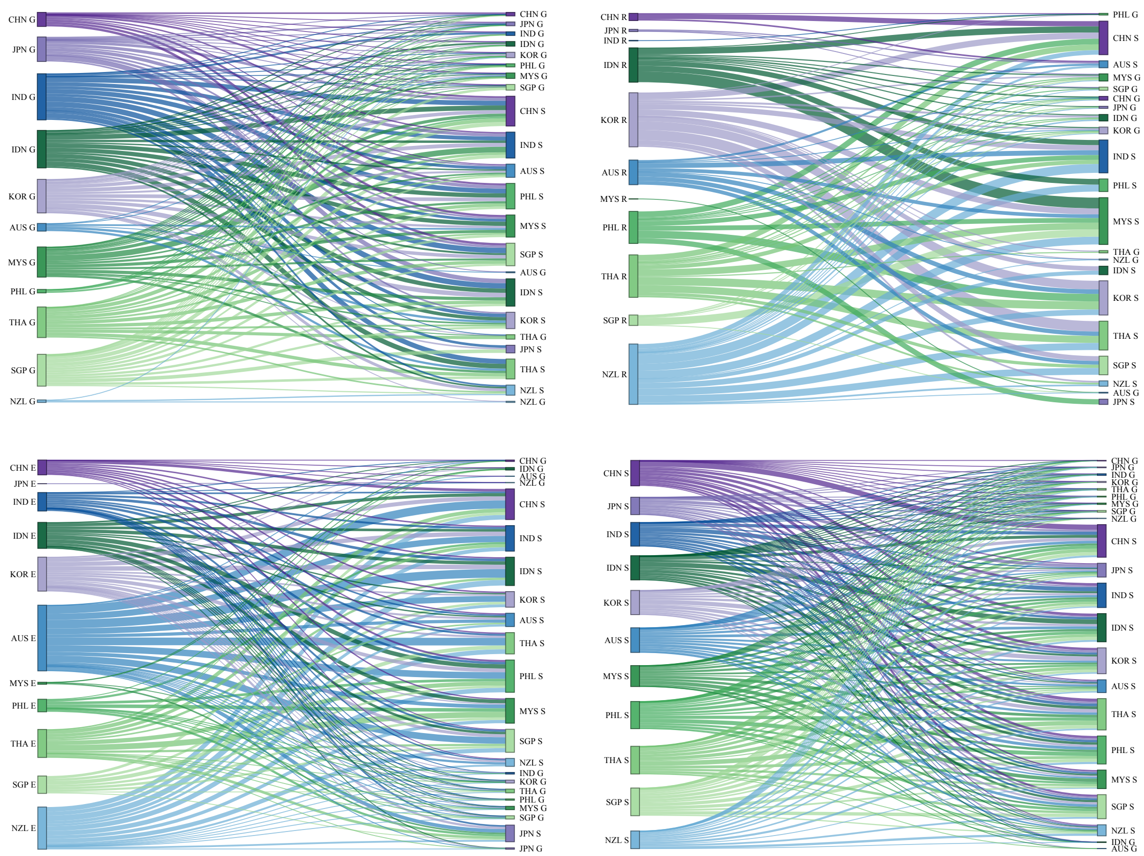
Figure 2.3: Summary of Impulse Responses Showing Important Declines in Real and Financial AP Growth Following Negative Extra-regional Shocks



Note: We report impulse response functions for GDP growth (G) and stock market (S) growth where there is an adverse 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.

The effects of regional monetary policy shocks (Figure 2.4, top right) are much more sparse and the magnitude of their impact is far smaller. The Korean and New Zealand monetary policy shocks are similar in magnitude to a Japanese GDP growth shock (Figure 2.4, top right). Shocks to international competitiveness in the region (Figure 2.4, bottom left) also have relatively sparse effects. However, their magnitude is more sizable with the effects of a sudden increase in Australia's international competitiveness more than twice the size of a sudden increase in Indonesian GDP growth. Japanese and Malaysian exchange rate changes have the most limited effects with the latter pursuing a fixed exchange rate regime till 2005.

Figure 2.4: Summary of Impulse Responses Showing Important Declines in Real and Financial AP Growth Following Negative Regional Shocks



Note: We report impulse response functions for GDP growth (G) and stock market (S) growth where there is an adverse 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 but this is not comparable across the four subfigures.

Regional financial shocks (Figure 2.4, bottom right) are frequently observed and large in magnitude. The effects of a shock to Chinese stock markets are the twice the size of a shock to Indian GDP growth. As in the case of GDP growth, New

Zealand plays the smallest role as the source of shocks. However, shocks to stock markets in other economies have sizable impacts on other economies. Australia, New Zealand and Japan are hit less adversely than other economies.

2.4.1.2 Forecast Error Variance Decompositions

We now assess the contribution of domestic shocks, other regional shocks and extra-regional shocks to the volatility of our AP economies 4 quarters ahead[4]. With 44 AP variables in our model, the importance of the region can be exaggerated if each AP variable contributes a negligible amount to the FEVD. With Canova (2005) focusing on contributions greater than 10%, we exclude contributions, from any given variable, below 5%. We examine the FEVDs of our eleven AP economies, averaged across variables, assessing the contribution from different regions and transmission channels in Figure 2.5. We then consider the FEVDs of our four AP variables, averaged across countries, assessing the contribution from different transmission channels in Figure 2.6.

Our first group of findings relate to cross-country variation in the relative importance of US[5], regional and domestic shocks (Figure 2.5 top). We find that in Australia and the small open economies of New Zealand and Singapore extra-regional shocks are relatively more important. These are also the economies in which regional shocks do not strongly dominate extra-regional shocks. This is consistent with Maćkowiak's (2007) finding that Singapore responds more strongly to extra-regional shocks than a typical emerging economy. In the case of Australia and

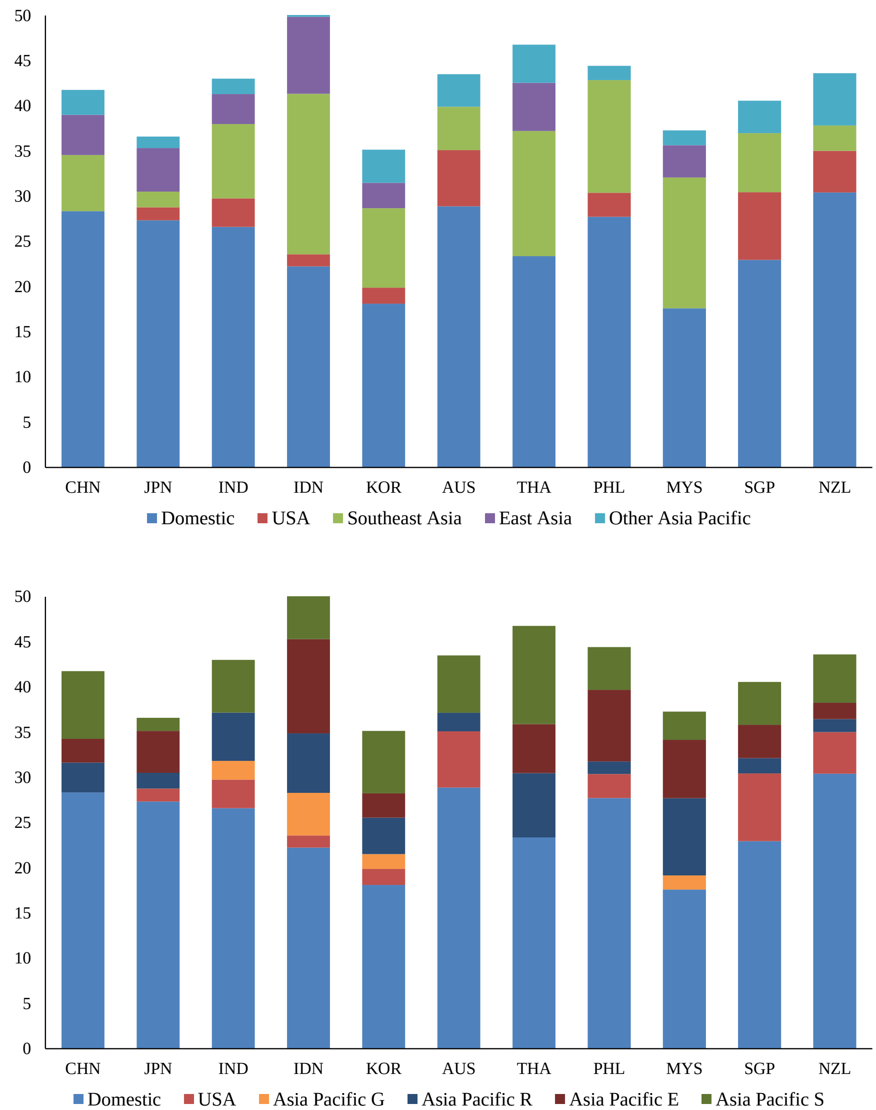
[4]The main findings also hold 12 quarters ahead

[5]US contributions reflect changes in US variables only since the oil price and non-fuel commodity price had no contributions greater than or equal to 5%.

New Zealand, domestic shocks are clearly most dominant. This reinforces findings from the previous section where Australia and New Zealand tended to be less vulnerable to foreign shocks. With the exception of Singapore, in ASEAN countries - Indonesia, Thailand, the Philippines and Malaysia - and Korea shocks from other Southeast Asian countries play a more prominent role than those from the USA, East Asia or other Asia Pacific countries. Indonesia is particularly vulnerable to foreign shocks and is also affected by East Asian shocks. By contrast, in China, Japan and India, domestic shocks clearly dominate but regional shocks explain a sizable fraction of the remaining variation. Overall, our results suggest that while extra-regional shocks cannot explain the majority of variation across economies, they still have an important role to play. This stands in contrast to Raddatz (2007) and Barrot et al. (2018) who find that extra-regional shocks have a limited role to play. Having accounted for regional shocks, neither does it fully align with Canova (2005) and Maćkowiak (2007) who find that extra-regional explain a large share of the variance.

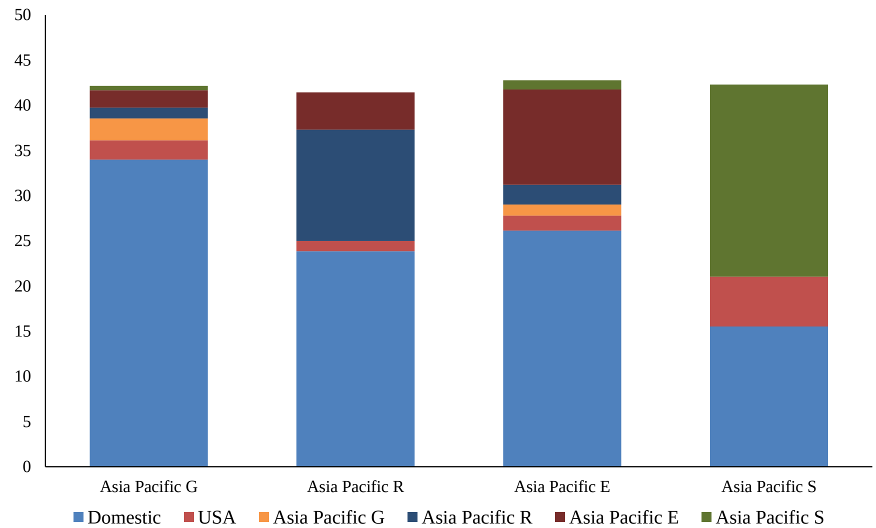
Turning to the relative importance of different transmission channels (Figure 2.5 bottom and Figure 2.6), we can see that regional movements in stock markets play an important role across countries by affecting domestic stock markets, most noticeably in China and the Philippines. In the ASEAN countries, exchange rate movements are also important influencing domestic exchnage rates and, to a lesser extent, interest rates and GDP growth. Monetary policy changes in the region matter most in Malaysia and Thailand while changes in GDP growth only play a role in Indonesia, India, Korea and Malaysia by affecting domestic GDP growth and exchange rates.

Figure 2.5: Summary of Asia Pacific Countries' Forecast Error Variance Decompositions: Contribution from each Region (Top) and Transmission Channel (Bottom)



Note: We report forecast error variance decompositions 4 quarters ahead and averaged across variables for each AP country. Southeast Asia = Singapore, Malaysia, Thailand, Phillipines, Indonesia. East Asia = China, Japan, Korea. Other Asia Pacific = India, Australia, New Zealand. We exclude contributions from individual variables below 5%.

Figure 2.6: Summary of Asia Pacific Variables' Forecast Error Variance Decompositions: Contribution from Transmission Channel



Note: We report forecast error variance decompositions 4 quarters ahead and averaged across countries for each AP variable. We exclude contributions from individual variables below 5%.

2.4.2 The Effects of Asia Pacific shocks on the US

2.4.2.1 Impulse Response Functions

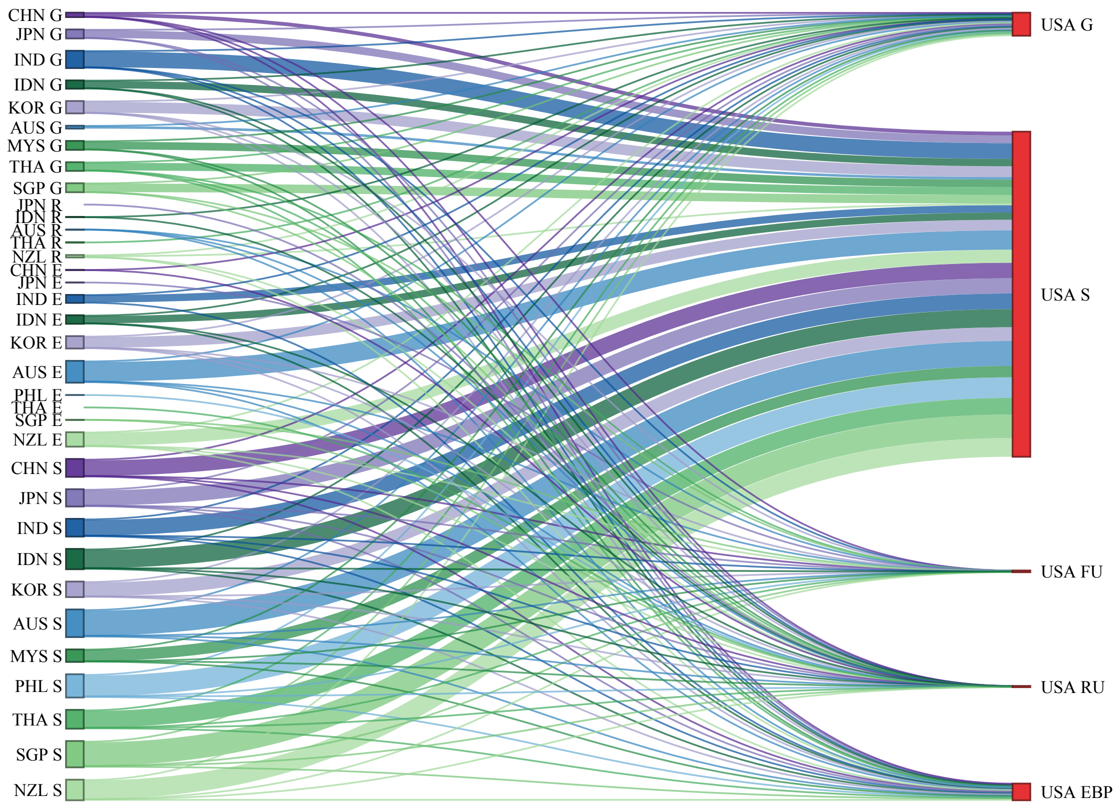
Having shown that regional shocks play a fundamental role in driving movements in AP variables, we now consider whether shocks in the Asia Pacific affect US variables[6]. Again we consider adverse shocks, summarising resulting troughs in the GIRFs of GDP growth (G), stock market growth (S) and peaks in the GIRFs of the excess bond premium (EBP) and real and financial uncertainty (RU and FU) [7] using Sankey diagrams as before. Again, we summarise our findings at the 84

[6]Domestic contributions reflect changes in US variables only since the oil price and non-fuel commodity price had no contributions greater than or equal to 5%

[7]These have been rescaled to reverse standardisation of the raw data.

percent credible interval in Figure 2.7. The full GIRFs (Figures A.53 - A.63) are provided in supplementary figure appendices (Appendix A.3.3).

Figure 2.7: Summary of Impulse Responses Showing Important Declines in Real and Financial Variables and Increases in Uncertainty Variables Following Negative Shocks



Note: We report impulse response functions for GDP growth (G), stock market growth (S), the excess bond premium (EBP), real uncertainty (RU) and financial uncertainty (FU) where there is an adverse effect which is non-zero according to the 84 percent credible interval. The width of each line corresponds to the depth of the median impulse response function's trough/peak.

We can clearly see in Figure 2.7 that the Asia Pacific has a considerable affect on US financial conditions. Stock markets in every AP country can adversely affect the US stock market. AP GDP growth also affects the US shock market although changes to economic conditions in New Zealand the Phillipines have no effect on any US variables. Australian GDP growth also plays a small role. Exchange rates movements which proved important regionally also tend to influence US variables. In contrast, Asia Pacific monetary policy exerts little affect on the US. While the Asia Pacific's affect on US stock markets is most considerable, it also exerts some influence on US GDP growth and, to a lesser extent, real and financial uncertainty.

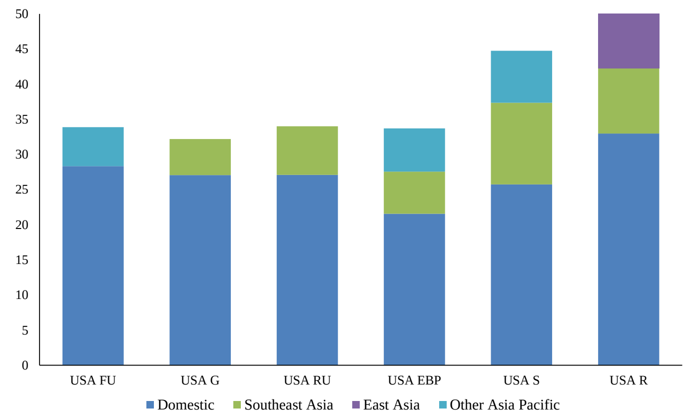
2.4.2.2 Forecast Error Variance Decompositions

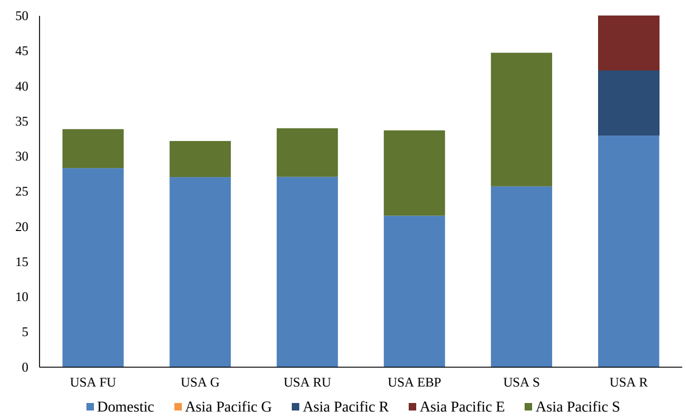
We can also assess the contribution of domestic shock and AP shocks to the volatility of our US variables 4 quarters ahead[8]. We again exclude contributions, from any given variable, below 5%. We examine the FEVDs of US variables, assessing the contribution from different regions and transmission channels in Figure 2.8.

We find Asian shocks to stock prices in Southeast Asia and other Asia Pacific countries explain a sizable fraction of the US excess bond premium and stock prices. They also affect GDP growth and, to a lesser extent, real and financial uncertainty . In contrast, monetary policy and exchange rate changes in East and Southeast Asia only explain a sizable fraction of variation in US interest rates.

[8]The main findings also hold 12 quarters ahead

Figure 2.8: Summary of US' Forecast Error Variance Decompositions: Contribution from each Region (Top) and Transmission Channel (Bottom)





Note: We report forecast error variance decompositions 4 quarters ahead and averaged across variables for each AP country. Southeast Asia = Singapore, Malaysia, Thailand, Phillipines, Indonesia. East Asia = China, Japan, Korea. Other Asia Pacific = India, Australia, New Zealand. We exclude contributions from individual variables below 5%.

2.5 Conclusion

Policymakers continue to debate whether Asia is decoupling from the US. In this chapter, we use a 52 variable Panel VAR to analyse interdependencies between the US and eleven countries in the Asia Pacific region. Unlike past research, we allow each of our twelve economies to affect one another through different transmission channels. This allows us to capture regional interdependencies and assess whether spillovers only occur from the US to Asia or whether the Asia Pacific can also influence the US.

Whilst existing studies focus on a limited set of external shocks, typically originating from the US, we depart from the literature, reclassifying external shocks as extra-regional shocks and accounting for a further set of regional shocks to economic conditions, monetary policy, financial markets and international competitiveness. We also consider the effect of shocks in the Asia Pacific on the US economy. Taking advantage of Bayesian variable selection methods, we allow irrelevant interdependencies to be excluded in a data-driven manner.

We reach one overarching conclusion: regional shocks matter. Although shocks to US economic conditions, financial markets and uncertainty are important, regional shocks play a larger role in a typical Asia Pacific country. Regional shocks to financial markets have the most sizable, widespread affects followed by shocks to regional economic conditions. Adverse effects resulting from shocks to international competitiveness in the region are less frequently observed but can be sizable. Foreign monetary policy shocks originating from the US and other AP countries are relatively less important compared to other extra-regional and regional shocks.

We also find considerable cross-country heterogeneity. In Australia and New Zealand, domestic shocks dominate with US shocks explaining a sizable fraction of the remaining variation. In Singapore, US shocks also play a more prominent role. In contrast, in China, Japan and India, domestic shocks clearly dominate but regional shocks explain a sizable fraction of the remaining variation. In ASEAN countries and Korea shocks from other Southeast Asian countries play a more prominent role than those from the USA or other parts of the Asia Pacific. Indonesia is particularly vulnerable to foreign shocks and is also affected by shocks in East Asian countries.

We also detect substantive spillovers from the Asia Pacific to the US stock market. These tend to be driven by movements in regional financial markets and, to a lesser extent, economic conditions with monetary policy in the Asia Pacific only affecting the US interest rate. Smaller spillovers are also seen to the US excess bond premium and US GDP growth.

Overall, we confirm that while Asian economies can maintain some degree of business cycle independence, regional and global integration are likely to be complementary rather than substitutable. As the Asia Pacific continues to grow, it is also important to analyse spillovers between the US and Asia Pacific from a bidirectional rather than unidirectional perspective.

Chapter 3

Interdependence or Contagion: A Model Switching Approach with a Focus on Latin America

3.1 Introduction

Contagion first gained attention in the late 1990s following a series of crises in emerging markets. More than a decade later, the global financial crisis and European sovereign debt crisis have illustrated the importance of establishing which interdependencies and transmission channels are relevant during different crises. The literature attempting to do so is already extensive. Successive surveys have summarised: different definitions of contagion (see reviews by Pericoli and Sbracia, 2003 and Forbes, 2013), different theories of contagion and early empirical methods for measuring contagion (see e.g. Claessens et al., 2000; Dungey et al., 2005 and Forbes and Rigobon, 2001a, 2001b) and the challenges associated with different empirical methods (Rigobon, 2002, 2016).

Nonetheless, despite this substantial body of research, two fundamental questions remain unresolved. First, how should we define contagion? In Forbes' survey (2013) eleven different academic definitions were listed. Second, how can we measure and test for contagion? Different definitions of contagion have resulted in different methods being deployed. It has become common practise for studies to adhere to a single definition of contagion which coheres with the method used. For instance, studies exploiting breaks in the data (e.g. using correlation breakdowns or regime switching models) often refer to "shift contagion" (see Forbes and Rigobon, 2002) where linkages between countries abruptly change or heighten. Another important issue when empirically analysing contagion is which variables to consider. With some definitions of contagion emphasising financial contagion in asset markets, the empirical literature focuses almost exclusively on financial transmission channels. This strategy risks isolating empirical work from theories of contagion which consider both real and financial transmission channels (Rigobon, 2016).

In response to the challenges above, this chapter devises a novel econometric strategy to analyse contagion. A model switching approach is used where the model dimension, model parameters and shrinkage parameters can change over time. Put differently, we allow the nature of interdependencies, magnitude of interdependencies and transmission channels selected for inclusion to change over time. We, therefore, pull together different strands of the literature in three respects. First, our framework acknowledges different theories of contagion, accounting for macroeconomic and uncertainty transmission channels as well as financial transmission channels. This allows us to analyse the relative importance and evolution of different transmission channels during different crises. Second, by incorporating a range of model features, we nest a number of different approaches to measuring contagion. We, therefore, move away from attempting to measure contagion using a single indicator. Rather, we report a range of indicators, building a holistic, but nuanced picture of interdependence and contagion over time. Third, our comprehensive approach allows us to appeal to multiple definitions of contagion, distinguishing between: interdependence (existing linkages between countries which do not heighten during crises), contagion through interdependence (existing linkages between countries which heighten during crises) and abrupt contagion (linkages between countries which abruptly change during crises).

To illustrate our approach we focus on different crisis episodes in Latin America, a region which lay at the centre of early research on contagion and continues to experience considerable economic turbulence. Our data spans 1988:01 - 2016:08. We consider the three largest economies in the region, Argentina, Brazil and Mexico, denoted the LA-3, whilst also accounting for linkages with the US. For each Latin American (LA) country, we estimate a set of nearly 30,000 different Bayesian Vector Autoregressions (VARs) and Panel Vector Autoregressions (PVARs) with time-varying coefficients, time-varying volatilities and exogenous variables. We thus denote our models as TVP-VAR-Xs and TVP-PVAR-Xs respectively. We switch between these different models, selecting the optimal model at each point in time.

Incorporating time-varying coefficients and time-varying volatilities has a number of advantages. First, we allow the magnitude of interdependencies to change over time. Specifically, we allow the magnitude of correlations between countries and the magnitude of volatility spillovers between countries to evolve over time.

Or, using the terminology of the PVAR literature (see Canova and Ciccarelli, 2013), we allow dynamic interdependencies (DIs) and static interdependencies (SIs) to be time-varying. Second, heteroskedasticity, a common feature of financial data, can falsely lead to the conclusion that contagion is present (Rigobon, 2016). By distinguishing between time-variation in the coefficient and covariance matrices we surmount this empirical challenge.

Each of our models has different characteristics. By selecting the optimal model at each point in time, relevant interdependencies and transmission channels are revealed. First, our models are characterised by different shrinkage parameters, allowing different groups of variables to be included/excluded. This allows for switching between models which include/exclude different transmission channels. Second, to capture different types of interdependencies, our set of models are characterised by different dimensions. This allows for switching between small "domestic" TVP-VAR-Xs, medium sized "bilateral" TVP-PVAR-Xs and "regional" TVP-PVAR-Xs. Across all dimensions, the variables associated with the LA country of interest are endogenous and US variables are exogenous. Importantly, however, we allow the variables associated with other LA countries to enter exogenously into our TVP-VAR-Xs and endogenously into our TVP-PVAR-Xs. This strategy is pursued in order to reveal and distinguish between DIs (i.e. correlations) and SIs (i.e. volatility spillovers). While interdependencies are possible in all our models, in our TVP-VAR-Xs only DIs can be selected whereas in our TVP-PVAR-Xs both DIs and SIs can be selected.

This chapter relates to different strands of the econometric literature. First, our model switching strategy combines and extends insights from the dynamic model selection literature. In particular, we build on the dynamic model learning strategy of Beckmann et al. (2020) by introducing dimension switching (see Koop, 2014 and Koop and Korobilis, 2013). We also tailor our shrinkage parameters so that different transmission channels can be included/excluded. Second, our approach draws on insights from the PVAR literature. Koop and Korobilis (2016) consider the existence of DIs and SIs in a constant parameter setting using variable selection methods. However, our approach allows us to establish the existence and magnitude of DIs and SIs over time.[9]

In terms of the contagion literature, our model switching approach relates to studies which use regime switching methods and time-varying parameters (TVP). Regime switching methods can capture crisis and non-crisis regimes without arbitrarily specifying when break dates occur (see, among many others, Gravelle, 2006 as an early example and Casarin et al., 2018a and Chan et al., 2018 for recent examples). However, if only focusing on two regimes, it may be difficult to discern between times when linkages between countries are weak and when they are strong (Ciccarelli and Rebucci, 2007). In response, Ciccarelli and Rebucci (2007) devise a TVP model which can be used in the presence of heteroskedasticity and omitted variables.

Our approach incorporates both the abrupt change seen in regime switching models and gradual change seen in TVP models. We achieve this by estimating the degree of model switching and time-variation in parameters at each point in time following Beckmann and Schüssler (2016) and Beckmann et al. (2020). Moreover, while we allow for model switching we are not restricted to focusing on two regimes.

[9]Koop and Korobilis (2019) also adapt dynamic model averaging/selection methods to estimate PVARs. However, their focus is on forecasting in a high-dimensional context rather than understanding the nature and evolution of interdependencies between countries.

We also draw inspiration from Ehrmann et al. (2011) and Beirne and Gieck (2014) who go beyond analysing individual asset prices movements. Instead, they jointly consider interest rates, stock prices, government bond yields and exchange rates. We move one step further incorporating macroeconomic and uncertainty variables into our framework.

Turning to our results (see Table 3.1 for a summary), we tend to find evidence of interdependence rather than contagion during the Mexican currency crisis of 1994, Brazilian currency crisis of 1999 and Argentine crisis. During these crises, financial interdependencies are most crucial, although macroeconomic interdependencies also play a role in the Mexican peso crisis and Argentine crisis. In Mexico, and to a lesser extent Argentina, volatility spillovers in exchange rates and stock markets are also important during the above crises.

In contrast, during the global financial crisis there is evidence of abrupt contagion spreading from the US to Brazil and Argentina. In particular, we find that US uncertainty abruptly affects both countries. The US excess bond premium, an indicator of financial distress, also becomes important while changes in US macroeconomic fundamentals affect Brazil more than Argentina. Importantly, movements in US uncertainty variables and the excess bond premium do not only affect stock prices in Argentina and Brazil. Instead, they also have a significant impact on industrial production. During the global financial crisis, contagion is also seen from the US to Mexico, but through pre-existing macroeconomic and financial interdependencies. US uncertainty variables also affect Mexico before and during the crisis. Overall, we demonstrate that contagion has only manifested in the recent global financial crisis. Our results also illustrate the importance of moving beyond financial variables to consider a wider range of transmission channels.

Table 3.1: Summary of Key Findings

	Interdependence	Contagion via Interdependence	Abrupt Contagion
Mexican Currency Crisis (1994)	✓ F, M		
Brazilian Currency Crisis (1999)	✓ F		
Argentine Crisis (1998 - 2002)	✓ F, M		
Financial Crisis (2007 - 2009)		✓ F, M, U	✓ F, M, U

Note: F, M and U correspond to financial, macroeconomic and uncertainty transmission channels. The table indicates which of these channels were present during different crises. For brevity, we refer to LA stock price and exchange rate channels under the broader term of financial transmission channels.

In the section that follows, we critically review and contrast different definitions of contagion. We then outline our empirical strategy in section 3.3, describing how our data and model switching approach relates to different definitions of contagion. Section 3.4 presents our results, first providing a comparative overview and then delving deeper into historical episodes of crisis. Section 3.5 summarises our key conclusions. The Chapter 3 appendix includes a data appendix (Appendix B.1) and additional figures (Appendix B.2).

3.2 Definitions of Contagion

Many attempts have been made to adequately define contagion with Forbes' survey (2013) revealing a broad spectrum of opinions. Forbes' survey also illustrates the trade-off between academic definitions of contagion and definitions likely to be favoured by policymakers. The former must be sufficiently precise to guide empirical work while the latter tend to be broader in order to encompass a wider range of crises. For instance, a looser but widely applicable definition of contagion is "when an extreme negative event in one country affects others" (Forbes, 2013, p.24). This can be contrasted with five academic definitions presented by Pericoli and Sbracia (2003, p.574-575) which continue to be widely cited in the literature. We reproduce them here to aid further discussion:

> Definition 1. *Contagion is a significant increase in the probability of a crisis in one country, conditional on a crisis occurring in another country.*
>
> Definition 2. *Contagion occurs when volatility of asset prices spills over from the crisis country to other countries.*
>
> Definition 3. *Contagion occurs when cross-country comovements of asset prices cannot be explained by fundamentals.*
>
> Definition 4. *Contagion is a significant increase in comovements of prices and quantities across markets, conditional on a crisis occurring in one market or group of markets.*
>
> Definition 5. *(Shift-)contagion occurs when the transmission channel intensifies or, more generally, changes after a shock in one market.*

While the above definitions appear diverse, they do share some common aspects. First, many definitions tend to provide an indication of the method required to measure and test for contagion. Definition 2, for instance, refers to volatility spillovers. This becomes a natural definition to work with when using methods which allow for time-varying volatility such as GARCH models. Definitions

3 and 4, on the other hand, make reference to comovements and may prove appropriate when examining how correlations among variables change over time. Finally, shift-contagion, discussed in definition 5, implies a break in the data generating process, making it popular among studies which deploy regime switching models or consider correlation breakdowns. The fact that there is often a direct relationship between definitions and methods may seem beneficial to empirical researchers, particularly when contrasted with the looser definition provided by Forbes (2013). However, it may be undesirable to focus on a single or narrow range of indicators to determine whether contagion is present.

The second feature shared by some definitions is the reference made to transmission channels. In definitions 2 and 3 financial markets are key. Definition 3 further requires that for comovements in asset prices to be indicative of contagion they should not be driven by changes in fundamentals. This caveat can be traced back to early work by Calvo and Reinhart (1996) who distinguish between "fundamentals-based" contagion and "true" contagion. Fundamentals-based contagion refers to shocks transmitted through pre-existing real and financial linkages while true contagion marks a change in conventional linkages. Over time, the literature has redefined fundamentals-based contagion simply as interdependence.

Despite definitions of contagion which stress fundamentals, recent empirical studies focus on financial markets. This may be driven by definitions which emphasise asset prices as well as a desire to capture the "fast and furious" contagion outlined by Kaminsky et al. (2003, p.55). Empirically, this rules out including macroeconomic time series which cannot be captured at a daily or weekly frequency. This failure to account for different transmission channels has resulted in the distinction between interdependence and contagion becoming more difficult to quantify empirically.

The third common feature across some definitions of contagion is the reference made to the strength of linkages between countries. Definitions 4 and 5 stress that there is a "significant increase" or "intensification" in linkages between countries if contagion is present. Similarly, Kaminsky et al. (2003, p.55) only consider the effects of a common external shock contagious if there is " 'excess comovement' in financial and economic variables across countries". These definitions express the same sentiment: if, following a shock, linkages are stronger than during "normal times" contagion is present. However, it is difficult to precisely pin down what should be considered "normal" or "in excess" (Rigobon, 2016). What is considered the "normal state" of the economy may vary over time as an economy develops or undergoes structural change. These issues are especially potent in emerging markets where greater economic turbulence and change is experienced.

3.3 Empirical Strategy

We begin this section by describing our data, emphasising how a wider range of variables can be included to capture different transmission channels. We then provide details of our econometric methods. We consider how different model specifications, shrinkage parameters and discount factors can be used to analyse how the relevance and strength of different interdependencies and transmission channels evolve over time. We then describe how we estimate our different models and select the optimal model at each point in time. Finally, we summarise how our model switching approach relates to multiple definitions of contagion.

3.3.1 Capturing Different Transmission Channels

We collect monthly data spanning 1988:01 - 2016:08 on Argentina (ARG), Brazil (BRA), Mexico (MEX) and the US. Our study, therefore, captures severe contagion which has long-lived consequences lasting months rather than days. This marks an important shift from the recent literature which focuses on high frequency data. Importantly, however, using monthly data allow us to introduce measures of macroeconomic fundamentals into our model and consider macroeconomic linkages between countries. Additionally, we can now also consider macroeconomic and financial uncertainty originating from the US. Accounting for a wider range of variables will aid us later when distinguishing between: interdependence, contagion through interdependence and abrupt contagion through a change in linkages.

Our choice to focus on Latin America, and the LA-3 in particular, is motivated by several factors. First, Latin America was prominent in early studies of contagion but has received relatively less attention in recent years. Latin America has, however, experienced numerous crises which differ in nature. This makes it an important and useful region should we wish to compare and understand different types of contagion. Second, we wish to demonstrate the applicability of our approach even when using data which is susceptible to structural breaks and greater time-variation. Third, we focus on the LA-3 in particular since these economies are unlikely to be affected by their smaller neighbours, reducing the risk of omitted variables bias. We do, however, account for the US which we would expect to have important effects on the LA-3, particularly Mexico.

Following Beirne and Gieck (2014) and Ehrmann et al. (2011), we begin by including different asset prices in our model. For all LA economies we include measures of the real effective exchange rate and the stock price index. Due to a lack of data, we omit government bond yields. To account for macroeconomic fundamentals we also include the following measures for each LA country: industrial production, inflation and short-term interest rates. Notably, it is important to obtain accurate inflation data given episodes of hyperinflation during the sample period.

For the US, we include measures of: the stock price index, industrial production, inflation and the short-term interest rate. During times when the interest rate is at the zero lower bound, the shadow interest rate developed by Wu and Xia (2016) is used so that we can capture the effects of unconventional monetary policy. Additionally, we include measures of US macroeconomic and financial uncertainty constructed by Ludvigson et al. (2019). This reflects recent research on the link between uncertainty and contagion (see e.g. Kannan and Koehler-Geib, 2011), a strand of the literature still in its infancy. We also include the US excess bond premium, an indicator of financial distress developed by Gilchrist and Zakrajšek (2012). Non-fuel commodity prices and the oil price are also included in the model. These are particularly important in our context, given the prominence of non-fuel commodities in Argentina's and Brazil's exports. Mexico's reliance on non-fuel commodities, over our sample period, is considerably less. All three countries, however, are oil producers. Traditionally, Brazil has been a net importer, Argentina has been relatively self-sufficient and Mexico has been a net exporter.

Table 3.2: Assigning Variables to Transmission Channels

Variable	Transmission Channel	Abb.	Transf.
Real industrial production	Macro fundamentals of country i	MF	Δ ln
Inflation (% MOM)	Macro fundamentals of country i	MF	levels
Short-term interest rate	Macro fundamentals of country i	MF	Δ
Real effective exchange rate	Exchange rate of country i	FX	Δ ln
Stock price index	Stock price index of country i	SP	Δ ln
Real industrial production	Macro fundamentals of country i	MF	Δ ln
Inflation (% MOM)	Macro fundamentals of country i	MF	levels
Short-term interest rate	Macro fundamentals of country i	MF	Δ
Stock price index	Financial indicators of US	F	Δ ln
Excess bond premium	Financial indicators of US	F	levels
Macro uncertainty	Uncertainty indicators of US	U	levels
Financial uncertainty	Uncertainty indicators of US	U	levels
Non-fuel commodity price	Commodity prices	$COMM$	Δ ln
Oil price	Commodity prices	$COMM$	Δ ln

Each variable is assigned a category according to the transmission channel it characterises. We have thirteen categories in total. There are three categories per LA country: macroeconomic fundamentals, the stock price index and the exchange rate. These account for macroeconomic and financial interdependencies. There are four categories relating to the US and commodities: macroeconomic fundamentals, financial indicators, uncertainty indicators and commodity prices. We can also think of these four categories as representing global transmission channels through which extra-regional shocks are transmitted. With the exception of commodity prices, we follow the transformations recommended by McCracken and Ng (2016) to achieve stationarity. All variables are also standardised.

Details regarding the variables, the transmission channel they belong to, the abbreviation associated with each transmission channel and data transformations are summarised in Table 3.2. Information relating to the LA-3 can be found in the upper section while details relating to the US and commodities can be found in the lower section. Further details on how data was sourced and selected, particularly for the LA-3, can be found in Appendix B.1.

3.3.2 Analysing the Evolution of Different Interdependencies and Transmission Channels

For each LA country, we estimate 29,952 TVP-VAR-Xs and TVP-PVAR-Xs. Our models are carefully chosen to reflect a wide array of possible restrictions in terms of interdependencies between countries. Moreover, the number of models under consideration exceed that considered in previous studies using dynamic model selection/averaging methods.[10]

Our characterisation of the model space adapts and extends the methods in Beckmann et al. (2020). However, we emphasise where our approach differs. Each of our models is characterised by four elements. First, unlike Beckmann et al. (2020), we define the model specification for each model. This describes the dimension of the model and the way in which other countries' variables enter the model. We follow Koop (2014) and Koop and Korobilis (2013) by allowing for dimension switching. Specifically, we can switch between "domestic", "bilateral" and "regional" models over time. By allowing different models to have different specifications for which variables are exogenous and endogenous, we can also switch

[10]Koop and Korobilis (2013) allow for 216 models in their forecasting exercise while Beckmann et al. (2020) consider 9,216 in their study of exchange rate predictability.

between models which allow for DIs (i.e. correlations) and models which allow for both DIs and SIs (i.e. volatility spillovers). Thus the nature of interdependencies can evolve over time.

Second, each model is characterised by a set of shrinkage parameters, γ. These determine which endogenous coefficients and exogenous variables are included/excluded from each model. Beckmann et al. (2020) assign a shrinkage parameter to each exogenous variable. However, we assign a shrinkage parameter to each group of variables belonging to the same transmission channel (see Table 3.2). Switching between models with different shrinkage parameter values allows us to identify which transmission channels are selected for inclusion/exclusion at each point in time.

Third, our models are characterised by a discount factor, λ, which determines the degree of time-variation in the coefficient matrix. Fourth, our models are characterised by a second discount factor, δ, which determines the degree of time-variation in the covariance matrix. Thus we can switch between models which have different degrees of time-variation in the coefficient and covariance matrices.

To begin formalising these ideas, let us write a single TVP-VAR-X in state space form

$$y_t = x_t\beta_t + \varepsilon_t, \quad \varepsilon_t \sim N(0, \Sigma_t), \tag{3.1}$$

$$\beta_{t+1} = \beta_t + u_t, \quad u_t \sim N(0, \Omega_t), \tag{3.2}$$

where y_t for $t = 1, ..., T$ is an $M \times 1$ vector containing observations on M time series variables. The matrix β_t is an $M \times k$ matrix where each row contains an intercept, N (lagged) exogenous variables and p lags of each of the M variables. This means that there are $k = M(1+pM+N)$ elements in β_t. To reflect the relatively fast nature of contagion we include the first lag of exogenous variables in all our models. Similarly, we set $p = 4$ so our models capture short-term movements in variables spanning months rather than years. Deviance information criteria also confirm that shorter lag lengths of 2, 3 and 4 are preferred to lag lengths between 5 and 12. Thus a lag length of 4 reflects a conservative choice.

Denoting the LA country under consideration as country 1, we describe our five possible model specifications in Table 3.3. Across all specifications, the variables associated with the LA country of interest are endogenous and US variables are exogenous. This follows Canova (2005) who verifies that current and lagged values of Latin American variables do not influence the US. We then specify whether we have (i) a domestic TVP-VAR-X where other LA variables, US variables and commodity prices enter the model exogenously or (ii) a bilateral/regional TVP-PVAR-X where other LA variables are endogenous and US variables and commodities are exogenous. In the former case, we only have DIs (i.e. correlations) between countries: lagged country 2 and 3 variables can affect country 1 variables. In the latter instance, SIs (i.e. volatility spillovers) are also present: we can have non-zero correlations between the reduced-form errors of different countries.

Exogenous variables can enter the domestic TVP-VAR-X in different ways. Model specification 1 differs from specification 2 by only allowing exogenous LA regressors to enter equivalent equations. For instance, country 2 and 3 stock prices can only enter country 1's stock price equation. Put differently, each exogenous LA variable can only affect a specific market rather than the entire economy. We find that this specification is necessary to capture certain crises.

Table 3.3: Model Specifications

	Dimension	Endog. Variables	Exog. Variables	Exog. Variables Enter	Links	No. of TCs
1.	Dom. VAR	Country 1	Countries 2,3,US	Equiv. equations (LA), all equations (US)	DIs	10
2.	Dom. VAR	Country 1	Countries 2,3,US	All equations	DIs	10
3.	Bil. PVAR	Countries 1,2	US	All equations	DIs, SIs	7
4.	Bil. PVAR	Countries 1,3	US	All equations	DIs, SIs	7
5.	Reg. PVAR	Countries 1,2,3	US	All equations	DIs, SIs	10

Note: TVP-(P)VAR-X has been abbreviated to (P)VAR for clarity. Country 3 is larger than country 2 as measured by GDP. TCs denotes transmission channels. The US denotes US variables and commodity prices.

A final point noted in Table 3.3 is the number of potential transmission channels through which shocks can be transmitted. For each model specification, shocks can be transmitted from country 2 and/or 3 via the following transmission channels: macroeconomic fundamentals, stock prices and the exchange rate. Thus if countries 2 and 3 are both included in a model they account for six transmission channels. US and commodity price shocks can also be transmitted via the following four global transmission channels: macroeconomic fundamentals, financial indicators, uncertainty indicators and commodities.

Having established a framework which allows us to assess how the nature of interdependencies evolve over time, we now develop an approach to assess the relative importance of different transmission channels over time. Since our estimation procedure is Bayesian, this can be achieved through setting a prior for the initial conditions:

$$\beta_0 = N(0, \Omega_0). \tag{3.3}$$

The prior mean on our VAR coefficients is set to zero. The diagonal elements, γ, of our prior covariance matrix, Ω_0, determine the degree of shrinkage associated with different groups of coefficients. If a shrinkage parameter is set to 0.01 the associated coefficients undergo moderate shrinkage and remain in the model. If instead a shrinkage parameter is set to 0 the associated coefficients are excluded from the model. Moreover, if the coefficients belong to an exogenous variable it is removed entirely from the model. Like Koop (2014) we are not required to rescale our shrinkage parameters since we standardise our variables.

We build on Beckmann et al. (2020) who use 10 independent shrinkage parameters to determine the degree of shrinkage associated with 10 groups of coefficients. Recall that the LA country under consideration is denoted country 1. We can include/exclude groups of coefficients from country 1 VAR equations (i.e. equations 1 - 5) by allowing different models to have different sets of shrinkage parameters. For any given model specification, 7 - 10 transmission channels will be of interest as shown in Table 3.3. We, therefore, assign a Minnesota shrinkage parameter, γ_j, to each group of coefficients belonging to the same transmission channel (i.e. for $j = 1, .., TC$ where $TC \in \{7, 10\}$). We allow $\gamma_j \in \{0, 0.01\}$ thus different models reflect different assumptions about which transmission channels are relevant. Switching between models with different shrinkage parameter values allows us to include/exclude different transmission channels at each point in time.

In practise, we must also specify shrinkage parameters for: intercepts, coefficients associated with country 1 own lags and country 1 cross lags. Denoting the coefficients associated with country 1 variables as "domestic" and other coefficients as "foreign", the shrinkage parameters associated with country 1 VAR equations are summarised in Table 3.4. The upper part of the table is required when estimating all 5 model specifications. Additionally, we require the second and third part of the table when estimating model specification 1. For model specification 2, we require the third part of the table. To estimate model specifications 3, 4 and 5 we require the third and fourth part of the table. Moreover, we specify that for country 2 and 3 equations coefficients on own lags have shrinkage parameter 0.01 and coefficients on all cross lags have shrinkage parameter $\frac{0.01}{2r^2}$ $r = 1, ...p$.

In addition to a model specification and a set of shrinkage parameters each model is characterised by two discount factors. The first discount factor, δ, must lie in the interval $0 < \delta \leq 1$ and determines the degree of time-variation in the covariance matrix. We use the following grid - $\delta \in \{0.8, 0.88, 0.96\}$ - where low values are associated with greater time-variation and high values are associated with a lower degree of time-variation. Since we work with heteroskedastic financial data we do not nest a model with constant covariance.

The second discount factor, λ, must also lie in the interval $0 < \lambda \leq 1$ and determines time-variation in the coefficient matrix. The following grid is used - $\lambda \in \{0.96, 0.99, 1\}$ - with high and low values having the same interpretation as above. In this case, we do nest the constant coefficient case since it is a possibility. Thus we can switch between models which have different values of δ and λ allowing the degree of time-variation to evolve over time.

Table 3.4: Shrinkage Parameters for Country 1 VAR Equations, Equations 1 - 5

Coefficients	Values of γ
Intercept	0.01
Coefficients on own lag $r = 1, ..., p$	0.01
Coefficients on domestic cross lags $r = 1, ..., p$	$\frac{0.01}{Dr^2}$
Coefficients on first group of equation-specific exogenous variables	0 or 0.01
...	
Coefficients on last group of equation-specific exogenous variables	0 or 0.01
Coefficients on first group of exogenous variables	0 or 0.01
...	
Coefficients on last group of exogenous variables	0 or 0.01
Coefficients on first group of foreign cross lags $r = 1, ..., p$	0 or $\frac{0.01}{r^2}$
...	
Coefficients on last group of foreign cross lags $r = 1, ..., p$	0 or $\frac{0.01}{r^2}$

Note: $D = 1$ if we have a domestic TVP-VAR-X whilst $D = 2$ if we have a bilateral or regional TVP-PVAR-X.

3.3.3 Estimation Procedure

Having outlined the four features which characterise each model, we now describe our estimation procedure. We deploy the same algorithm as Beckmann et al. (2020), updating the parameters for each period using the Kalman filter. Here, we discuss important steps in the procedure, but for further details the reader is referred to Beckmann et al.'s Online Appendix. Let $y^s = (y_1, ..., y_s)'$ denote observations from $t = 1, ..., s$ and $t|t-1$ denote estimates of this period's parameters using information available last period. The key ingredient required to evaluate each model is the predictive density

$$\hat{y}_t|y^{t-1} \sim t(y_{t|t-1}, x_t \Omega_{t|t-1} x_t' + Q_{t|t-1}), \tag{3.4}$$

where $\hat{y}_t = x_t \beta_{t|t-1}$.

Since Ω_t is unobserved we use our discount factor λ to produce an approximation

$$\Omega_{t|t-1} = \frac{1}{\lambda} \Omega_{t-1|t-1}. \tag{3.5}$$

Similarly, since Σ_t is unobserved, we specify that it follows an Inverse Wishart distribution with δn_{t-1} degrees of freedom and scale matrix S_{t-1}

$$\Sigma_{t|t-1} \sim IW(\delta n_{t-1}, S_{t-1}), \tag{3.6}$$

with expected value

$$E(\Sigma_{t|t-1}) := Q_{t|t-1} = \frac{S_{t-1}}{\delta n_{t-1} + M - 1}, \tag{3.7}$$

and where the degrees of freedom and scale matrix are initialised as follows using

$$n_0 = \frac{1}{1 - \delta}, \tag{3.8}$$

$$S_0 = I_M, \tag{3.9}$$

both of which are common choices in the literature.

After estimating the parameters for each of our 29,952 models we must select the optimal model at each point in time. We do so using dynamic model learning (see Beckmann and Schüssler, 2016 and Beckmann et al., 2020), selecting the model with the highest discounted joint log predictive likelihood at each point in time. Since they have a different number of dependent variables, the predictive likelihoods (i.e. the predictive density for the dependent variables evaluated at the actual outcome) from VARs of different dimensions are not directly comparable (Koop, 2014). We, therefore, use the predictive likelihood for the country 1 variables which are common to all models. The discounted joint predictive likelihood (DPL) can be calculated as

$$DPL_{t|t-1,j} = \prod_{i=1}^{t-1} [p_j(y_{t-i}|y^{t-i-1})]^{\alpha^i}, \tag{3.10}$$

where $[p_j(y_{t-i}|y^{t-i-1})]^{\alpha^i}$ denotes the predictive likelihood of model j in period i.

It can be seen that at time τ the DPL utilises information on past model performance from $t = 1, ..., \tau - 1$. Thus, at any given point in time, model j receives a higher DPL if past model performance has been effective as measured by the predictive likelihood. The extent to which past model performance is considered is determined by the discount factor α which can adopt a range of values reflecting different degrees of model switching: $\alpha \in \{0.001, 0.01, 0.1, 0.2, 0.4, 0.6, 0.8, 0.9, 0.95, 1\}$. Model performance k periods ago receives approximately α^k as much weight as last period's model performance when calculating the DPL. For example, if $\alpha = 0.4, 0.6, 0.9$ or 0.95, model performance 6 months ago receives approximately 1%, 5%, 53% and 74% as much weight respectively. If $\alpha = 1$ we simply have Bayesian model selection using marginal likelihoods. Our grid, therefore, spans rapid to moderate model switching.

It should be emphasised that at each point in time, τ, we select the value of α which produces the model with the highest product of predictive likelihoods from $t = 1, ..., \tau$. This allows us to select the degree of model switching using a real-time data-driven approach. For a given value of α, we then calculate the DPL for each of our models. By having two discount factors which control time-variation in model parameters, λ and δ, and a discount factor, α, which later determines the degree of model switching we capture both gradual and abrupt time-variation.

3.3.4 Relating Our Model Switching Approach to Multiple Definitions of Contagion

In section 3.2, we demonstrated that different definitions of contagion typically have three features in common: they provide an indication of which method should be used to analyse contagion, they make reference to specific transmission channels and they make reference to an increase in the magnitude of linkages between countries. In selecting our data and devising our model switching approach, we have considered these three aspects in order to appeal to multiple definitions of contagion.

First, we appeal to multiple definitions by incorporating a number of different methods for measuring contagion into our approach. In particular, we can jointly consider DIs between countries via the coefficient matrix (i.e. correlations), SIs between countries via the covariance matrix (i.e. volatility spillovers) and sudden shifts in linkages indicated by model switching. Our approach thus allows us to combine the insights that would be obtained from using GARCH models, regime switching models and analysing correlation breakdowns.

Second, we have included a wide range of transmission channels and devised a means to assess their changing relevance. This allows us to establish when crises spread through pre-existing linkages between countries or through a sudden change in linkages. We can thus appeal to definitions of contagion which focus on asset markets as well as definitions which distinguish between fundamentals-based contagion (i.e. contagion through interdependence) and true contagion (i.e. contagion through an abrupt change in linkages).

Third, by allowing for time-varying parameters, we can analyse magnitude: the extent to which DIs and SIs intensify or weaken over time. This appeals to definitions of contagion which stress that linkages between countries should intensify. When recording DIs in bilateral and regional TVP-PVAR-Xs, where all LA variables are endogenous, we record the values associated with first lags to retain comparability with our other model specifications.

By assessing the relevancy of different transmission channels and the evolution and magnitude of DIs and SIs we distinguish between: interdependence, contagion through interdependence and abrupt contagion. If linkages are present between countries prior to a crisis and these do not change during a crisis, we call this interdependence. If, however, linkages are present between countries prior to a crisis and they increase in magnitude during a crisis, we call this contagion through interdependence. If the nature of linkages between countries abruptly change during a crisis, with different transmission channels becoming relevant, we call this abrupt contagion. Importantly, DIs can intensify when coefficients are constant if a transmission channel is selected for inclusion following several periods of exclusion.

We explore DIs and SIs rather than estimating impulse response functions for a number of reasons. First, our model specifications have been devised to illustrate different interdependencies, but make it difficult to compare impulse responses over time. This is exacerbated by the fact that specifications are often chosen in which other country variables are exogenous and only enter specific equations. DIs and SIs are, however, comparable over time. Second, our results indicate that it would be difficult to impose a causal ordering on our countries and variables without making unrealistic identifying assumptions. This is unsurprising given that we focus on countries which have experienced considerable economic turbulence over the sample period. We, therefore, follow Canova and Ciccarelli (2013) and Koop and Korobilis (2016) in extracting economically relevant information from the reduced-form of our TVP-VAR-Xs and TVP-PVAR-Xs. However, when examining the magnitude of DIs and SIs we interpret our results with caution since we have not disentangled causality.

3.4 Results

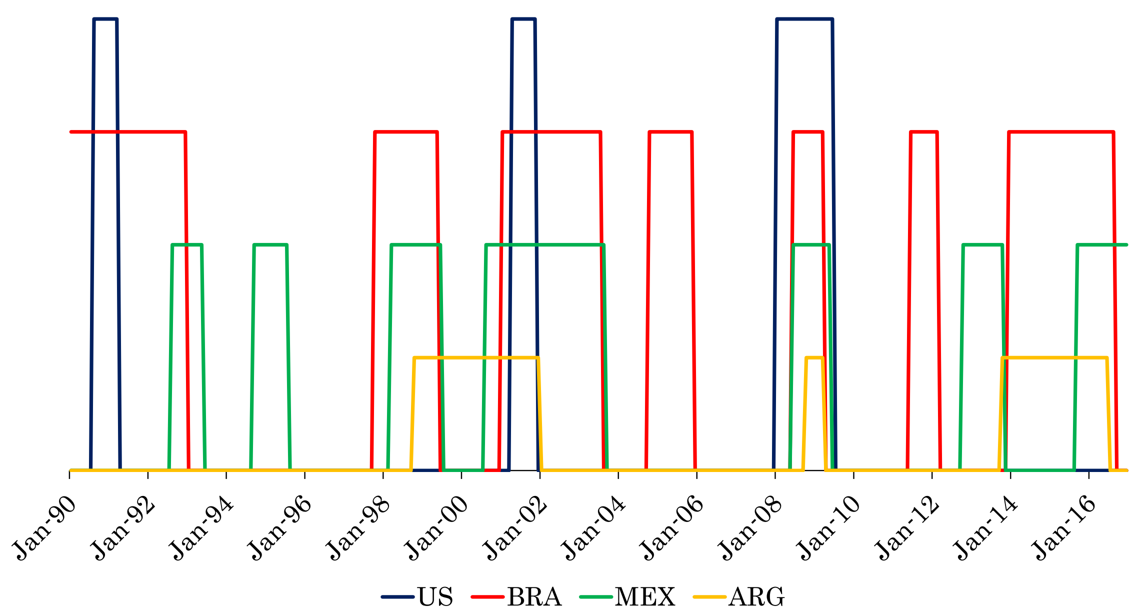
We begin by presenting a timeline of events in our countries of interest. We then provide a comparative overview of our results. Focusing on January 1990 onwards, we then select and examine in detail three crisis episodes.[11] In considering these episodes, we analyse whether interdependence, contagion through interdependence or abrupt contagion were present. Notably, results presented are for the transformed variable unless otherwise stated. We do not consider the role played by the 1997 Asian financial crisis or 1998 Russian financial crisis.

[11]For clarity, we focus on three episodes but there are undoubtedly others we could consider.

3.4.1 Timeline of Events

To aid interpretation of our results, we provide a timeline of recessions (see Figure 3.1 where a non-zero event indicates a recession for the respective country) and key economic and financial events (see Table 3.5) in the LA-3 and US from 1990 - 2016. We briefly summarise the experience of each of the LA-3 economies as follows.

Figure 3.1: Recessionary Periods in the LA-3 and US: 1990 - 2016



Sources: NBER and OECD recession indicators for the US, Brazil and Mexico were obtained from St Louis Fed data. Dates are approximate for Brazil prior to 1996 and Argentina.

Argentina experienced considerable economic turbulence from 1998 - 2002. This culminated in banking, sovereign debt and currency crises. Thereafter, Argentina experienced high growth rates with a quick recovery following the global financial crisis. In subsequent years currency controls were imposed, inflation rose with official figures being discredited and Argentina selectively defaulted after failing to reach an agreement with holdout investors.

In Brazil, the 1990s began with a severe recession and ended with the 1999 currency crisis. Consequently, Brazil abandoned the US dollar peg and adopted inflation targeting. Despite pursuing more conventional policies, Brazil has experienced modest growth rates compared to Argentina. Recently, the fall in commodity prices, rising fiscal deficit and political crisis led to Brazil entering its worst recession over the sample period.

Relative to Argentina and Brazil, Mexico has pursued increased trade and, to a lesser extent, financial openness. The North American Free Trade Agreement came into effect in January 1994. Nonetheless, after recovering from a currency crisis in 1994, Mexico has continued to experience sluggish growth rates and mild recessions. The exception was the recession following the global financial crisis which was short but deep.

As shown in Table 3.5, we can split our sample into three distinct periods which we examine in subsequent sections. First, we focus on currency crises experienced by Mexico and Brazil in the 1990s, the subject of early contagion research. Second, we analyse whether interdependence and contagion were present in the Argentine crisis from 1998 - 2002. Last, we consider the global financial crisis which inspired a new wave of literature on contagion. Before considering each of these, however, we present a comparative overview of our results.

Table 3.5: Selected Economic and Financial Events in the LA-3 and US: 1990 - 2016

Date	Description
1994, Dec	Brazilian banking crisis begins.
1994, Dec	Mexican banking crisis begins.
1994, Dec	**Mexican currency crisis: peso is devalued and allowed to float.**
1996	Mexican banking crisis ends.
1998	Brazilian banking crisis ends.
1999, Jan	**Brazilian currency crisis: real is devalued and allowed to float.**
2000, Mar	Dotcom bubble bursts.
2001, Nov	**Argentine banking crisis begins.**
2001, Dec	**Argentine sovereign debt crisis: intention to default announced.**
2002, Jan	**Argentine currency crisis: peso is devalued and allowed to float.**
2003	**Argentine banking crisis ends.**
2007, Feb	First signs of the subprime mortgage crisis.
2007, Jul	**Global liquidity crisis begins.**
2007, Dec	US banking crisis begins, followed by banking crises worldwide.
2008, Sep	Lehman Brothers files for bankruptcy.
2011, Nov	Argentina imposes currency controls.
2014, July	Argentine selective default.
2015, Dec	Argentina lifts currency controls allowing peso to float freely.

Sources: Information on banking crises, sovereign debt crises and currency crises was extracted from Laeven and Valencia (2013) and the corresponding database on systemic banking crises. We exclude crises which Laeven and Valencia (2013) consider borderline.

3.4.2 A Comparative Overview

We first consider which types of interdependencies are important over time. To do so, for each country, we examine which model specification is selected at each point in time. This is shown in the top panels of Figures 3.2 - 3.4. Recall that model specifications 1 and 2 involve TVP-VAR-Xs where only DIs (i.e. correlations) are present between countries. Model specifications 3 - 5 involve TVP-PVAR-Xs where both DIs and SIs (i.e. volatility spillovers) are present. Results from all three countries indicate that model specifications 1 and 2 are selected more frequently than 3, 4 and 5. Additionally, for Argentina and Brazil model specification 1, which only allows for cross-market linkages between countries, is often sufficient to capture interdependencies. Thus DIs are, on average, more important than SIs.

TVP-PVAR-Xs, where SIs are present in addition to DIs, tend to be selected during crisis periods. More specifically, they tend to be selected during domestic crises. In Argentina, TVP-PVAR-Xs are selected during 2002, 2008 and 2014 - 2015. These dates correspond to the Argentine crisis, global financial crisis and Argentine selective default respectively. In Brazil, TVP-PVAR-Xs are not selected in the 2000s until a severe recession is experienced. In Mexico, however, TVP-PVAR-Xs and thus SIs are selected throughout the sample.

For each country, we then consider which transmission channels are selected for inclusion at each point in time. This is shown in the second panels of Figures 3.2 - 3.4. Figures B.1. - B.6. (in Appendix B.2) provide a further breakdown, detailing how often transmission channels associated with different countries are included.

Figure 3.2: Argentina: An Overview of Key Features

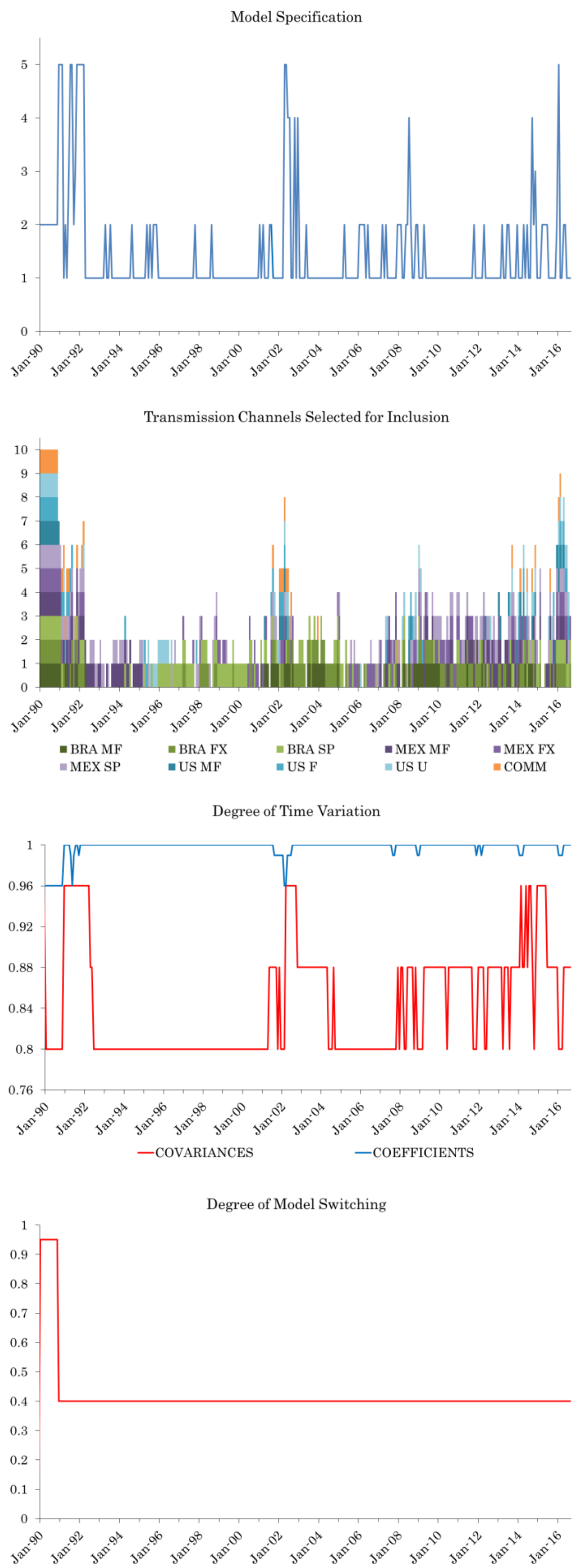


Figure 3.3: Brazil: An Overview of Key Features

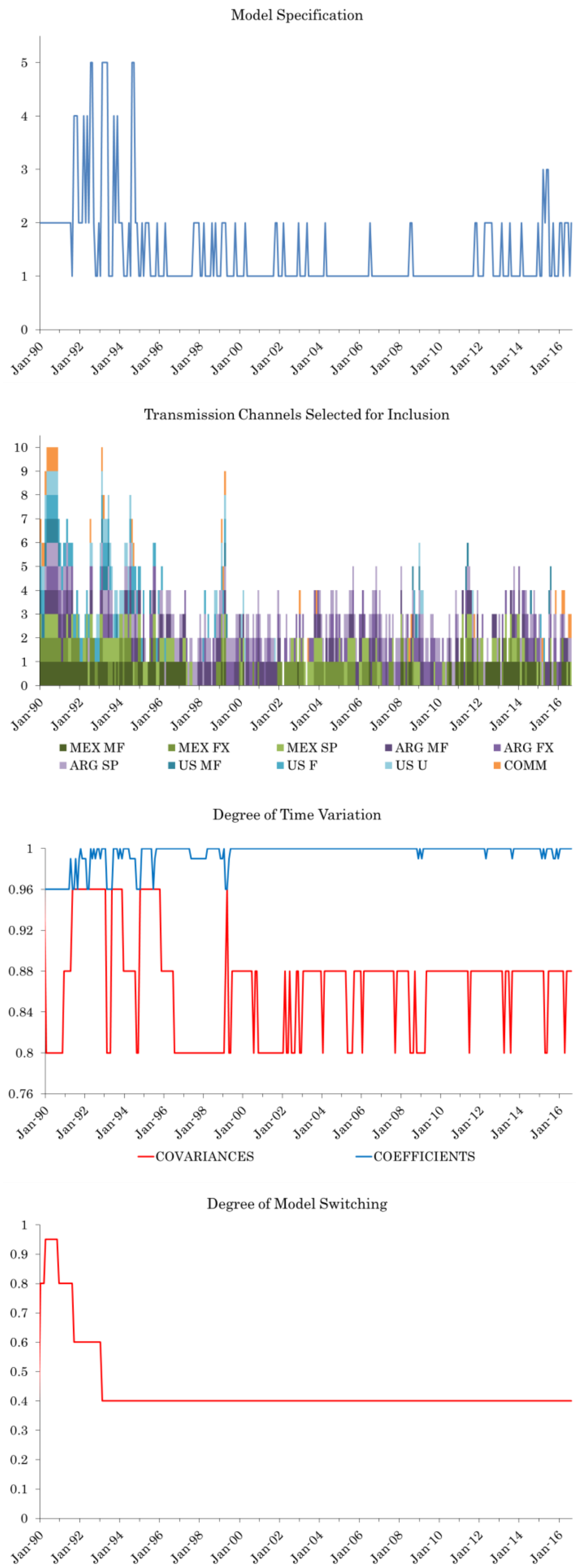
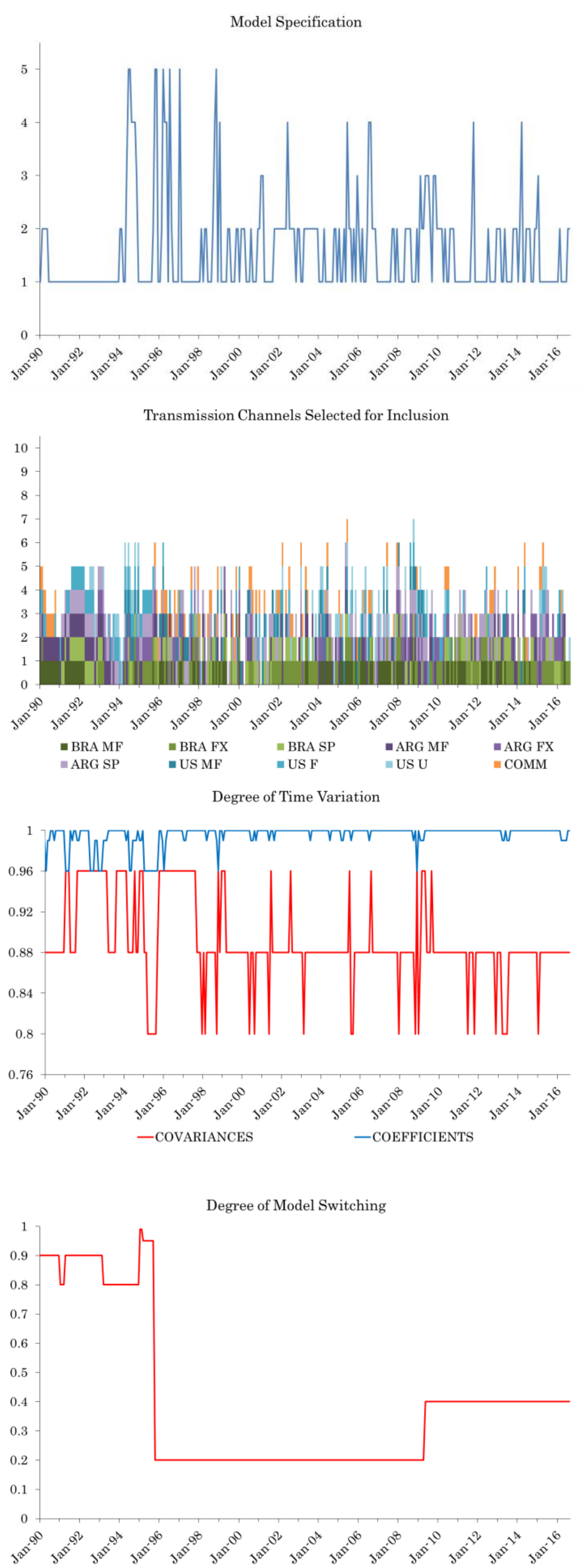


Figure 3.4: Mexico: An Overview of Key Features



To compute how many times each transmission channel is included we simply count how often the corresponding shrinkage parameter is non-zero throughout the sample. Notably, we cannot directly compare how often LA channels are included relative to global channels. This is because model specification 1 allows each exogenous LA variable to either enter a single equation or none. By contrast, across all specifications, each exogenous US/commodity price variable can either enter all equations or none.

If we consider the Argentine results, other countries' variables are selected for inclusion less frequently than when we model Brazil and Mexico. When modelling Argentina, the LA channels included least frequently are Brazilian and Mexican macroeconomic fundamentals. However, Brazilian macroeconomic fundamentals are included more regularly during 2001 - 2004, 2008 - 2010 and, to a lesser extent, 2014. These correspond to the Argentine crisis and subsequent recovery, the global financial crisis and the Argentine selective default respectively. US uncertainty and financial channels are the global channels included most frequently. This validates the importance of including uncertainty measures. We find that US transmission channels are included more regularly from 1990 - 1992, 2001 - 2003, 2007 - 10 and 2013 onwards. Commodities also play a role during these periods, particularly near the end of the sample when commodity prices slumped.

In our Brazilian results, Argentine stock prices, the exchange rate and macroeconomic fundamentals are the LA channels included most frequently followed by Mexican stock prices and the exchange rate. However, we find evidence of Mexican macroeconomic fundamentals entering the model from 1990 - 1998, appearing abruptly in 2008 and then from 2010 onwards. These correspond to Brazil and Mexico experiencing recessions and banking crises, the global financial crisis and

Brazil moving in and out of recessions respectively. Like in Argentina, we also find that US financial and uncertainty channels are the global channels included most frequently. These channels are included more frequently in the early 1990s, 1998 - 2001 and 2008 - 2010. These correspond to a Brazilian recession, a Brazilian currency crisis and the global financial crisis. We also see commodity prices take on a prominent role near the end of the sample as the drop in prices contribute to the most recent Brazilian recession.

Mexico's results present a different, less predictable pattern. Argentine and Brazilian transmission channels do not tend to undergo long periods of exclusion. Moreover, US variables are included more frequently than when modelling Argentina and Brazil. These indications of greater interdependence are unsurprising given Mexico's higher levels of trade and financial openness. Argentine stock prices, the Brazilian exchange rate and Argentine macroeconomic fundamentals are the LA channels most frequently included. This is interesting given that Brazil is larger than Argentina but may reflect the greater economic turbulence seen in Argentina. US financial indicators and commodities are the global channels included most often. The latter reflects the important role of oil prices in Mexico.

Turning to the third panels of Figures 3.2 - 3.4, we recall that the discount factor λ (plotted in blue) determines the degree of time-variation in the coefficient matrix and the extent to which DIs evolve over time. The discount factor δ (plotted in red) determines the degree of time-variation in the covariance matrix and the extent to which SIs evolve over time. Lower values reflect greater time-variation. Importantly, if a TVP-VAR-X is selected, no SIs are present and we simply have volatility spillovers between domestic variables. Across all three economies, we find greater time-variation in covariance matrices than in coefficient matrices which are often constant for several years. This coheres with Koop and Korobilis (2013) who find limited time-variation in coefficient matrices. That said, during times of crisis there are departures from the constant coefficient case. This is most evident during domestic crises, for instance, in Mexico, Brazil and Argentina during their respective currency devaluations.

In the fourth panels of Figures 3.2 - 3.4, we plot the discount factor α. Lower values reflect a greater degree of model switching. For Argentina and Brazil a value of 0.4 is selected across most of our sample indicating rapid model switching. In Mexico we see a value of 0.2 from late 1995 - mid 2009 increasing to 0.4 following the global financial crisis. This shows that the interval $\alpha \in [0.95, 1]$, commonly used in early studies which did not estimate α, is unsuitable in our context. This also emphasises the importance of allowing for model switching to capture the evolution of different interdependencies and transmission channels.

Figures B.7 - B.15 (in Appendix B.2) show the evolving magnitude of DIs and SIs. Figures B.7, B.8 and B.13 pertain to Argentine estimations; B.9 ,B.10 and B.14 to Brazil; and B.11, B.12 and B.15 to Mexico. In terms of DIs, for brevity, we focus on the standard deviation responses of industrial production and stock prices to a one standard deviation increase in selected predictors, all things held constant. For SIs, the standardised covariance matrices are transformed so that we have the correlation of reduced-form shocks. Again, for brevity, we focus on cross-market SIs. For instance, we look at volatility spillovers between stock markets in different countries. We delay detailed discussion of intensifying and weakening DIs and SIs to subsequent sections.

In summary, we find evidence of regional business cycles with stronger ties between

(i) Argentina and Brazil, our Southern American countries and (ii) the US and its neighbour Mexico. We also find that Mexico, our most open economy in terms of trade and finance, is the most vulnerable to external conditions on a consistent basis. We further find that interdependencies tend to be driven by DIs rather than SIs, particularly during non-crisis periods, with the exception of Mexico which sees more volatility spillovers. We overturn the possible misconception that macroeconomic linkages between countries are more consistent over time compared to financial linkages. Rather, other countries' macroeconomic fundamentals are sometimes abruptly included during times of crisis. Across economies, US financial conditions followed by uncertainty tend to be the most frequently included global channels. Our discount factors show the importance of allowing for rapid model switching and time-varying volatility rather than time-varying coefficients. However, departures from the constant coefficient case can be important when DIs evolve during times of crisis.

3.4.3 Early Currency Crises: 1990 - 2000

For clarity and brevity, we do not refer to specific figures in the following sections. However, all results are in Figures 3.2 - 3.4 and B.1 - B.15. We first consider currency crises experienced by Mexico and Brazil starting with the Mexican peso crisis. In December 1994, pressures on the exchange rate and banking system led to the sudden devaluation of the peso against the US dollar. We consider the effects of the crisis on Argentina and Brazil. We also discuss which linkages proved important in Mexico.

First, we consider Argentine results, analysing whether the Mexican crisis affected

Argentina. Before and after the devaluation, the model specification predominantly selected is 1. Thus we have no SIs and only allow for cross-market linkages between Mexico and Argentina.[12] Put differently, Mexican stock prices only enter the Argentine stock price equation and so on. Mexican macroeconomic fundamentals are consistently included in our model of Argentina from August 1993, even before the Mexican economy entered a recession. DIs from the Mexican stock market to the Argentine stock market are present from July 1992 - May 1994 and from January - June 1995 immediately following the devaluation.

While DIs from Mexican industrial production to Argentine industrial production are positive from May 1992 - February 1995 they do not increase in magnitude following the Mexican crisis. Similarly, DIs from the Mexican stock market to the Argentine stock market do not significantly intensify following their re-inclusion following the devaluation. We, therefore, find evidence of macroeconomic and financial interdependence between Mexico and Argentina during the currency crisis. With Mexican stock markets becoming relevant after several months of exclusion there is weak evidence of contagion confined to stock markets.

Next we consider the effect of the Mexican devaluation on Brazil. Prior to the devaluation, specifications 1, 2, 4 and 5 are selected. If we examine SIs between Mexico and Brazil, however, they tend to either remain stable or weaken over time. Following the devaluation, model specifications 1 and 2 are selected. All three Mexican transmission channels are included relatively consistently before and after the Mexican devaluation.

We see a slight intensification of DIs from Mexican industrial production to Brazilian

[12]Model specification 2 is also selected during this period. However, when this occurs, all LA transmission channels are excluded from the model.

industrial production from April - September 1994. DIs from the Mexican stock market to Brazilian industrial production are strong, but have periods of intensification before and after the devaluation. Finally, DIs from the Mexican stock market to the Brazilian stock market show no sign of intensifying following the devaluation. We thus find evidence in favour of financial, and to a lesser extent macroeconomic, interdependence rather than contagion.

Finally, we consider Mexico, assessing which linkages proved important before and after the devaluation. Model specifications 1,2,4 and 5 are selected prior to the devaluation. Model specification 1 is then selected from December 1994 - August 1995. SIs between Mexico and Argentina tend to intensify from May 1994 to November 1994 especially in stock markets. These SIs did not come through in the Argentine results suggesting that the volatility spillovers are more important for Mexico. In terms of DIs, Brazilian and Argentine exchange rates and Argentine stock prices are present on a more consistent basis after the devaluation. In contrast, all US transmission channels are included in the model before the crisis with US financial indicators remaining important after the crisis.

Evolving DIs play a role from February 1994 - February 1996. During this time, constant coefficient models are no longer selected. All US DIs intensify in the build up to the crisis. DIs from US industrial production to Mexican industrial production are particularly high in April and May 1994 and are included till December 1994. Similarly, DIs from US macroeconomic and financial uncertainty indicate that a rise in these variables leads to a decline in Mexican industrial production from October 1993 - December 1994. DIs from the US stock market indicate a lack of comovement with Mexican industrial production, but positive comovement with the Mexican stock market. These findings show that external conditions, particularly those in the US, become more important in the build up to the Mexican devaluation. After the devaluation, a more specific set of external conditions - US, Argentine and Brazilian financial indicators and exchange rates - are selected for inclusion.

We next consider the 1999 Brazilian currency crisis. In 1994 the Real Plan was implemented, partly to stabilise hyperinflation. The Real was pegged to the dollar and inflation gradually subsided as the 1990s progressed. However, by January 1999 the Real had become significantly overvalued and was suddenly devalued. We consider the effects of the crisis on Argentina and Mexico. We also explore which linkages proved important in Brazil.

First, we consider the effect on Argentina. From November 1997 - December 2000 model specification 1 is selected. Brazilian stock prices and, to a much lesser extent, exchange rates are included before and after the devaluation. If we examine DIs from the Brazilian to the Argentine stock market, however, they are negative, suggesting a lack of synchronicity between financial markets. Therefore, over this time period, where both Brazil and Argentina were in crisis, we find little evidence of interdependence or contagion.

Then we consider Mexico which itself entered a recession in March 1998. Model specifications 1,2,4 and 5 are all selected in the run up to the Brazilian devaluation. During the month of the devaluation, model specification 4 is selected. In terms of volatility spillovers, SIs between Brazil and Mexico intensify between October 1998 and November 1998 before dropping back down slightly in January 1999. This intensification is most noticeable between stock markets. Thereafter SIs are excluded with model specifications 1 and 2 being selected until January 2001.

We find that all three Brazilian transmission channels tend to be included, albeit intermittently, before and after the crisis.

DIs from the Brazilian stock market and industrial production to Mexican industrial production, however, generally indicate a lack of comovement. By contrast, DIs from the Brazilian stock market to the Mexican stock market indicate comovement from October 1997 - November 1999. The period October 1998 - March 1999 was the exception with the positive correlation between stock markets breaking down. Given DIs from the Brazilian to the Mexican stock market and volatility spillovers between the two markets we find some evidence of financial interdependence which temporarily weakens following the devaluation.

Finally, let us consider the experience of Brazil during the crisis. From October 1994 - February 2015 we switch between model specifications 1 and 2. All three Argentine transmission channels feature intermittently from January 1998. In contrast, having been excluded from the Brazilian model for more than a year, all three Mexican and US transmission channels are included with the onset of the devaluation in January 1999.

Mirroring Mexico during the peso crisis, DIs to Brazil evolve during the crisis. From November 1998 - April 1999 coefficients are no longer constant and instead vary over time. If we consider the magnitude of interdependencies, DIs from Argentine industrial production to Brazilian industrial production are stronger than those from Mexican or US industrial production. However, these DIs do not increase in magnitude. DIs from the Argentine and Mexican stock markets to the Brazilian stock market and industrial production intensify markedly during the crisis. However, of these DIs, only those from the Argentine stock market were positive indicating comovement. A rise in the US excess bond premium in February and March 1999 corresponded to a marked fall in Brazilian industrial production. We thus find that existing interdependencies with Argentina continue to be included throughout the devaluation whilst US transmission channels suddenly become important in 1999.

3.4.4 The Argentine Crisis: 1997 - 2003

We now consider the Argentine crisis. The economy entered a recession in October 1998. In December 2001, amidst rioting and a bank freeze on deposits, Argentina defaulted on its sovereign debt. Then in January 2002 the peso was suddenly devalued. We consider the effects of the crisis on Brazil and Mexico. We also examine which linkages proved important in Argentina.

First, we consider the effect on Brazil. Model specifications 1 and 2 are selected during the Argentine crisis. All Argentine transmission channels are regularly selected for inclusion between February 1998 - February 2002. Given the Brazilian devaluation in January 1999, we focus on results from the 2000s when examining the magnitude of DIs to clearly distinguish between the two crises. DIs from Argentine industrial production to Brazilian industrial production are positive but do not intensify. Starting in February 2002, Argentine industrial production is not selected for inclusion for 20 months, Similarly, DIs from the Argentine stock market to the Brazilian stock market remain positive until August 2002 before being excluded for 17 months. Thus we find strong evidence of macroeconomic and financial interdependence which wanes following the sovereign debt and currency crisis.

Next we turn to Mexico. All model specifications are selected during the Argentine crisis. If we examine volatility spillovers, SIs between Mexican and Argentine exchange rates and Mexican and Argentine stock prices heighten between 1998 - 2002. During this period, Mexico also experienced two recessions. All Argentine transmission channels are included intermittently with stock prices included most often. DIs from Argentine industrial production to Mexican industrial production indicate a lack of comovement until February 2002. At this point, DIs, although small, become positive. DIs from the Argentine stock market to Mexican industrial production show slight intensification. DIs from the Argentine stock market to the Mexican market are of a larger magnitude, showing intensification in the months from May 2000 - December 2001. Overall, we have evidence of financial interdependence and some evidence of abrupt contagion resulting from volatility spillovers.

Finally, we consider Argentina itself. Prior to the default and devaluation, model specifications 1 and 2 are selected. After the devaluation, from April 2002 - December 2002, model specifications 1, 2, 4 and 5 are selected. At these points, SIs intensify particularly between the Argentine and Brazilian stock market. In terms of DIs, initially Brazilian exchange rates and stock prices are selected for inclusion. However, in 2001 Brazilian macroeconomic fundamentals become important. From June 1999 - May 2000, Mexican transmission channels are not selected for inclusion. Thereafter, all three Mexican transmission channels are intermittently included until October 2002. Similarly, US transmission channels and commodities are abruptly included in 2001 and 2002.

Some DIs to Argentina evolve during the crisis. Models with constant coefficients are no longer selected from August 2001 - June 2002. DIs from Brazilian industrial production to Argentine industrial production intensify between February - May 2001. DIs from US industrial production to Argentine industrial production peak rapidly between January - June 2002. An increase in US macroeconomic uncertainty has a pronounced negative effect on Argentine industrial production from October 2001, peaking in June 2002. In contrast, DIs from the US stock market and excess bond premium to the Argentine stock market and industrial production indicate a lack of comovement. Thus existing macroeconomic interdependencies with Brazil remain important during the crisis. US macroeconomic fundamentals and uncertainty abruptly become important following the default and devaluation.

3.4.5 The Global Financial Crisis: 2006 - 2010

Finally, we examine the global financial crisis. Following the collapse of the US subprime mortgage market, a global liquidity crisis ensued with countries facing banking crises worldwide. For each LA economy, we examine linkages with the US before and after the crisis. If contagion is detected, we also explore how the LA economies affect one another.

First, we consider Argentina. Model specifications 1 and 2 are selected during the crisis. Thus volatility spillovers are rarely relevant. The exception is July 2008 when model specification 4, a bilateral TVP-PVAR-X with Brazil, is selected. US financial and uncertainty transmission channels are briefly included in May and June 2007 as the liquidity crisis unfolds. US uncertainty then re-enters the model intermittently from March 2008 - February 2009. US financial indicators and macroeconomic fundamentals briefly reappear from July - September 2008 and in March 2009.

DIs evolve to a lesser extent: departures from the constant coefficient case are seen from August - September 2007 as well as November - December 2008. We now examine the magnitude of DIs from US uncertainty to the Argentine stock market and industrial production. In both cases, a rise in uncertainty between 2007 - 2008 has a negative effect. Financial uncertainty, in particular, has a larger negative effect on industrial production. A rise in the excess bond premium also negatively affects industrial production but only in 2008 and 2009. We thus find strong evidence in favour of abrupt contagion, initiated by a rise in US financial uncertainty in 2007. We also find evidence that macro-financial linkages play a part in the spread of contagion. Changes in US uncertainty and later financial conditions affect Argentine industrial production.

Next, we consider the effect of Brazil and Mexico on Argentina during the crisis. When a bilateral TVP-PVAR-X is selected in July 2008, volatility spillovers between Argentine and Brazilian exchange rates and stock markets heighten. However, volatility spillovers between macroeconomic fundamentals weaken. Turning to DIs, from January 2005 - March 2008, Brazilian transmission channels are included very intermittently. Thereafter, however, Brazilian transmission channels, particularly macroeconomic fundamentals, are more consistently selected for inclusion until 2010. Having not been included in the model since April 2002, Mexican macroeconomic fundamentals are intermittently included from February 2007. Having been intermittently included prior to the crisis, Mexican exchange rates continue to be intermittently included while stock prices are more regularly included from June 2008.

DIs from Mexican industrial production to Argentine industrial production heighten earlier in 2007. However, DIs from Brazilian industrial production to Argentine industrial production intensify to an even greater degree in late 2008 and 2009. These findings suggest that Argentina was not solely affected by the US during the global financial crisis. Instead, Argentina was also indirectly affected through macroeconomic linkages with Mexico and Brazil which abruptly became important. These findings are consistent with Argentina being the last LA-3 economy to enter a recession following the financial crisis.

Turning to Brazil, model specification 1 is selected from May 2004 - September 2011 with three exceptions: model specification 2 is selected in July 2006 and July and August 2008. Thus volatility spillovers play no role in Brazil. Having not been selected for inclusion since October 2001, all US transmission channels are included at some point between September 2008 - March 2009. Macroeconomic fundamentals are included first. Uncertainty becomes more important in 2009. Financial indicators are only included for one period.

As was the case when modelling Argentina, DIs evolve to a lesser extent during the financial crisis: departures from the constant coefficient case are only seen in November 2008 and January 2009. DIs from US industrial production to Brazilian industrial production heighten considerably in November 2008 after the Lehman Brothers collapse. Moreover, the negative response of industrial production to a rise in financial and macroeconomic uncertainty heightens. To a lesser extent, the negative response of industrial production to a rise in the excess bond premium, also heightens. DIs to the Brazilian stock market show similar patterns but are of a smaller magnitude. Thus we have abrupt contagion from the US, particularly in terms of macroeconomic and uncertainty transmission channels. Again, changes in US financial and uncertainty indicators also have real effects.

Now, we examine the effect of Argentina and Mexico on Brazil during the crisis. All Argentine transmission channels are intermittently selected for inclusion before and during the crisis. Mexican transmission channels are included from 2002 onwards, but become more intermittent in 2007. Mexican macroeconomic fundamentals are included more consistently in 2008. DIs from Argentine industrial production to Brazilian industrial production only intensify slightly in August and September 2009. DIs from the Argentine to Brazilian stock market also intensify in January 2009. The magnitude of DIs from Mexico to Brazil are, however, small. We find evidence of interdependencies between Brazil and Argentina and, to a lesser extent, between Brazil and Mexico but these interdependencies do not play a significant role in our largest Latin American economy, Brazil.

Finally, we consider how Mexico was affected during the global financial crisis. Despite showing the greatest tendency to switch between models of different sizes, Mexico only switches between model specifications 1, 2 and 3. Unlike the Argentine and Brazilian cases, US macroeconomic and uncertainty transmission channels do not show abrupt inclusion. Rather, they continue to be included before and after the crisis. US financial indicators are included prior to the crisis but are included more regularly from August 2008 - August 2010.

Evolving DIs play a greater role in Mexico with a departure from the constant coefficient case from September 2008 - March 2009. If we consider DIs from US to Mexican industrial production, there is some intensification from January - March 2009. Macroeconomic uncertainty negatively affects industrial production but does not intensify noticeably. The excess bond premium also negatively affects industrial production, intensifying from August 2008 - August 2010. If we next examine the Mexican stock market, a drop in US industrial production has a severe negative impact in November 2008. The negative effects of a drop in US stock prices or rise in the excess bond premium is smaller although linkages heighten from April - November 2009. The negative effect of a rise in financial uncertainty starts increasing from late 2001 peaking in September 2008. We thus find evidence of contagion in Mexico through existing macroeconomic and financial interdependencies with the US. US uncertainty variables are also important before and during the crisis.

We conclude this section by examining how Argentina and Brazil affected Mexico during the crisis. Bilateral TVP-PVAR-Xs with Argentina are selected from February - November 2009. The magnitude of volatility spillovers between the Argentine and Brazilian stock market and, to a lesser extent, Argentine and Brazilian industrial production heighten over this period. We find that all Brazilian and Argentinean transmission channels are included intermittently before the crisis. Argentinean macroeconomic fundamentals, exchange rates and Brazilian stock prices are included more regularly during the crisis. DIs from Argentine to Mexican industrial production heighten, peaking in November 2008. Similarly, DIs from the Argentine to the Mexican stock market heighten considerably, again peaking in November 2008. In contrast, DIs from Brazilian to Mexican industrial production indicate a lack of comovement while DIs from the Brazilian to the Mexican stock market are small in magnitude. We, therefore, find that Argentina affected Mexico through existing interdependencies during the financial crisis.

3.4.6 Overarching Trends from our Three Crisis Episodes

During the currency crises of the 1990s, we find evidence in favour of interdependence or even a lack of linkages rather than contagion. In Argentina and, to a lesser extent, Brazil model specification 1, which only allows for cross-market linkages, is often selected. These cross-market interdependencies, where present, tend to be particularly strong in financial markets. Macroeconomic interdependencies also play a role in the Mexican peso crisis. Similarly, when TVP-PVAR-Xs are selected, which is most common in Mexico, volatility spillovers are strongest between exchange rates and between stock markets.

Our results on the Argentine crisis are also more indicative of interdependence than contagion. While financial interdependence also continues to be important in terms of DIs, macroeconomic fundamentals play a more prominent role in terms of interdependencies between Brazil and Argentina. In Mexico and Argentina, as the crisis worsens in late 2001 and early 2002, model specifications 2 - 5 become more important. As seen during the 1990s, the resulting volatility spillovers tend to strengthen in exchange rate markets and stock markets.

In contrast, during the global financial crisis, without exception, we find evidence of contagion from the US to all LA countries. In Argentina and Brazil, we detect abrupt contagion from the US. However, in Mexico results indicate that contagion spreads through existing macroeconomic, financial and uncertainty transmission channels. Unlike previous crises, we also see evidence of macro-financial linkages proving important in the spread of contagion with movements in the US excess bond premium and uncertainty variables, in particular, affecting industrial production across all LA economies. Financial uncertainty dominates in Argentina but in Brazil and Mexico macroeconomic uncertainty plays a greater role in affecting domestic industrial production.

As discussed in section 3.4.2., we also uncover another indicator of economic distress: departures for the constant coefficient case indicate that the magnitude of DIs are evolving. This occurs during domestic crises in Argentina, Brazil and Mexico. It also occurs, to a lesser extent, in all LA-3 economies during the global financial crisis.

3.5 Conclusion

Was contagion present? Many studies have sought to definitively answer this question, first in the context of currency crises in emerging economies and more recently following the global financial crisis and European sovereign debt crisis. The existing literature, however, has become increasingly fragmented with different definitions of contagion making reference to different methods. Moreover, although the wider literature acknowledges the importance of macroeconomic transmission channels, financial transmission channels have been the focus of recent empirical studies.

In this chapter, drawing on insights from the dynamic model selection literature, we develop a model switching approach to analyse contagion. We allow the nature of interdependencies, magnitude of interdependencies and transmission channels selected for inclusion to change over time. We also account for macroeconomic fundamentals and changes in US uncertainty in addition to various financial indicators. We thus appeal to multiple definitions of contagion, distinguishing between: interdependence, contagion arising from interdependence and contagion arising through an abrupt change in linkages between countries.

Focusing on Latin America, we examine the early currency crises of the 1990s, the Argentine crisis spanning 1998 - 2002 and the global financial crisis. Following currency devaluations in Mexico and Brazil, results indicate interdependence, particularly in financial markets. Macroeconomic interdependencies are also present during the Mexican devaluation. Our results on the Argentine crisis are similar, however, macroeconomic fundamentals play a more prominent role in terms of interdependencies between Argentina and Brazil. During the global financial crisis, the abrupt inclusion of US transmission channels, particularly uncertainty transmission channels, is clearly indicative of abrupt contagion in Argentina and Brazil. Mexico, however, experiences contagion through pre-existing macroeconomic and financial interdependencies with the US. US uncertainty also affects Mexico before and during the crisis. Overall, our findings demonstrate that contagion was only present during the global financial crisis. We also find that macroeconomic and uncertainty transmission channels play a role during some crises not just financial transmission channels.

Chapter 4

Measuring International Spillovers in Uncertainty and their Impact on the Economy

4.1 Introduction

Following the global financial crisis of 2007, there is a growing consensus that uncertainty has an adverse affect on the economy (e.g. Bloom, 2009) and requires the consideration of policymakers (e.g. Bekaert et al., 2013). But there are many components of uncertainty. There is for example uncertainty surrounding growth prospects, uncertainty stemming from global imbalances and monetary policy uncertainty. There are also different ways to proxy uncertainty. While some studies use econometric or text-based proxies others use surveys of professional forecasters. And, despite deepening trade and financial integration, it is still unclear to what extent uncertainty shocks occurring in a specific economy can affect other economies.

Inspired by these concerns, this chapter analyses international spillovers in different components of uncertainty across advanced and emerging economies. Three key features characterise our high-dimensional approach. First, we consider spillovers between seven major advanced and emerging economies: the US, Canada, the Eurozone, UK, Japan, China and India. This allows us to investigate which economies are sources of uncertainty spillovers and which economies are vulnerable to foreign uncertainty. Second, for each economy, we use survey data from *Consensus Forecasts* to consider spillovers in five components of uncertainty. We consider uncertainty surrounding: output growth, inflation, the short-term interest rate, the current account and the exchange rate. This allows us to disentangle which components of uncertainty are most important and whether the role played by different components varies across economies. Third, we distinguish between different survey-based empirical proxies for our five uncertainty components. We consider disagreement among survey participants and the conditional variance of participants' mean forecast errors. The former reflects idiosyncratic uncertainty while the latter represents common uncertainty arising from participants' exposure to the same future shocks. Aggregate uncertainty is obtained by combining idiosyncratic and common uncertainty. We therefore investigate how our results vary depending on whether we include idiosyncratic, common or aggregate uncertainty in our analysis.

To analyse spillovers in uncertainty at the economy level and component level, we estimate three multi-country Bayesian Panel VARs (PVARs), assessing the effects of our uncertainty measures in turn. PVARs allow us to jointly model uncertainty and macro-financial variables for each economy, but also allow for interdependencies between economies. However, this great flexibility comes with a cost in that there are so many possible interdependencies between economies to estimate that it can be difficult to sort through them all. Furthermore, the PVAR can be over-parameterised. We address these problems by extending 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, thus surmounting over-parameterization 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 extend their approach by making these restrictions more granular, focusing on whether one economy's uncertainty components can affect another economy's macro-financial variables. In our context, a restriction might be that all components of uncertainty in Japan have no contemporaneous impact on the real and financial sectors of the US. Another one would be that all Eurozone uncertainty components in a particular month has no impact on the real and financial Chinese economy the following month. We are able to sort through hundreds of restrictions in our high-dimensional PVARs[13]. This allows us to explore our first layer of granularity at the economy level, assessing which economies are key sources of uncertainty spillovers and which economies are vulnerable to foreign uncertainty. We can then consider our second layer of granularity at the component level using impulse response analysis and forecast error variance de-

[13]Our PVARs involves 7 economies and, for each, we have 7 dependent variables leading to a 49 dimensional PVAR. The dependent variables comprise the five uncertainty variables as well as stock prices and industrial production.

compositions, investigating how a shock to one component of uncertainty in an economy affects either the real or financial sectors of other economies.

Overall, this chapter demonstrates that there are considerable spillovers in uncertainty between different economies. While uncertainty from the US is important it does not play a dominant role as a source of foreign uncertainty to any domestic economy. Rather spillovers of different types originate from each economy and affect foreign uncertainty or the foreign real and financial sectors. This fact suggests that there is no single global uncertainty measure, highlighting the advantages of our VAR-based approach. In terms of the relative importance of different uncertainty components, we find that the US affects other economies through interest rate, exchange rate and current account uncertainty, important transmission channels linking the US to the global economy. The UK and Eurozone are important sources of interest rate and inflation uncertainty. Japan, China and India are most affected by foreign uncertainty. Across economies, the financial sector is affected more by foreign uncertainty spillovers than the real sector. If we consider our different uncertainty proxies, different types of analysis all show that international spillovers in disagreement uncertainty are more frequently observed than spillovers in uncertainty arising from the variance of mean forecast errors. However, when they do occur, forecast error uncertainty shocks produce larger negative responses.

The rest of the chapter is structured as follows. Section 4.2 discusses how this chapter's contributions relate to the literature. Section 4.3 describes our data and how we measure uncertainty. Section 4.4 describes how our multi-country PVARs sheds light on uncertainty spillovers at different levels of granularity. We present our results on uncertainty spillovers between different economies and different components of uncertainty in Section 4.5. Section 4.6 concludes. The appendix includes a data appendix (Appendix C.1) and supplementary empirical results (Appendix C.2).

4.2 Relationship to the Literature

In this brief discussion of the large and growing economic uncertainty literature, we will emphasise two themes that are most relevant for our work. These are the the international transmission of uncertainty shocks and the measurement of uncertainty. We make clear what differentiates our work from past studies with respect to each theme.

An important issue we investigate in this chapter is whether uncertainty shocks are transmitted across economies. The existing literature primarily addresses this through the concept of an international uncertainty shock, econometrically estimated from a broad set of variables. In most papers, uncertainty is simply proxied by volatility estimates from large-scale VARs or factor models with stochastic volatility components. Cuaresma et al. (2020) and Carriero et al. (2019) are examples of the large-scale VAR approach. Using data on advanced economies, they jointly estimate a measure of international uncertainty and its effects on each economy. Cross et al. (2019) 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 to decompose the effects of global and country-specific uncertainty. Focusing on OECD economies, Mumtaz and Theodoridis

(2017) use a factor model with stochastic volatility to decompose changes in real and financial variables into contributions from country-specific and global uncertainty. This approach is later generalised by Mumtaz and Musso (2019) who introduce time-varying coefficients, more OECD countries and region-specific uncertainty. Again, focusing on OECD economies, Berger et al. (2016) use a factor model with stochastic volatility to 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.

PVAR approaches considering uncertainty shocks include Miescu (2019) who uses a Panel proxy structural VAR to investigate the effects of a global uncertainty shock on emerging economies. Casarin et al. (2018b) use a mixed-frequency PVAR to examine the effects of global macroeconomic and financial uncertainty shocks across industrialised economies. They find that financial uncertainty tends to have a more adverse affect on the economy than macroeconomic uncertainty. Importantly, while both studies take advantage of the panel structure of the data, they do not allow for interdependencies and spillovers between economies.

A smaller strand of the literature on international uncertainty spillovers focuses on economic policy uncertainty (EPU) spillovers. These can be readily investigated using cross-country measures of EPU constructed through textual analysis of newspapers by Baker et al. (2016). 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 economy. Caggiano et al. (2020) and Biljanovska et al. (2017) consider EPU spillovers from the US to Canada and the UK and between Europe, China and the US respectively.

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 chapter is the measurement of uncertainty shocks. Uncertainty is unobservable and the literature has proposed various empirical proxies[14]. While we have discussed volatility based estimates of uncertainty, there are other means to econometrically estimate uncertainty. Jurado et al. (2015) and Ludvigson et al. (forthcoming) develop proxies of macroeconomic and financial uncertainty based on the common unpredictable component of a large set of variables. Rossi and Sekhposyan (2015, 2017) develop macroeconomic uncertainty proxies for the Euro area by assessing whether realised forecast errors of GDP growth occur in the tail of the historical forecast error distribution.

Another strand of the literature focuses constructs uncertainty proxies using textual analysis. Studies have considered global and country-specific EPU (Baker

[14]Castelnuovo (2019) provides a recent review.

et al., 2016), US monetary policy uncertainty (Husted et al., 2019), different components of Norwegian uncertainty (Larsen, 2017) and uncertainty in the US and Australian economies (Castelnuovo and Tran, 2017). With the exception of Baker et al. (2016) and Rossi and Sekysposen (2017), these studies do not 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.

Another recent strand of literature uses surveys of professional forecasters to measure and analyse uncertainty. One proxy believed to be correlated with uncertainty is disagreement among forecasters reflecting idiosyncratic uncertainty. However, some contend that disagreement among survey participants is not always a reliable uncertainty proxy (Zarnowitz and Lambros, 1987, D'Amico and Orphanides, 2014, Rich and Tracy, 2010, 2018). Recently, Lahiri and Sheng (2010) argue that disagreement is a reliable proxy for uncertainty in stable times and at shorter forecast horizons. However, during unstable times we must account for common uncertainty arising from participants' exposure to the same future shocks. Common uncertainty aligns with the concept of uncertainty presented in Jurado et al. (2015). Using survey data, it can be captured by the variance of participants' mean forecast errors. A combination of disagreement among forecasters and forecast error variances can then be used to capture aggregate uncertainty.

There are only two studies which decompose aggregate uncertainty into idiosyncratic and common uncertainty using *Consensus Economics* 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 industrialised economies. Both studies find that common uncertainty shocks have a more adverse affect on the real economy. To our knowledge, the only other study utilising *Consensus Economics* forecast data in the context of international spillover modeling is the study of Lahiri and Zhao (2019). They do not explicitly focus on uncertainty. Rather they use GDP growth forecasts to consider the propagation of shocks among industrialised and emerging Asian economies. By using GDP growth forecasts rather than actual values they can consider the transmission of shocks at a monthly frequency.

Despite data dating back to 1989 on a wide range of variables, *Consensus Forecasts*, has seldom been used to consider international spillovers (Lahiri and Zhao, 2019). In this chapter, we use this forecast data set to construct our uncertainty proxies. The theoretical starting point is the idea that overall forecast uncertainty is captured via the average of the individual forecast error variances and forecaster disagreement (Lahiri and Sheng, 2010). Given the lack of consensus, we follow the empirical literature and repeat all of our empirical exercises three times. First using disagreement as a proxy of uncertainty, second using the variance of forecast errors and finally using the combination of both. By considering a model with disagreement alone, we also ensure that including industrial production forecast error variances and realizations of industrial production together in the same VAR does not drive our results.

4.3 Measuring International Uncertainty Spillovers

We use monthly 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 *Consensus Economics* surveys of professional 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 a broad dimension of uncertainty related to monetary policy (interest rate and inflation uncertainty), the business cycle (GDP uncertainty) and the international economy (exchange rate and current account uncertainty). The names of the forecasters are published monthly, resulting in a reputation effect and assuring that data quality remains high. When a series is unavailable for one economy, we use a suitable alternative - details are given in Appendix C.1.

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. 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.

For each component of uncertainty, we 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 (Lahiri and Sheng, 2010 and Istrefi and Mouabbi, 2018):

$$U_{t,h} = D_{t,h} + V_{t,h}, \tag{4.1}$$

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 $k = 1, \dots, K$ 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,

$$D_{t,h} = \frac{\sum_{k=1}^{K} (f_{k,t,h} - f_{t,h})^2}{K}. \tag{4.2}$$

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

$$e_{k,t,h} = y_{t+h} - f_{k,t,h}. \tag{4.3}$$

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.

Current account data is unavailable at a monthly frequency across economies. So we do not calculate forecast errors and therefore $V_{t,h}$ 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.

For each economy, we have therefore constructed five components of uncertainty and proxied each component in three ways with the exception of the current account. 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 controls 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[15]. Details on data sources are provided in Appendix C.1.

4.4 Econometric Methods

In this section, we describe our econometric methods. 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

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

are extended to explore and summarise 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.

4.4.1 Restrictions in Multi-Country PVAR Models

Our multi-country PVAR[16] model is defined as:

$$y_{it} = A_{1,i}Y_{t-1} + ... + A_{P,i}Y_{t-P} + \varepsilon_{it}, \tag{4.4}$$

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 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 $p = 1, ..., P$.

[16]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 standardised so we do not include an intercept.

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 chapter, 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 summarise 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 analyse uncertainty spillovers at the component level. We focus on generalised 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 generalised forecast error variance decompositions (GFEVDs). We calculate GIRFs and GFEVDs as in Koop et al. (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 we have a large number of variables and do not wish to impose a specific ordering.

4.4.2 Extending Stochastic Search Specification Selection

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 et al. (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:

$$\alpha \sim N\left(\alpha_0, v_0^2\right). \tag{4.5}$$

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:

$$\alpha|\gamma \sim (1-\gamma)\, N\left(0, \tau_1^2\right) + \gamma N\left(0, \tau_2^2\right) \tag{4.6}$$

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 chapter, 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 minimise the marginal likelihood.

4.5 Results

In this section, we present empirical results from three different high-dimensional PVAR(1) models with exogenous variables as described in Section 4.3. 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 summarising 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, discussing how a shock to each component of uncertainty affects the real and financial sectors of the seven economies analysed. We do so by summarising our GIRFs for each uncertainty proxy. Third, remaining at a high level of granularity, we compare whether the magnitude of spillovers vary depending on the uncertainty proxy used. We do so by presenting Diebold-Yilmaz (2014) directional spillover indices.

4.5.1 International Uncertainty Spillovers at the Economy Level

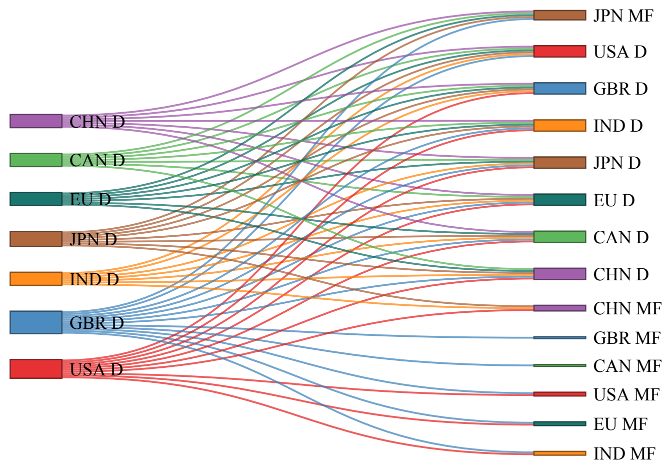
For each of our seven economies, we have five uncertainty and two macro-financial variables. Therefore the number of potential interdependencies is huge. To consider spillovers in uncertainty at the economy level, we group our variables into two blocks for each economy: an uncertainty block (D, V or 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 summarise 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 six Sankey diagrams summarising the PIPs corresponding to the DIs (Figures 4.1 - 4.3) and SIs (Figures 4.4 - 4.6) 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 colour. 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 colour indicating which economy the spillover originates from.

The general pattern which emerges is that there are important dynamic and static international spillovers in uncertainty across economies for all three uncertainty proxies. However, these are more frequently observed for idiosyncratic and aggregate uncertainty where we find evidence that uncertainty in one economy can spillover to another economies' real and financial sectors. Results using common uncertainty only show static spillovers between uncertainty blocks and foreign macro-financial blocks.

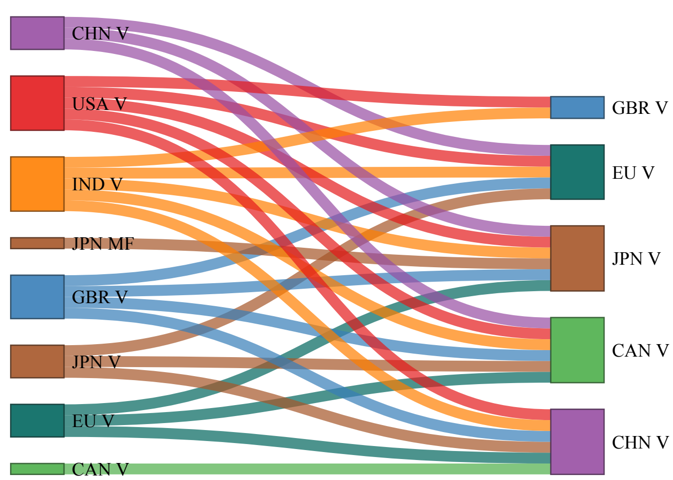
We also find that spillovers from domestic uncertainty to domestic macro-financial blocks are less common, reinforcing the finding in the literature that international uncertainty is more important than country-specific uncertainty. However, while uncertainty from the US is important, it does not play a dominant role as a source of foreign uncertainty to any domestic economy. Rather, spillovers of different types originate from each economy and affect foreign uncertainty or the foreign real and financial sectors. The fact that there is not one simple source of uncertainty suggests there is no single global uncertainty measure and highlights the advantages of our VAR-based approach which disentangles the individual sources of uncertainty and how they spillover across economies.

Figure 4.1: Idiosyncratic Uncertainty: Dynamic Spillovers Across Economies



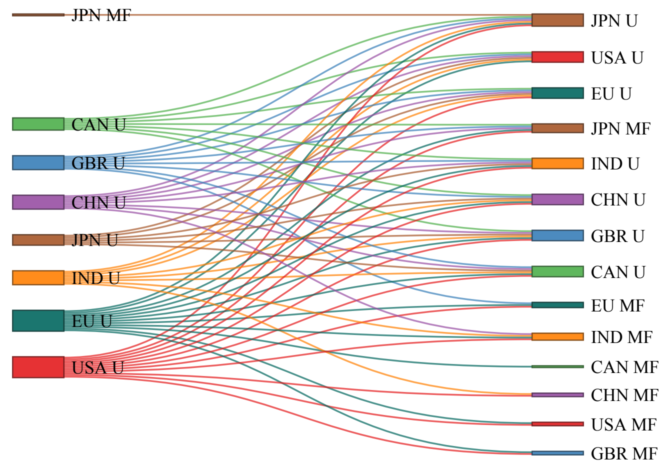
Note: We report dynamic interdependencies where the posterior inclusion probability ≥ 0.5. We have two groups of variables for each economy: uncertainty variables proxied by disagreement (D) and macro-financial variables (MF).

Figure 4.2: Common Uncertainty: Dynamic Spillovers Across Economies



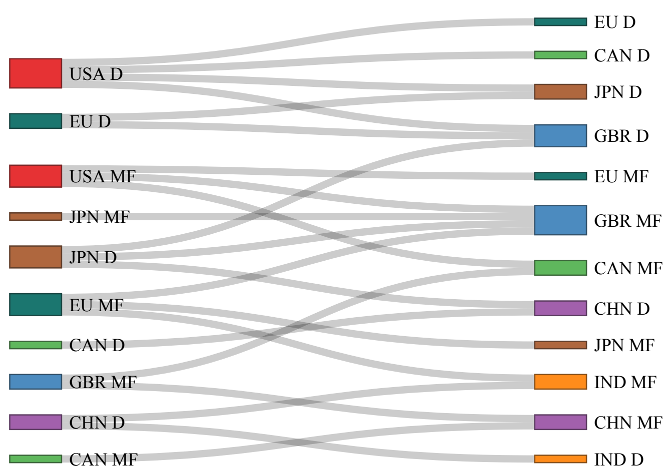
Note: We report dynamic interdependencies where the posterior inclusion probability ≥ 0.5. We have two groups of variables for each economy: uncertainty variables proxied by variance of forecast errors (V) and macro-financial variables (MF).

Figure 4.3: Aggregate Uncertainty: Dynamic Spillovers Across Economies



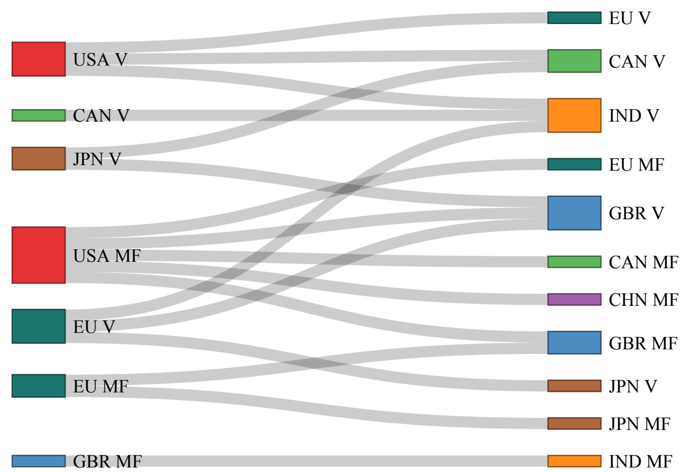
Note: We report dynamic interdependencies where the posterior inclusion probability $\geq$ 0.5. We have two groups of variables for each economy: uncertainty variables proxied by combined uncertainty (U) and macro-financial variables (MF).

Figure 4.4: Idiosyncratic Uncertainty: Static Spillovers Across Economies



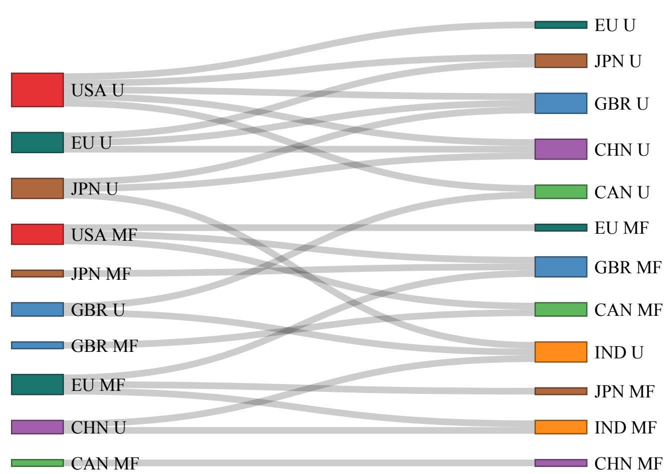
Note: We report static interdependencies where the posterior inclusion probability $\geq$ 0.5. We have two groups of variables for each economy: uncertainty variables proxied by disagreement (D) and macro-financial variables (MF).

Figure 4.5: Common Uncertainty: Static Spillovers Across Economies



Note: We report static interdependencies where the posterior inclusion probability ≥ 0.5. We have two groups of variables for each economy: uncertainty variables proxied by variance of forecast errors (V) and macro-financial variables (MF).

Figure 4.6: Aggregate Uncertainty: Static Spillovers Across Economies



Note: We report static interdependencies where the posterior inclusion probability ≥ 0.5. We have two groups of variables for each economy: uncertainty variables proxied by combined uncertainty (U) and macro-financial variables (MF).

The SIs and DIs exhibit somewhat different patterns. In general, we find more interdependencies in our DI figures than our SI 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 idiosyncratic uncertainty (Figure 4.1) has many more dynamic linkages, including several with macro-financial blocks. In contrast, US idiosyncratic uncertainty (Figure 4.1) is statically linked with disagreement measures in four 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 static interdependencies while the effects of uncertainty materialise with a delay. A possible explanation is the timing of the underlying *Consensus Economics* surveys which tend to be conducted in the first half of the month, making it unlikely that participants are able to respond to developments in industrial production and stock prices in the corresponding month. At the same time, it is plausible that effects of uncertainty on the real or financial sector occur with a lag, for example, due to the need for industrial production to adjust to new shocks or new information.

Figures 4.1 - 4.3 show considerable evidence of international uncertainty spillovers with dynamic spillovers almost exclusively originating from the uncertainty block of different economies. For instance, Figure 4.1 shows that idiosyncratic uncertainty for all seven economies has a lagged impact on at least five other economies. But there is no economy where the macro-financial block affects another economy. Unsurprisingly, DIs indicate that uncertainty in the US plays a particularly strong role internationally regardless of the proxy used. For instance, if we consider spillovers in US aggregate uncertainty we find spillovers to the real and financial sectors domestically and in the UK, Eurozone, China, India and Japan. The

UK and Eurozone are also important sources of uncertainty. While the former 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. In terms of economies which are strongly affected by uncertainty spillovers, the Japanese macro-financial and uncertainty blocks experience the greatest number of uncertainty spillovers. For instance, if we consider aggregate uncertainty, Japanese macro-financial variables experience foreign uncertainty spillovers from all economies except India. Finally, we find that uncertainty shocks in each of our emerging economies - China and India - affect uncertainty and/or macro-financial variables in the other emerging economy. This is most pronounced in Figure 4.3 where we consider aggregate uncertainty.

Figures 4.4 - 4.6 show that several key SI findings are robust across all uncertainty measures. For instance, uncertainty increases in the US always coincide with higher uncertainty in the Eurozone and Canada while Eurozone uncertainty always transmits into uncertainty in Japan and the UK. However, there are some differences in SI patterns, too. Spillovers across economies are more frequently observed for idiosyncratic uncertainty or aggregate uncertainty compared to common uncertainty. This can be seen by counting the number of linkages in Figures 4.4 and 4.6 (22 and 24, respectively) and comparing this to the number of linkages in Figure 4.5 (only 17). This is largely due to the China-India relationship. Figures 4.4 and 4.6 indicate Chinese uncertainty affects uncertainty and macro-financial variables in India for both idiosyncratic and aggregate uncertainty. In contrast, Figure 4.5 indicates a complete lack of linkages between these two economies.

4.5.2 International Uncertainty Spillovers at the Component Level

4.5.2.1 Impulse Response Analysis

In the preceding sub-section, we discussed spillovers between economies at a low level of granularity. In this sub-section, 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 summarise industrial production growth (IP) and stock market growth (MSCI) GIRFs[17] using Sankey diagrams. A link is shown if a large uncertainty shock[18] has a negative effect which is non-zero according to the credible interval. The width of the link reflects the depth of the median GIRF's trough. For brevity, in this section, we will focus on summarising our findings and presenting Sankey diagrams for the 84 percent interval (Figures 4.7 - 4.9). However, Sankey diagrams for the 68 percent credible interval (Figures C.1 - C.3) and full GIRFs (Figures C.4 - C.24) are provided in Appendix C.2.

Figures 4.7 - 4.9 and our GIRFs (many of which have credible intervals containing zero at all horizons) show that our flexible modelling 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 con-

[17]These have been rescaled to reverse standardisation of the raw data.

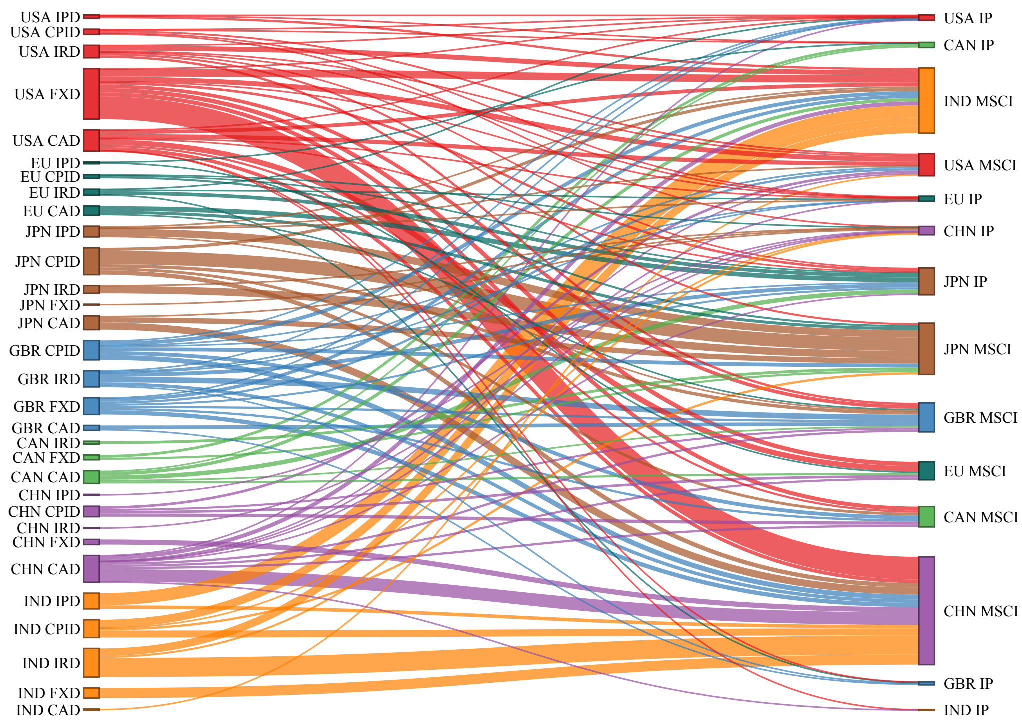
[18]We consider large uncertainty shocks equal to four standard deviations following Bloom, 2009, Jurado et al., 2015 and Istrefi and Mouabbi, 2018.

firm that there are important international spillovers in different components of uncertainty across economies for all three uncertainty proxies. As in the previous section, these are more frequently observed for idiosyncratic and aggregate uncertainty. We also find that the role played by different components of uncertainty is heterogeneous across economies. Compared to the previous subsection, we find more evidence of spillovers from domestic uncertainty to the domestic economy but in most cases, foreign uncertainty shocks play a similar or larger role. We find that the US is a key source of idiosyncratic uncertainty and that these patterns become accentuated when we consider aggregate uncertainty. Importantly, however, we find that every economy adversely affects the real or financial sectors of other economies through idiosyncratic or aggregate uncertainty shocks. In contrast, the UK is the dominant source of common uncertainty. Across uncertainty proxies, the financial sectors of different economies tend to be hit harder and by a larger number of uncertainty shocks relative to the real sectors. Emerging stock markets are most affected by idiosyncratic and aggregate uncertainty shocks while advanced stock markets are most affected by common uncertainty shocks. As expected, all our findings hold when we consider Sankey diagrams using the 68 percent credible interval but the lack of a dominant economy or component of uncertainty becomes even more pronounced.

Focusing on Figure 4.7 and the corresponding GIRFs, the response of domestic variables to domestic disagreement shocks mostly confirm existing results in the literature. That is, the effect of domestic uncertainty on the domestic real and financial sectors are mostly negative when the GIRFs are non-zero. However, we observe some interesting differences across the various components of uncertainty. Current account and exchange rate disagreement, which directly relate to the global economy, frequently tend to trigger a short-lived negative response in domestic stock prices and industrial production. India and the Eurozone are exceptions since some GIRFs tend be slightly positive. In the case of the Eurozone, this might reflect heterogeneity across Euro area countries. There are also some notable differences with regard to inflation and interest rate disagreement. Note that these are the variables most closely linked to monetary policy. Domestic inflation uncertainty actually has positive effects in Canada, China and the Eurozone. However, negative effects materialise in the US and the UK (on industrial production) and Japan and India (on stock markets). Domestic negative effects of interest rate disagreement are more pronounced (the US is a notable exception to this). China and the Eurozone are also the only economies where disagreement related to industrial production has a slightly positive effect on industrial production while the effect is mostly negative for the other economies.

Next we consider international uncertainty spillovers, still focusing on Figure 4.7 and the corresponding GIRFs. Unsurprisingly, disagreement spillovers arising from different components of US uncertainty have negative affects on several economies. 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 linking the US to the global economy. For all economies including the US idiosyncratic uncertainty surrounding industrial production growth - sometimes used to measure macroeconomic uncertainty - seldom plays a dominant role. Negative disagreement spillovers from the UK and Eurozone primarily arise from inflation and interest rate uncertainty, components which are related to monetary policy. Eurozone spillovers tend to be confined to the US, UK and Japan whereas British spillovers also spread to Indian and Chinese stock markets. British exchange rate disagreement also has adverse affects on all stock markets and British and Japanese industrial production. Japanese and Canadian spillovers have smaller affects on other economies. However, Canadian current account disagreement causes a decline in Indian, European and British stock markets and Japanese industrial production. Japaneses current account disagreement has a negative effect on Chinese stock markets.

Figure 4.7: Idiosyncratic Uncertainty: Summary of Impulse Responses Showing Important Declines in Real and Financial Growth Following a Shock to a Component of Uncertainty



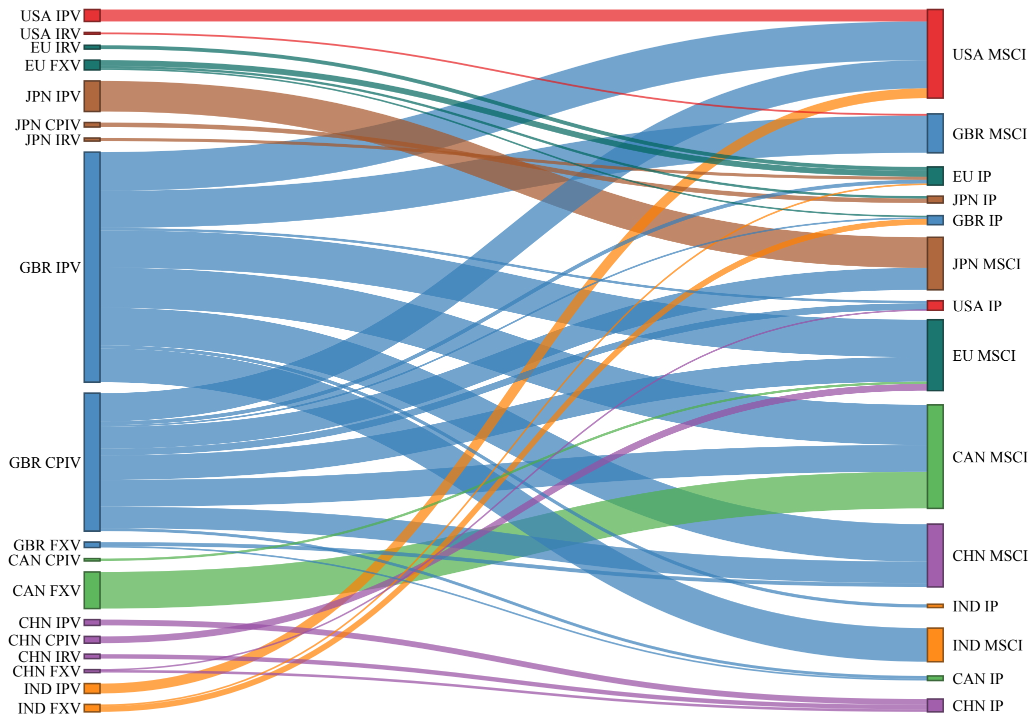
Note: We report impulse response functions for industrial production growth (IP) and stock market (MSCI) growth where the uncertainty shock has a negative effect which is non-zero according to the 84 percent credible interval. The width of each line corresponds to the depth of the median impulse response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

Still considering Figure 4.7, in terms of our two emerging markets, India's spillovers are large but primarily affect China's and its own stock market. In contrast, Chinese disagreement spillovers have more widespread affects. China's inflation uncertainty has negative effects on stock prices in the UK, Eurozone, Canada and the US. A rise in Chinese current account uncertainty also triggers a drop in industrial production in the US, Eurozone, UK, Canada and India and a decline in all stock markets apart from Japan. Our emerging stock markets - India and China - are also particularly affected by spillovers in idiosyncratic uncertainty.

When considering these findings, it is important to keep in mind that forecasters can be in agreement in both "good" and "bad" times. For instance, the positive effect of US interest rate uncertainty on domestic variables could be due to uncertainty among forecasters relating to the Federal Reserve's monetary policy which has been mostly expansionary over the sample. Disagreement regarding future inflation or industrial production can also arise during recovery periods. Our findings suggest that disagreement spillovers mostly occur during bad times since they trigger negative responses abroad while disagreement in good times do not seem to transmit to other economies, pointing to possible asymmetries in the international transmission of uncertainty.

We now turn to Figure 4.8 and the corresponding GIRFs which present responses to common uncertainty shocks. Recall that we were unable to construct common uncertainty measures for the current account and, hence, there are no GIRFs to this component of uncertainty.

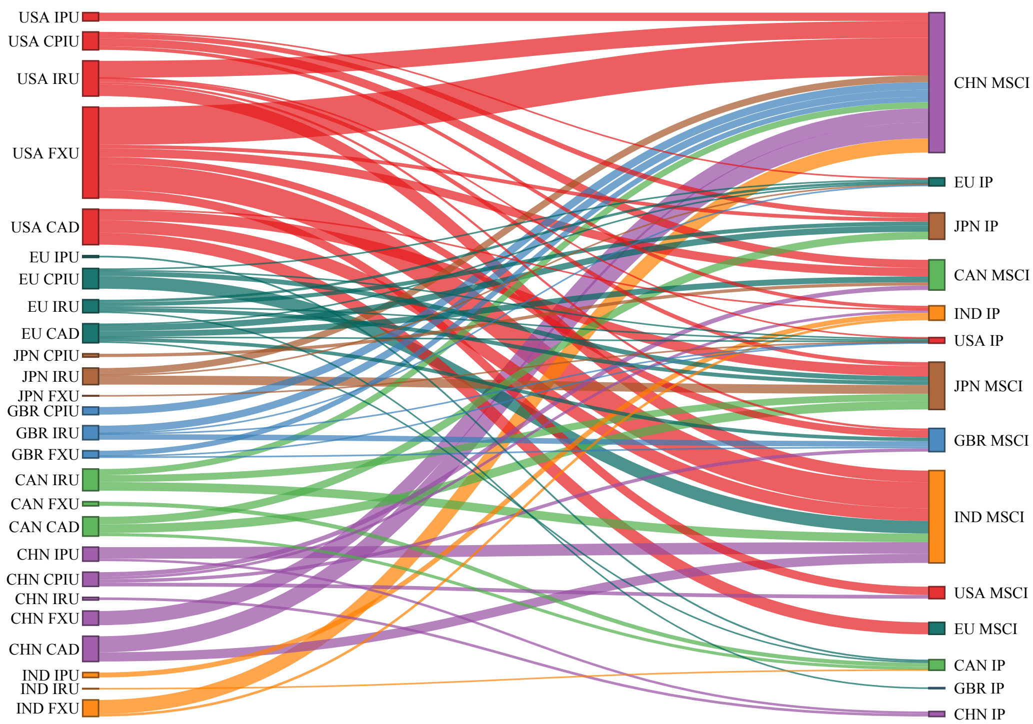
Figure 4.8: Common Uncertainty: Summary of Impulse Responses Showing Important Declines in Real and Financial Growth Following a Shock to a Component of Uncertainty



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. The width of each line corresponds to the depth of the median impulse response function's trough.

Overall, we detect fewer international spillover from common uncertainty in one economy to stock prices or industrial production in other economies. The exception is the UK which is a dominant source of common uncertainty surrounding industrial production growth and inflation. Responses to and recoveries from common uncertainty shocks such as these occur relatively quickly. However, like Ozturk and Sheng (2018) and Istrefi and Mouabbi (2018) we also find that where common uncertainty shocks are non-zero, the adverse affect on the economy is larger relative to idiosyncratic uncertainty shocks. Stock markets continue to be hit harder than the real sector but advanced markets in the US, Canada and Euro-zone are affected more strongly.

Figure 4.9: Aggregate Uncertainty: Summary of Impulse Responses Showing Important Declines in Real and Financial Growth Following a Shock to a Component of Uncertainty



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

Our third proxy for aggregate uncertainty, combines disagreement with the variance of forecast errors (apart from aggregate current account uncertainty which, as discussed above, simply equals current account disagreement). This is depicted in Figure 4.9. This figure is similar to but more sparse than Figure 4.7, with the key results for disagreement tending to hold for aggregate uncertainty. Japanese stock markets are affected more by foreign as oppose to domestic uncertainty shocks in this instance. Additionally, the relationship between India and China becomes more pronounced. Specifically, Indian exchange rate uncertainty has a large negative affect on Chinese stock market growth while Chinese output growth and current account uncertainty has adverse affects on Indian stock market growth.

4.5.2.2 Spillover Indices

Our findings so far illustrate the importance of international uncertainty spillovers. We have uncovered which economies tend to be important sources of uncertainty or which economies are most affected by spillovers. We have also considered the relative importance of different components of uncertainty. Throughout, we have also discussed how our results vary depending on which uncertainty proxy is used. But we have focused primarily on the existence (or lack of thereof) of interdependencies rather than their magnitude. And we have not made numerical comparisons across different uncertainty proxies. To address these issues, we now directly compare how the magnitude of different spillovers vary depending on the uncertainty proxy used. We do so by presenting Diebold-Yilmaz (2014) directional spillover indices based on our GFEVDs at a horizon of 12 months[19].

Our approach can be explained using table 4.1 below. If we have $K = NG$ endogenous variables, the upper-left $K \times K$ matrix contains our GFEVDs. If we delete the main diagonal, sum each column and divide by K, we obtain our "to"

[19] 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.

measures. The last step ensures that we can directly compare results from our three PVARs. We compare spillovers transmitted by each component of uncertainty (Figure 4.10) and by each macro-financial variable (Figure 4.11) to all other uncertainty and macro-financial variables. This allows us to consider the relative role played by uncertainty and macro-financial variables and how these change according to the uncertainty proxy used. Returning to our more specific question of how uncertainty spillovers affect macro-financial variables, we examine spillovers received by each macro-financial variable from uncertainty variables in the model (Figure 4.12). Again, we begin by deleting the main diagonal of the GFEVD matrix but we also delete the contribution of macro-financial shocks in each row. We then sum our rows and divide by K to obtain our "from" measures. We exclude current account uncertainty from these figures since, for reasons discussed previously, we cannot construct common current account uncertainty.

Table 4.1: Connectedness Table Representation

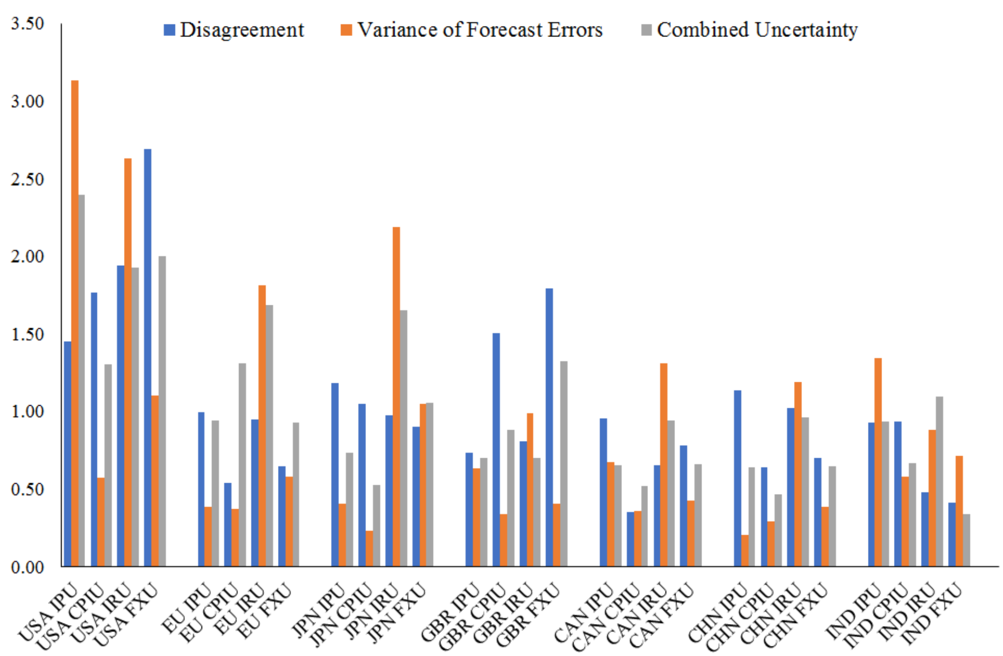
	x_1	x_2	$\cdots$	x_K	**From Others**
x_1	d_{11}	d_{12}	$\cdots$	d_{1K}	$\frac{\sum d_{1w,w\neq 1}}{K}$
x_2	d_{21}	d_{22}	$\cdots$	d_{2K}	$\frac{\sum d_{2w,w\neq 2}}{K}$
$\vdots$	$\vdots$	$\vdots$	$\ddots$	$\vdots$	$\vdots$
x_K	d_{K1}	d_{K2}	$\cdots$	d_{KK}	$\frac{\sum d_{Kw,w\neq K}}{K}$
To Others	$\frac{\sum d_{v1,v\neq 1}}{K}$	$\frac{\sum d_{v2,v\neq 2}}{K}$	$\cdots$	$\frac{\sum d_{vN,v\neq K}}{K}$	$\frac{\sum_{v,w=1}^{K} d_{vw,v\neq w}}{K}$

Figure 4.10 reinforces several important insights. In terms of economies, the findings confirm that spillovers from US uncertainty are largest, with the interest rate, exchange rate and, unlike before, industrial production, all important. We also find that the most prominent component of uncertainty (in terms of spillovers to

other variables) varies across economies. Interest rate uncertainty is most prominent for Canada, the Eurozone and Japan, while industrial production uncertainty dominates for India. Both are of equal importance to China while exchange rate uncertainty has the strongest effects for the UK.

The results also illustrate that neither idiosyncratic nor common uncertainty consistently has the largest spillovers. We identify 16 cases where idiosyncratic uncertainty has stronger effects and 11 cases where common uncertainty has stronger effects. The effects of the combined uncertainty measure usually lies between the two measures.

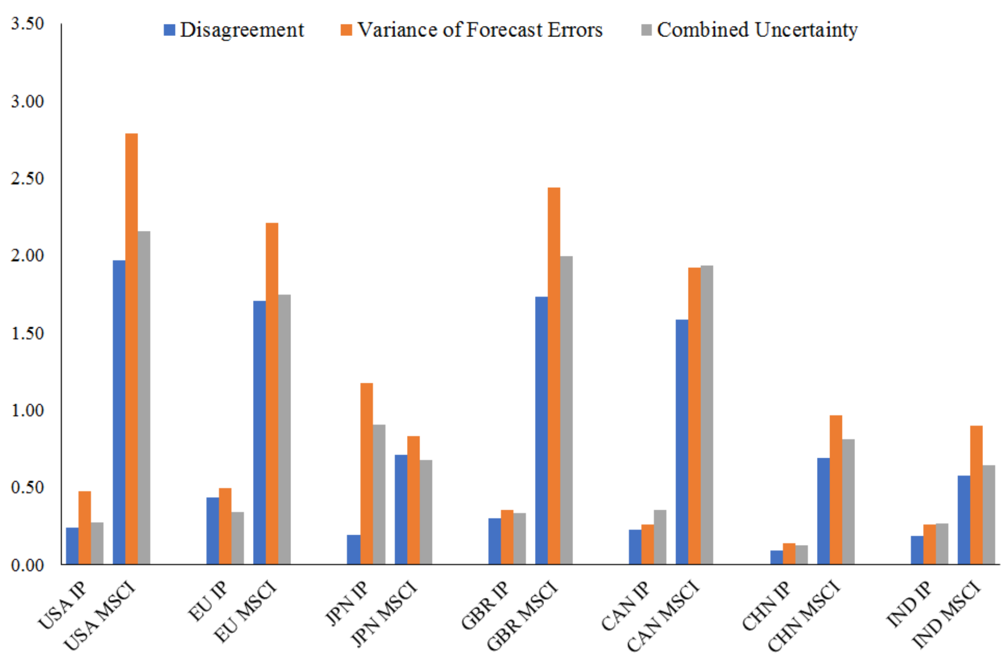
Figure 4.10: Spillovers from each Component of Uncertainty to Other Variables



The figure shows spillovers transmitted by each component of uncertainty to other uncertainty and macro-financial variables. These are obtained by summing the relevant columns of the GFEVDs.

Figure 4.11 shows that spillovers from industrial production are quite small while stock price spillovers are broadly in the same ranges as uncertainty spillovers. The degree of spillovers do not vary significantly across our three uncertainty proxies. This makes sense given that stock prices and industrial production variables remain the same across the three VARs which differ only in which uncertainty proxy they use. This also suggests that there are either few spillover effects from macro-financial variables to uncertainty variables or that these effects do not change depending on the uncertainty proxy used.

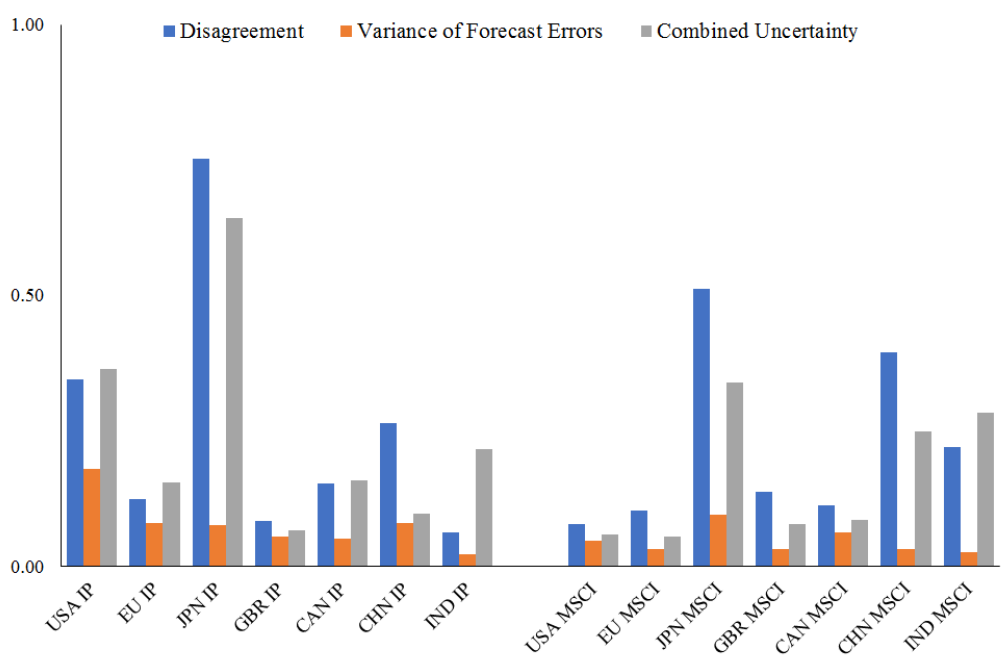
Figure 4.11: Spillovers from each Macro-Financial Variable to Other Variables



The figure shows spillovers transmitted by each macro-financial variable to other macro-financial and uncertainty variables.These are obtained by summing the relevant columns of the GFEVDs.

Figure 4.12 provides spillovers received by stock prices and industrial production in each economy from uncertainty variables. Uncertainty explains the largest fraction of variation in Japanese stock prices and industrial production, followed by Chinese and Indian stock prices and US industrial production. This figure also confirms our early findings and shows that, among our three proxies for uncertainty, disagreement and aggregate uncertainty have much stronger effects on the real or financial sectors compared to common uncertainty. This finding holds across all macro-financial variables. Industrial production in the US, stock prices and industrial production in China and Japan, and Indian stock prices are affected considerably by disagreement. In Figure 4.10 we found that common uncertainty had a similar or larger impact on other variables than disagreement. Combining this finding with those of Figure 4.12 suggests that this reflects effects on other uncertainty variables and not stock prices and industrial production.

Figure 4.12: Spillovers Received by each Macro-Financial Variable from all Uncertainty Variables



The figure shows spillovers received by each macro-financial variable from all uncertainty variables.These are obtained by summing the relevant rows of the GFEVDs.

There is no unique definition of what makes a good proxy for uncertainty. However, if a good proxy is one which has stronger effects on the real or financial sectors, then our findings indicate that disagreement is preferable. Figures 4.10 and 4.12 indicate (with only a few exceptions) that disagreement has a much larger impact on industrial production and stock prices than common uncertainty. Furthermore, in Section 4.2 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). Disagreement does not suffer from this criticism.

4.6 Conclusion

This chapter contributes to the literature on international uncertainty spillovers in two ways. First, we consider spillovers between seven advanced and emerging economies, distinguishing between five components of uncertainty regarding: output growth, inflation, the current account, the short-term interest rate and the exchange rate. Second, 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 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.

We show that various uncertainty spillovers between economies exist. While US interest rate, exchange rate and current account uncertainty are important, we also find that uncertainty shocks originate from all economies, affecting both uncertainty and the real and financial sector in other economies. The fact suggests that there is no single global uncertainty shock and emphasises the advantages of our VAR-based approach. Across economies, the financial sector is affected more by foreign uncertainty spillovers than the real sector with Japan, China and India most affected by foreign uncertainty shocks. 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.

Chapter 5

Conclusions

5.1 Summary of Contributions and Implications

Globalisation, regionalism and interdependencies between countries present new, often politicised challenges to policymakers. In this thesis, we took the literature on large multi-country Bayesian Vector Autoregressions and Panel Vector Autoregressions as our starting point. We demonstrated that to analyse these challenges econometricians need to develop new methods and reconsider old modelling assumptions so that our analysis reflects today's fast changing world.

In chapter 2, we reconsidered whether the Asia Pacific is decoupling from the US, modelling empirically relevant interdependencies between the US and eleven Asia Pacific countries. Previous studies focused on estimating a group of country-specific VARs. However, we sought to allow for interdependencies between all twelve countries and account for a range of transmission channels. Additionally, we did not presume that the block exogeneity assumption was valid and sought to allow Asia Pacific countries to affect the US as well as vice versa. To achieve these aims, a large 52 variable Panel VAR was estimated using Bayesian variable selection techniques. In doing so, we could consider the relative importance of extra-regional US shocks, regional Asia Pacific shocks and domestic shocks. We could also capture the extent to which Asia Pacific countries can affect the US.

We found that shocks originating from the Asia Pacific matter, not only affecting other Asia Pacific countries but the US. While shocks to US economic conditions, financial markets and uncertainty are important, regional shocks play a larger role in a typical Asia Pacific country. That said, there is considerable cross-country heterogeneity. We also detected substantive spillovers from the Asia Pacific to US financial markets indicating a bidirectional not unidirectional relationship. These findings have important policy implications, suggesting that Asian policymakers should be wary of the notion that Asia has decoupled from the US while also recognising that regional business cycles play an important role. Conversely, as the dominance of the US in the world economy slowly lessens, US policymakers will need to pay closer attention to external developments with its financial sector more vulnerable than its real sector.

In chapter 3, we sought to reconcile empirical research analysing contagion which has become increasingly fragmented. Different definitions of contagion have resulted in different methods being deployed. Contrary to theories of contagion, the literature has also focused on analysing financial transmission channels. We devised a novel econometric strategy where the nature of interdependencies, magnitude of interdependencies and transmission channels selected for inclusion can change over time. This allowed us to provide a unified approach, appealing to multiple definitions of contagion and distinguishing between: interdependence, contagion through interdependence and abrupt contagion through changing linkages.

Using our approach we analysed different crisis episodes in Latin America. Results generally indicated interdependence not contagion during the currency crises of the 1990s and Argentine crisis of 1998 - 2002. During the global financial crisis, results indicated abrupt contagion from the US to Argentina and Brazil. Mexico, however, experienced contagion through existing interdependencies with the US. With adverse shocks often spreading through existing interdependencies, this highlights the importance of carefully appraising the benefits and risks arising from deepening economic integration, particularly where a country's resilience to external shocks is low. Our results also showed that macroeconomic and uncertainty channels play a role during different crises not just financial channels, suggesting that future research must continue to consider a wider range of transmission channels.

In chapter 4, we used a large professional forecasts data set to analyse spillovers in uncertainty across countries. Unlike previous studies which focus on one single global uncertainty shock or spillovers in economic policy uncertainty, we considered spillovers in uncertainty surrounding output growth, inflation, the interest rate, exchange rate and current account. We also considered the role of emerging economies in our analysis, allowing for spillovers between the G7 economies, China and India. We also examined how our results varied depending on whether we proxied each component of uncertainty using disagreement among forecasters, the variance of their mean forecast errors or a combination of these two measures. These issues were investigated by estimating three multi-country

Bayesian Panel VARs arising from our three uncertainty proxies reflecting idiosyncratic, common and aggregate uncertainty.

We found that the US affects other economies through interest rate, exchange rate and current account uncertainty but does not dominate as a source of foreign uncertainty. Instead, uncertainty spillovers arise from all economies with spillovers in interest rate and inflation uncertainty from the Eurozone and UK particularly prominent. This delivers a similar message to that seen in Chapter 2, demonstrating that pre-existing ideas surrounding which interdependencies play the largest role in the global economy require reconsideration. Across economies, the financial sector is hit harder by foreign uncertainty than the real sector with China, India and Japan being most affected. Idiosyncratic uncertainty spillovers are more frequently observed than spillovers in common uncertainty. However, when they do occur, foreign common uncertainty shocks produce larger negative responses.

5.2 Directions for Future Research

There are still many challenges to be overcome when modelling interdependencies between countries. In the future, it would be beneficial to extend the approaches seen in Chapters 2 and 4 by introducing time-variation. This would allow us to consider how regional and global linkages in the world economy have evolved over time. Notably, recent papers seeking to deploy large time-varying parameter models typically focus on forecasting (see, among many others, Carriero et al., forthcoming, Chan, 2019, Chan et al., forthcoming and Huber et al., 2020), however, considerably less focus has been placed on using large time varying parameter VARs for structural analysis. While this thesis has provided strategies to produce and visualise the impulse response functions which result from large Panel VARs, only Korobilis (2020) has provided an alternative to cholesky decompositions or generalised impulse response functions in the large VAR setting. This presents another avenue for future research.

Chapter 3 on contagion points towards two further extensions. First, it would be beneficial to re-examine possible methods which could be deployed in light of the literature on large time-varying parameter models discussed above. Second, with a range of transmission channels proving important, a mixed-frequency approach (see, among many others, Carriero et al., 2015, Cotter et al., 2017, Schorfheide and Song, 2015, Ghysels, 2016, McCracken et al., 2020, Koop et al., 2020) which can accomodate high frequency financial data and low frequency macroeconomic and uncertainty data may allow us to improve on existing methods.

The literature on uncertainty also requires further research from an applied empirical perspective and econometric perspective. As previously noted, *Consensus Forecasts* data provides a means to analyse an array of different uncertainty shocks - we are currently exploring different projects which could complement the analysis in Chapter 4. Additionally, recent research uses VARs with stochastic volatility to econometrically estimate uncertainty (see, for example, Carriero et al., 2019, Cross et al., 2019, Curaresma et al., 2020). The scalability of such models presents a challenge if we wish to move beyond examining macroeconomic and financial uncertainty or consider spillovers between countries. While factor models with stochastic volatility are more parsimonious (see, for example, Mumtaz and Theodoridis, 2017 and Mumtaz and Musso, 2019) they do not provide the same flexibility as VARs. Again, this is another research area which is currently being explored.

References

[1] Allegret, J.P., Couharde, C. and Guillaumin, C., 2012. The impact of external shocks in East Asia: Lessons from a structural VAR model with block exogeneity. *International Economics*, 132, pp.35-89.

[2] Athukorala, P.C. and Kohpaiboon, A., 2009. *Intra-regional trade in East Asia: The decoupling fallacy, crisis, and policy challenges*. ADBI Working Paper Series No.177.

[3] Baker, S., Bloom, N. and Davis, S., 2016. Measuring economic policy uncertainty. *Quarterly Journal of Economics*, 131(4), pp.1593-1636.

[4] Bańbura, M., Giannone, D. and Reichlin, L., 2010. Large Bayesian vector auto regressions. *Journal of Applied Econometrics*, 25(1), pp.71-92.

[5] Barrot, L.D., Calderón, C. and Sérven, L., 2018. Openness, specialization, and the external vulnerability of developing countries. *Journal of Development Economics*, 134, pp.310-328.

[6] Beckmann, J., Davidson, S.N., Koop, G. and Schüssler, R., 2020. *Measuring International Uncertainty Spillovers and their Impact on the Economy*. Manuscript.

[7] Beckmann, J., Koop, G., Korobilis, D. and Schüssler, R., 2020. Exchange rate predictability and dynamic Bayesian learning. *Journal of Applied Econometrics*,35(4), pp.410-421.

[8] Beckmann, J. and Schüssler, R., 2016. Forecasting exchange rates under parameter and model uncertainty. *Journal of International Money and Finance*, 60, pp. 267-28.

[9] Bekaert, G, Hoerova, M. and Duca, M.L., 2013. Risk, uncertainty and monetary policy. *Journal of Monetary Economics*, 60(7), pp. 771-788.

[10] Beirne, J. and Gieck, J., 2014. Interdependence and contagion in global asset markets. *Review of International Economics*, 22(4), pp.639-659.

[11] Berger, T., Grabert, S. and Kempa, B., 2016. Global and country-specific output growth uncertainty and macroeconomic performance. *Oxford Bulletin of Economics and Statistics*, 78(5), pp.694-716.

[12] Biljanovska, N., Grigoli, F. and Hengge, M., 2017. *Fear thy neighbor: Spillovers from economic policy uncertainty*. IMF Working Papers.

[13] Billio, M., Casarin, R., Ravazzolo, F. and Van Dijk, H.K., 2016. Interconnections between eurozone and US booms and busts using a Bayesian panel Markov-switching VAR model. *Journal of Applied Econometrics*, 31(7), pp.1352-1370.

[14] Bloom, N., 2009. The impact of uncertainty shocks. *Econometrica*, 77, pp.623-685.

[15] Caggiano, G., Castelnuovo, E. and Figueres, J.M., 2020. Economic policy uncertainty spillovers in booms and busts. *Oxford Bulletin of Economics and Statistics*, 82(1), pp.125-155.

[16] Calvo, S. and Reinhart, C., 1996. Capital Flows to Latin America: Is There Evidence of Contagion Effects?. *Private Capital Flows to Emerging Markets after the Mexican Crisis*, pp.151-171, Washington, D.C.: Institute for International Economics.

[17] Canova, F., 2005. The transmission of US shocks to Latin America. *Journal of Applied Econometrics*, 20(2), pp.229-251.

[18] Canova, F. and Ciccarelli,M., 2013. Panel Vector Autoregressive Models: A Survey. *VAR Models in Macroeconomics-New Developments and Applications: Essays in Honor of Christopher A. Sims*, Emerald Group Publishing Limited, pp.205-246.

[19] Canova, F. and Ciccarelli, M., 2009. Estimating multicountry VAR models. *International Economic Review*, 50, pp. 929-959.

[20] Carriero, A., Clark, T.E. and Marcellino, M., forthcoming. *Large Vector Autoregressions with stochastic volatility and non-conjugate priors.* Journal of Econometrics.

[21] Carriero, A., Clark, T.E. and Marcellino, M., 2019. Assessing International Commonality in Macroeconomic Uncertainty and Its Effects. *Journal of Applied Econometrics*, 35(3), pp.273-293.

[22] Carriero, A., Clark, T. and Marcellino, M. 2015. Realtime nowcasting with a Bayesian mixed frequency model with stochastic volatility. *Journal of the Royal Statistical Society Series A*, 178, pp.837-862.

[23] Casarin, R., Sartore, D. and Tronzano, M., 2018a. A Bayesian Markov-switching correlation model for contagion analysis on exchange rate markets. *Journal of Business and Economic Statistics*, 36(1), pp.101-114.

[24] Casarin, R., Foroni, C., Marcellino, M. and Ravazzolo, F., 2018b. Uncertainty through the lenses of a mixed-frequency Bayesian panel Markov-switching model. *The Annals of Applied Statistics*, 12(4), pp.2559-2586.

[25] Castelnuovo, E., 2019. *Domestic and global uncertainty: A survey and some new results*. Manuscript.

[26] Castelnuovo, E. and Tran, T., 2017. Google it up! a google trends-based uncertainty index for the United States and Australia. *Economics Letters*, 153, pp. 161-149.

[27] Cavallo, A. and Bertolotto, M., 2016. *Filling the Gap in Argentina's Inflation Data*. Manuscript.

[28] Cavusoglu, N. and Neveu, A., 2015. The predictive power of survey-based exchange rate forecasts: Is there a role for dispersion? *Journal of Forecasting*, 34, pp. 337-353.

[29] Chan, J.C.C., 2019. *Large Hybrid Time-Varying Parameter VARs*. Manuscript.

[30] Chan, J.C.C., Eisenstat, E., Hou, C. and Koop, G., forthcoming. Composite likelihood methods for large Bayesian VARs with stochastic volatility. *Journal of Applied Econometrics*.

[31] Chan, J., Fry-McKibbin, R. and Hsiao, C., 2018. A Regime Switching Skew-normal Model of Contagion. *Studies in Nonlinear Dynamics and Econometrics*, 23(1).

[32] Chang, C., Chen, K., Waggoner, D. and Zha, T., 2015. Trends and Cycles in China's Macroeconomy. *NBER Macroeconomics Annual 2015*, Volume 30, Eichenbaum and Parker.

[33] Ciccarelli, M. and Rebucci, A., 2007. Measuring contagion and interdependence with a Bayesian time-varying coefficient model: An application to the Chilean FX market during the Argentine crisis. *Journal of Financial Econometrics*, 5(2), pp.285-320.

[34] Claessens, S., Dornbusch, R. and Park, Y.C, 2000. Contagion: understanding how it spreads. *The World Bank Research Observer*, 15(2), pp.177-197.

[35] Cotter, J., Hallam, M. and Yilmaz, K., 2017. *Mixed frequency macro-financial spillovers*. Koc University Working Paper 1704.

[36] Cross, J., Hou, C. and Poon, A., 2019. *International transmission of macroeconomic uncertainty in small open economies: An empirical approach*. Manuscript.

[37] Cuadro-Sáez, L., Fratzscher, M. and Thimann, C., 2009. The transmission of emerging market shocks to global equity markets. *Journal of Empirical Finance*, 16(1), pp.2-17.

[38] Cuaresma, J.C., Huber, F. and Onorante, L., 2020. Fragility and the effect of international uncertainty shocks. *Journal of International Money and Finance*, pp. 102-151.

[39] Cushman, D.O. and Zha, T., 1997. Identifying monetary policy in a small open economy under flexible exchange rates. *Journal of Monetary Economics*, 39(3), pp.433-448.

[40] D'Amico, S. and Orphanides, A., 2014. *Inflation uncertainty and disagreement in bond risk premia*. Federal Reserve Bank of Chicago Working Paper 2014-24.

[41] Darvas, Z., 2012. *Real effective exchange rates for 178 countries: a new database*, Working Paper 2012/06, Bruegel, 15 March 2012.

[42] Diebold, F. and Yilmaz, K., 2014. On the network topology of variance decompositions: Measuring the connectedness of financial firms. *Journal of Econometrics*, 182, pp. 119-134.

[43] Dovern, J., Fritsche, U. and Slacalek, J., 2012. Disagreement among forecasters in G7 countries. *Review of Economics and Statistics*, 94(4), pp. 1081-1096.

[44] Dungey, M., Fry, R., González-Hermosillo, B. and Martin, V.L., 2005. Empirical modelling of contagion: a review of methodologies. *Quantitative Finance*, 5(1), pp.9-24.

[45] Ehrmann, M., Fratzscher, M. and Rigobon, R., 2011. Stocks, bonds, money markets and exchange rates: measuring international financial transmission. *Journal of Applied Econometrics*, 26(6), pp.948-974.

[46] Engle, R.F., 1983. Estimates of the variance of US inflation based upon the ARCH model. *Journal of Money, Credit and Banking*, 15(3), pp. 286-301.

[47] Forbes, K., 2013. *The "Big C": Identifying and Mitigating Contagion*. The Changing Policy Landscape. 2012 Jackson Hole Symposium hosted by the Federal Reserve Bank of Kansas City, pp.23-87.

[48] Forbes, K., and Rigobon, R., 2002. No Contagion, Only Interdependence: Measuring Stock Market Comovements. *Journal of Finance*, 57(5), pp. 2223-2261.

[49] Forbes, K. and Rigobon, R., 2001a. Measuring contagion: conceptual and empirical issues. *International financial contagion*, pp. 43-66. Springer, Boston, MA.

[50] Forbes, K. and Rigobon, R., 2001b. Contagion in Latin America: Definitions, measurement, and policy implications. *Economia*, 1(2), pp. 1-46.

[51] George, E.I., Sun, D. and Ni, S., 2008. Bayesian stochastic search for VAR model restrictions. *Journal of Econometrics*, 142(1), pp.553-580.

[52] Georgiadis, G., 2017. To bi, or not to bi? Differences between spillover estimates from bilateral and multilateral multi-country models. *Journal of International Economics*, 107, pp.1-18.

[53]] Ghysels, E., 2016. Macroeconomics and the reality of mixed frequency data. *Journal of Econometrics*, 193, 294-314.

[54] Gilchrist, S. and Zakrajšek, E., 2012. Credit Spreads and Business Cycle Fluctuations. *American Economic Review*, 102(4), pp.1692-1720.

[55] Gravelle, T., Kichian, M. and Morley, J., 2006. Detecting shift-contagion in currency and bond markets. *Journal of International Economics*, 68(2), pp.409-423.

[56] Ha, J., Kose, M.A., Otrok, C. and Prasad, E.S., 2020. *Global macro-financial cycles and spillovers*. National Bureau of Economic Research No. w26798.

[57] He, D. and Liao, W., 2012. Asian business cycle synchronization. *Pacific Economic Review*, 17(1), pp.106-135.

[58] He, D., Cheung, L. and Chang, J., 2007. *Sense and nonsense on Asia's export dependency and the decoupling thesis*. Hong Kong Monetary Authority Working Paper.

[59] Huber, F., Koop, G. and Onorante, L., 2020. Inducing sparsity and shrinkage in time-varying parameter models. *Journal of Business and Economic Statistics*, pp.1-15.

[60] Huber, F. and Pfarrhofer, M., 2019. *Dealing with cross-country heterogeneity in panel VARs using finite mixture models*. Manuscript.

[61] Husted, L., Rogers, J. and Sun, B., 2019. Monetary policy uncertainty. *Journal of Monetary Economics*.

[62] Istrefi, K. and Mouabbi, S., 2018. Subjective interest rate uncertainty and the macroeconomy: A cross-country analysis. *Journal of International Money and Finance*, 88, pp.296-313.

[63] Ito, T., 2012. Can Asia Overcome the IMF Stigma? *American Economic Review*, 102(3), pp.198-202.

[64] Jurado, K., Ludvigson, S.C. and Ng, S., 2015. Measuring uncertainty. *American Economic Review*, 105(3), pp.1177-1216.

[65] Kaminsky, G.L., Reinhart, C.M. and Vegh, C.A., 2003. The unholy trinity of financial contagion. *Journal of Economic Perspectives*, 17(4), pp.51-74.

[66] Kannan, P. and Koehler-Geib, F, 2011. Uncertainty and Contagion. *Financial Contagion: The Viral Threat to the Wealth of Nations*, pp.21-28. John Wiley and Sons.

[67] Kim, S., Lee, J.W. and Park, C.Y., 2011. Emerging Asia: decoupling or recoupling. *The World Economy*, 34(1), pp.23-53.

[68] King Jr, M.L., 1967. *Conscience for Change: Massey Lectures*, Seventh Series. Toronto: Canadian Broadcasting Corporation I, 967.

[69] Klössner, S. and Sekkel, R., 2014. International spillovers of policy uncertainty. *Economics Letters*, 124(3), pp. 508-512.

[70] Koop, G. and Korobilis, D., 2019. Forecasting with high dimensional panel VARs. *Oxford Bulletin of Economics and Statistics*, 81(5), pp.937-959.

[71] Koop, G., 2014. Forecasting with dimension switching VARs. *International Journal of Forecasting*, 30(2), pp.280-290.

[72] Koop, G., McIntyre, S., Mitchell, J. and Poon, A., 2020. Regional output growth in the United Kingdom: More timely and higher frequency estimates, 1970-2017. *Journal of Applied Econometrics*, 35(2), pp.176-197.

[73] Koop, G. and Korobilis, D., 2016. Model uncertainty in panel vector autoregressive models. *European Economic Review*, 81, pp.115-131.

[74] Koop, G. and Korobilis, D., 2013. Large time-varying parameter VARs. *Journal of Econometrics*, 177(2), pp.185-198.

[75] Koop, G., Pesaran, M.H. and Potter, S., 1996. Impulse response analysis in nonlinear multivariate models. *Journal of Econometrics*, 74, pp. 119-147.

[76] Korobilis, D., 2020. *Sign Restrictions in High Dimension Vector Autoregressions*,

[77] Korobilis, D., 2016. Prior selection for panel vector autoregressions. *Computational Statistics and Data Analysis*, 101, pp.110-120.

[78] Kose, M.A., Prasad, E.S. and Terrones, M.E., 2005. Growth and volatility in an era of globalisation. *IMF Staff Papers*, 52(1), pp.31-63.

[79] Laeven, L. and Valencia, F., 2013. Systemic banking crises database. *IMF Economic Review*, 61(2), pp.225-270.

bibitemLS10 Lahiri, K and Sheng, X., 2010. Measuring forecast uncertainty by disagreement: The missing link. *Journal of Applied Econometrics*, 25(4), pp. 514-538.

[80] Lahiri, K and Zhao, X., 2019. International propagation of shocks: A dynamic factor model using survey forecasts. *International Journal of Forecasting*, 35(3), pp. pp. 929-947.

[81] Lam, L. and Yetman, J., 2013. Asia's Decoupling: Fact, Fairytale or Forecast?. *Pacific Economic Review*, 18(3), pp.321-344.

[82] Lanne, M. and Nyberg, H., 2016. Generalized forecast error variance decomposition for linear and nonlinear multivariate models. *Oxford Bulletin of Economics and Statistics*, 78(4), pp.595-603.

[83] Larsen, V., 2017. *Components of uncertainty*. Norges Bank Working Paper 5/2017.

[84] Leduc, S. and Spiegel, M.M., 2013. Is Asia Decoupling from the United States (Again)?. *Pacific Economic Review*, 18(3), pp.345-369.

[85] Loayza, N.V. and Raddatz, C., 2007. The structural determinants of external vulnerability. *World Bank Economic Review*, 21(3), pp. 359-387.

[86] Loayza, N.V., Rancíere, R., Servén, L. and Ventura, J.,2007. Macroeconomic Volatility and Welfare in Developing Countries: An Introduction. *World Bank Economic Review*, 21(3), pp. 343-357.

[87] Ludvigson, S.C., Ma, S. and Ng, S., forthcoming. Uncertainty and business cycles: exogenous impulse or endogenous response? *American Economic Journal: Macroeconomics*.

[88] Maćkowiak, B., 2007. External shocks, US monetary policy and macroeconomic fluctuations in emerging markets. *Journal of Monetary Economics*, 54(8), pp.2512-2520.

[89] McCracken, M.W. and Ng, S., 2016. FRED-MD: A monthly database for macroeconomic research. *Journal of Business and Economic Statistics*, 34(4), pp.574-589.

[90] McCracken, M.W., Owyang, M. and Sekhposyan, T., 2020. *Real-time forecasting with a large, mixed frequency Bayesian VAR*. Manuscript.

[91] Miescu, M., 2019. *Uncertainty shocks in emerging economies: a global to local approach for identification*. Manuscript.

[92] Mohaddes, K. and Raissi, M., 2018. *Compilation, Revision and Updating of the Global VAR (GVAR) Database, 1979Q2-2016Q4*. University of Cambridge: Faculty of Economics (mimeo).

[93] Mumtaz, H. and Musso, A., 2019. The Evolving Impact of Global, Region-Specific, and Country-Specific Uncertainty. *Journal of Business and Economic Statistics*, pp. 1-16.

[94] Mumtaz, H. and Theodoridis, K., 2017. Common and country specific economic uncertainty. *Journal of International Economics*, 105, pp. 205-216.

[95] OECD, 2016. Graph 2.1 - Intra-regional trade in ASEAN, ASEAN+3 and ASEAN+6, by country group, 1990-2014: Total within-group trade as a share of groups' total world trade, in *Economic Outlook for Southeast Asia, China and India 2016: Enhancing Regional Ties*, OECD Publishing, Paris.

[96] Ozturk, E.O. and Sheng, X.S., 2018. Measuring global and country-specific uncertainty. *Journal of International Money and Finance*, 88, pp. 276-295.

[97] Park, C.Y., 2017. Decoupling Asia Revisited. *Asian Economic Integration in an Era of Global Uncertainty*, p.81. Australia National University Press.

[98] Park, C.Y., 2011. *The global financial crisis: decoupling of East Asia–myth or reality?* ADBI Working Paper No. 289.

[99] Park, C.Y. and Shin, K., 2009. Economic integration and changes in the business cycle in East Asia: is the region decoupling from the rest of the world?. *Asian Economic Papers*, 8(1), pp.107-140.

[100] Patton, A. and Timmermann, A., 2011. Why do forecasters disagree? Lessons from the term structure of cross-sectional dispersion. *Journal of Monetary Economics*, 57, pp. 803-820.

[101] Pericoli, M. and Sbracia, M., 2003. A primer on financial contagion. *Journal of Economic Surveys*, 17(4), pp.571-608.

[102] Pesaran, M.H. and Shin, Y., 1998. Generalized impulse response analysis in linear multivariate models. *Economics Letters*, 58, pp. 17-29.

[103] Raddatz, C., 2007. Are external shocks responsible for the instability of output in low-income countries? *Journal of Development Economics*, 84(1), pp. 155-187.

[104] Rich, R.W. and Tracy, J., 2018. *A closer look at the behavior of uncertainty and disagreement: micro evidence from the Euro area*. Working Paper 1811, Federal Reserve Bank of Dallas.

[105] Rich, R.W. and Tracy, J., 2010. The relationships among expected inflation, disagreement, and uncertainty: evidence from matched point and density forecasts. *The Review of Economics and Statistics*, 92(1), pp. 200-207.

[106] Rigobon, R., 2016.*Contagion, spillover and interdependence*. ECB Working Paper No. 1975.

[107] Rigobon, R., 2002. Contagion: how to measure it?. *Preventing currency crises in emerging markets*,pp. 269-334. University of Chicago Press.

[108] Rossi, B. and Sekhposyan, T., 2017. Macroeconomic uncertainty indices for the euro area and its individual member countries. *Empirical Economics*, 53(1), pp.41-62.

[109] Rossi, B. and Sekhposyan, T., 2015. Macroeconomic uncertainty indices based on nowcast and forecast error distributions. *American Economic Review*, 105(5), pp. 650-55.

[110] Schorfheide, F. and Song, D., 2015. Real-time forecasting with a mixed-frequency VAR. *Journal of Business and Economic Statistics*, 33(3), 366-380.

[111] Sims, C.A., 1980. Macroeconomics and reality. *Econometrica*, pp.1-48.

[112] Wu, J.C. and Xia, F.D., 2016. Measuring the macroeconomic impact of monetary policy at the zero lower bound. *Journal of Money, Credit and Banking*, 48(2-3), pp.253-291.

[113] Zarnowitz, V. and Lambros, L.A., 1987. Consensus and uncertainty in economic prediction. *Journal of Political Economy*, 95(3), pp. 591-621.

[114] Zha, T., 1999. Block recursion and structural vector autoregressions. *Journal of Econometrics*, 20(2), pp. 291-316.

Appendix A

Chapter 2 Appendix

A.1 Data Appendix

The following table describes the data sources and transformations applied.

Table A.1: Data

Variables	Description	Source	Trans.
OIL	Deflated crude oil three spot price index	IMF IFS	Δ ln
$USA\ FU$	Financial uncertainty	LMN	levels
$USA\ G$	Real GDP index of US	MR	Δ ln
$USA\ RU$	Real uncertainty	LMN	levels
$USA\ EBP$	Excess bond premium	GZ	levels
$USA\ S$	Deflated S&P 500 Index	FRED	Δ ln
COM	Deflated non-fuel commodity price index	IMF IFS	Δ ln
$USA\ R$	US 3 month T-Bill rate (%)	FRED	levels
G_i	Real GDP index of country i	MR	Δ ln
R_i	Short-term interest rate of country i (%)	MR	levels
E_i	Real effective exchange rate of country i	Darvas	Δ ln
S_i	Deflated MSCI Index of country i	Datastream	Δ ln

Note: The crude oil price index, non-fuel commodity price index and S&P 500 Index are all deflated by the US GDP deflator extracted from FRED. The MSCI indices are all deflated by inflation computed using CPI data from the IMF IFS. EX_i is measured so that an increase indicates an appreciation of the home currency against a basket of trading partners' currencies. IMF IFS = IMF international financial statistics database. LMN = Ludvigson et al. (2017). MR = Global VAR data 2016 vintage compiled, revised and updated by Mohaddes and Raissi (2018). GZ = Gilchrist and Zakrajšek (2012). Darvas = Zsolt Darvas (2012). FRED = St Louis. Federal Reserve Economic Data.

A.2 Technical Appendix

For full details of the hierarchical priors and Gibbs sampler algorithm used the reader is referred to Koop and Korobilis' (2016) technical appendix. Using their notation, we alter their approach by setting $N = 41$ and $G = 1$ to facilitate element by element restrictions. We also set $\gamma^{CSH} = 1$ so that we do not search for cross-sectional homogeneity restrictions. In this case, this would simply amount to checking for homogeneity in the persistence of each variable. The following table describes the hyperparameter values chosen relative to those chosen by Koop and Korobilis (2016) denoted KK.

Table A.2: Hyperparameter Values

Hyperparameter	KK Value	Value
$\underline{c}^{DI}$	1e-6	1e-6
$\underline{c}^{CSH}$	1e-5	1e-5
$\underline{c}^{SI}$	1e-5	1e-6
$\underline{\theta}^{DI}$	10	10
$\underline{\theta}^{CSH}$	60	60
$\underline{\theta}^{SI}$	10	10
$\underline{\psi}$	1	1
$\underline{\kappa}_2^2$	4	4
$\underline{\rho}_1$	0.01	0.01
$\underline{\rho}_2$	0.01	0.01

A.3 Supplementary Figures

A.3.1 Response of AP countries to Adverse Extra-Regional Shocks

Figure A.1: Impulse Response Functions to a One Standard Deviation Oil Price Shock

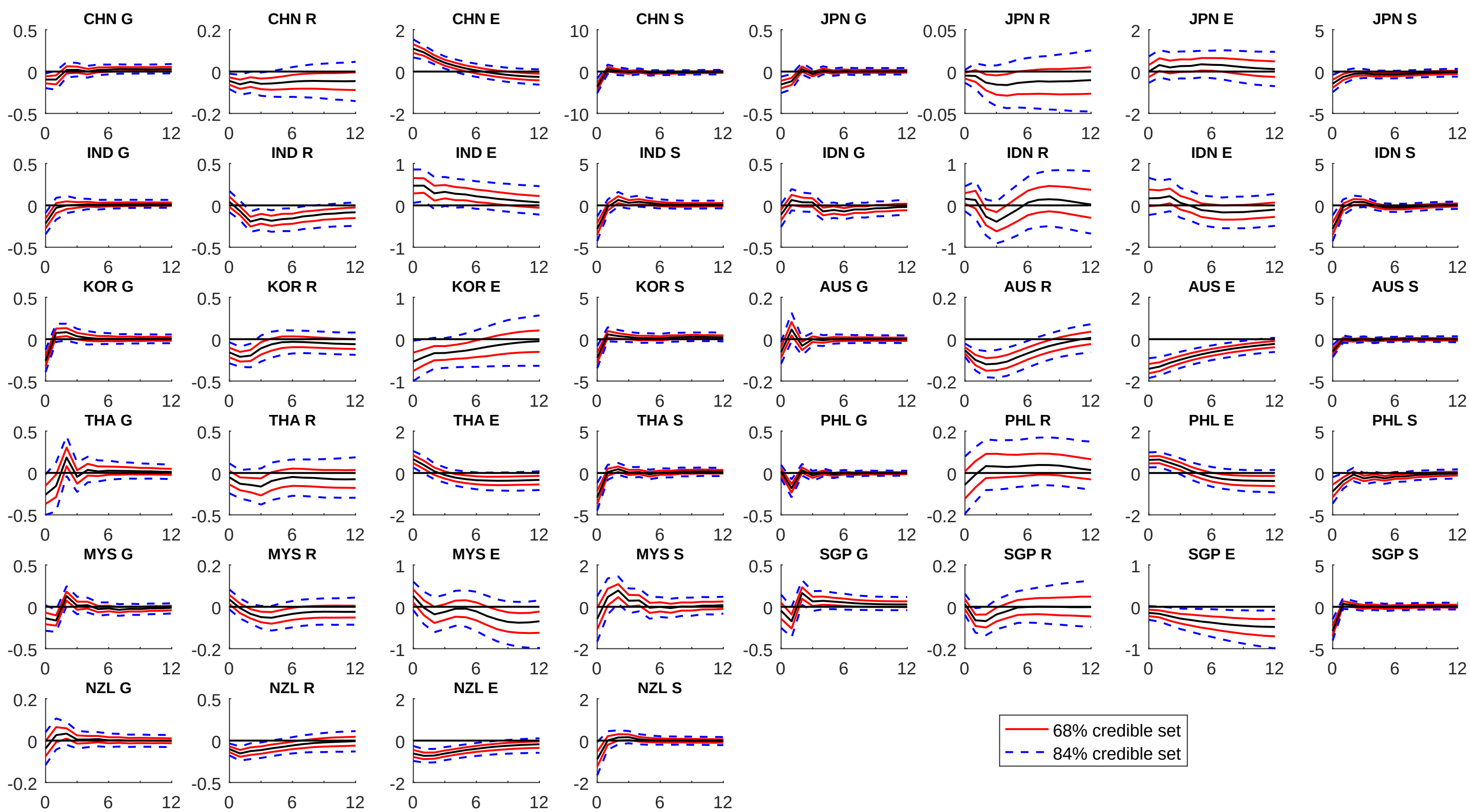


Figure A.2: Impulse Response Functions to a One Standard Deviation Commodity Price Shock

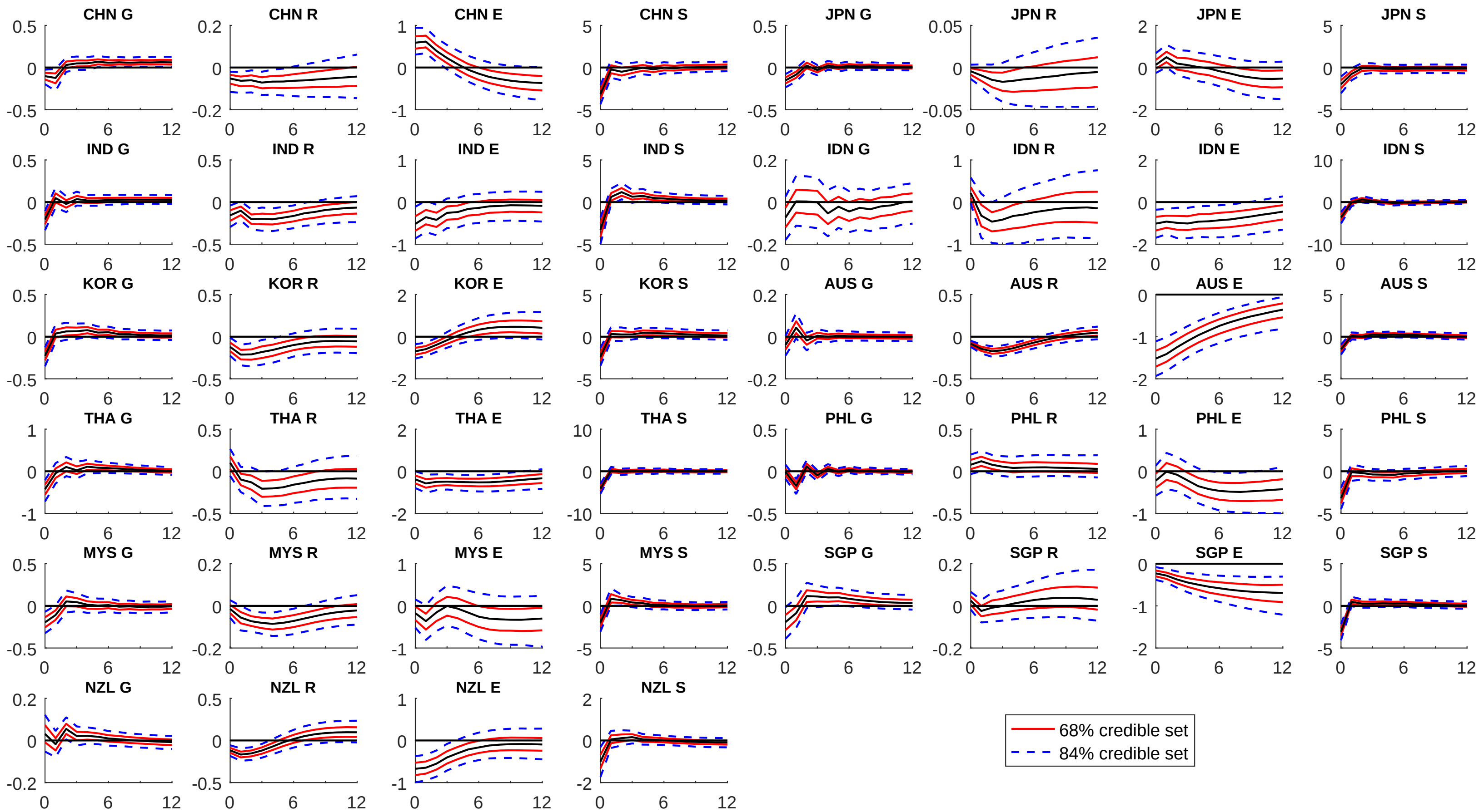


Figure A.3: Impulse Response Functions to a One Standard Deviation US GDP Growth Shock

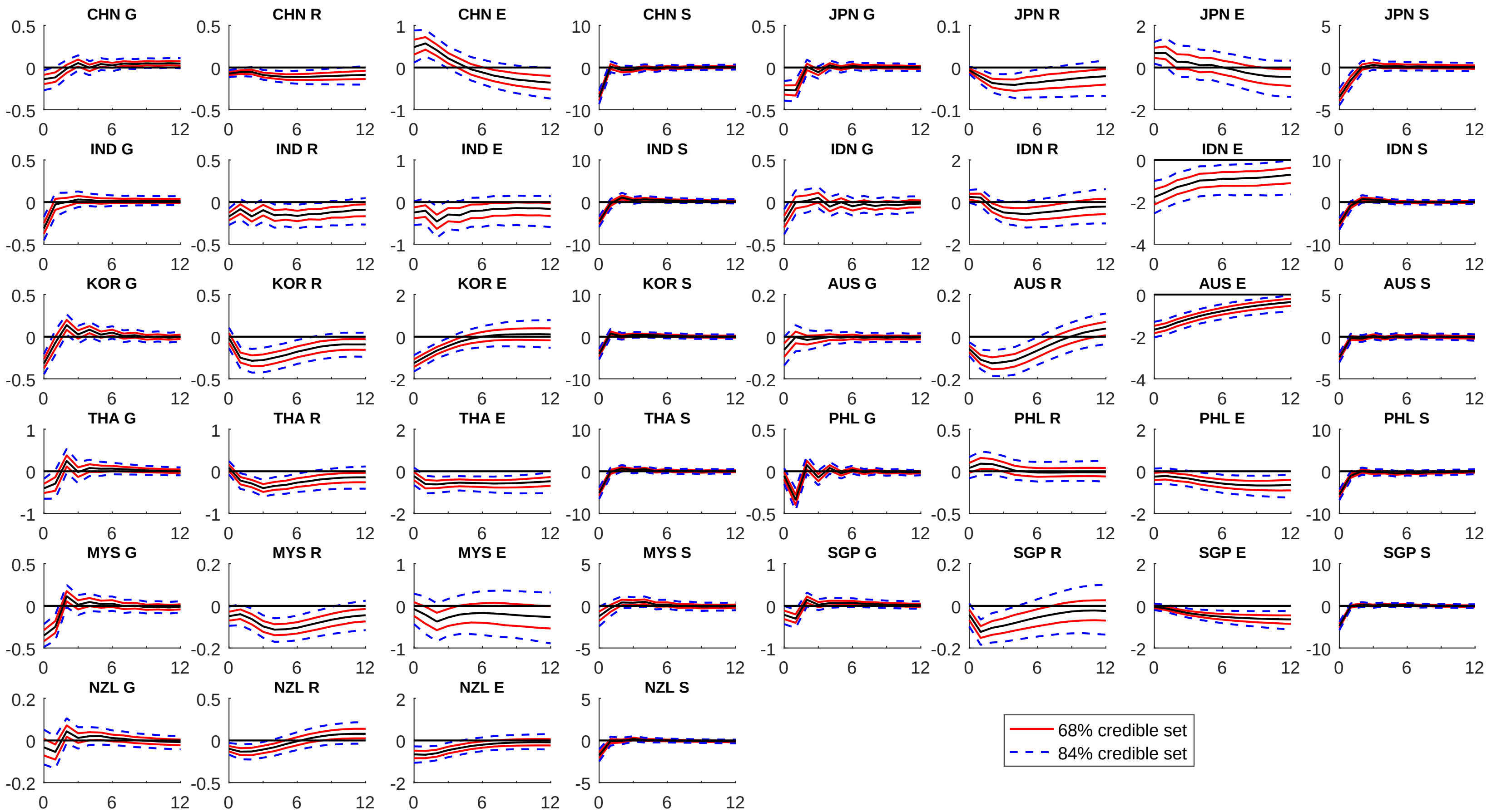


Figure A.4: Impulse Response Functions to a One Standard Deviation US Monetary Policy Shock

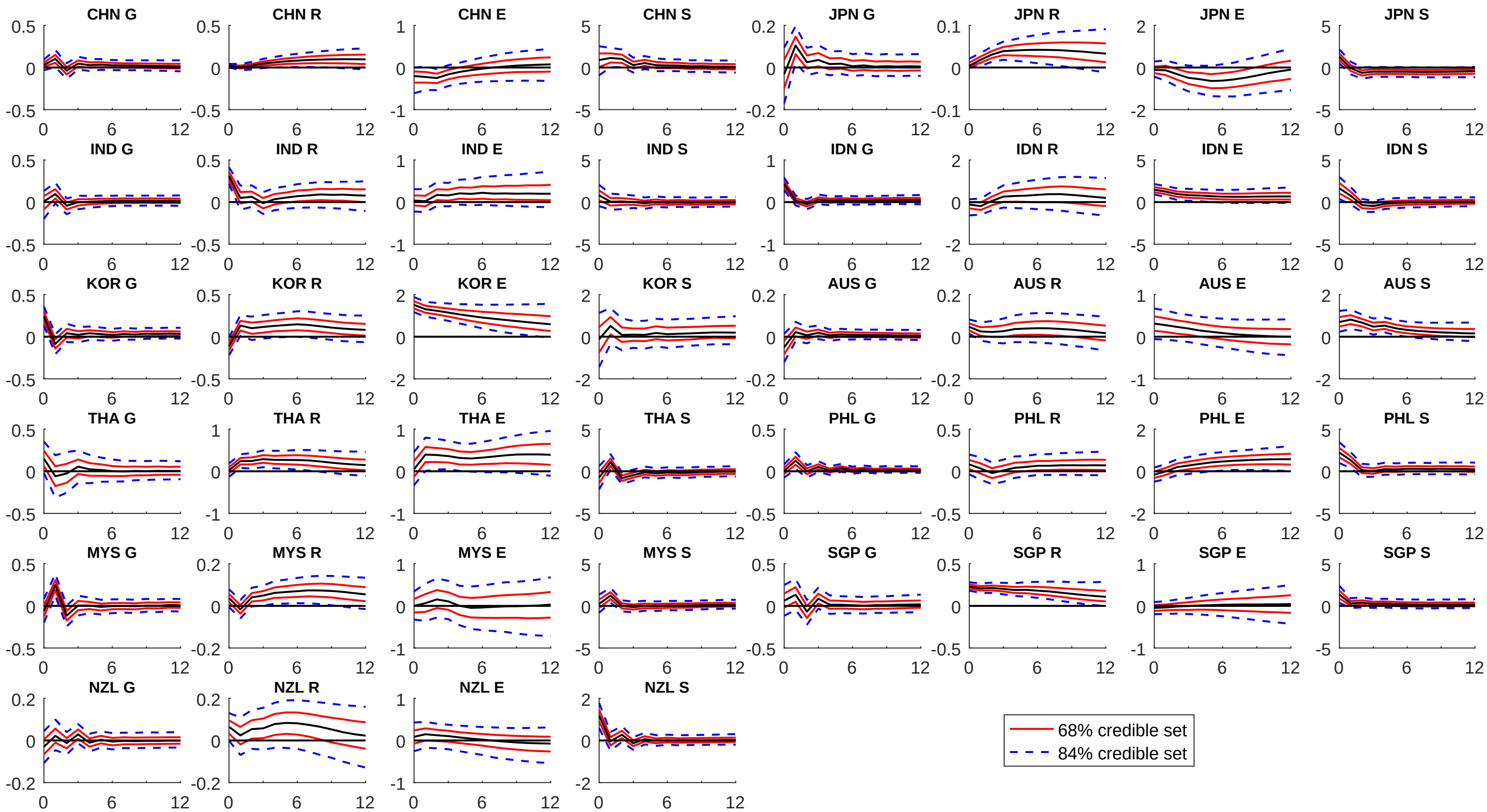


Figure A.5: Impulse Response Functions to a One Standard Deviation EBP Shock

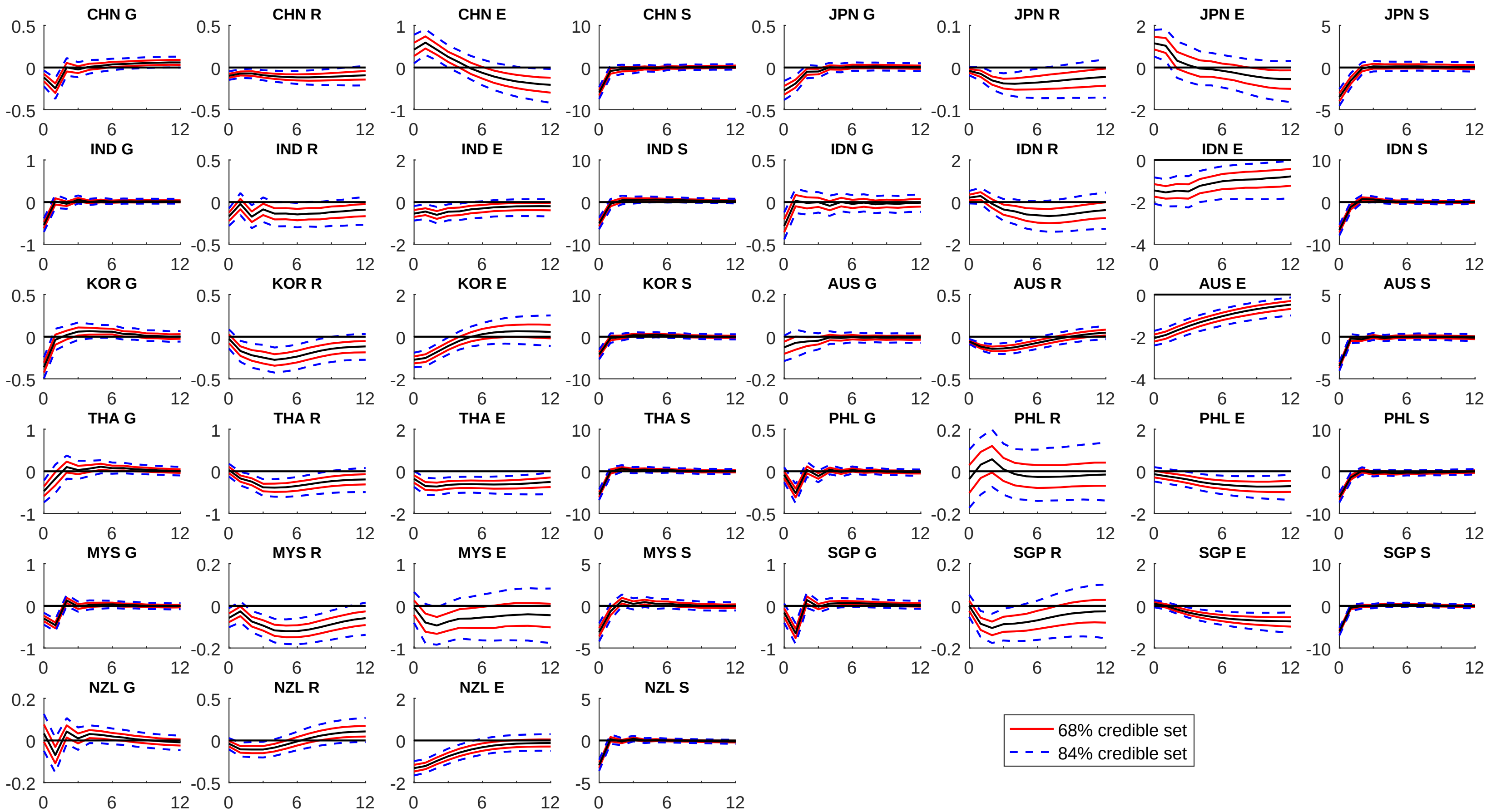


Figure A.6: Impulse Response Functions to a One Standard Deviation Stock Price Growth Shock

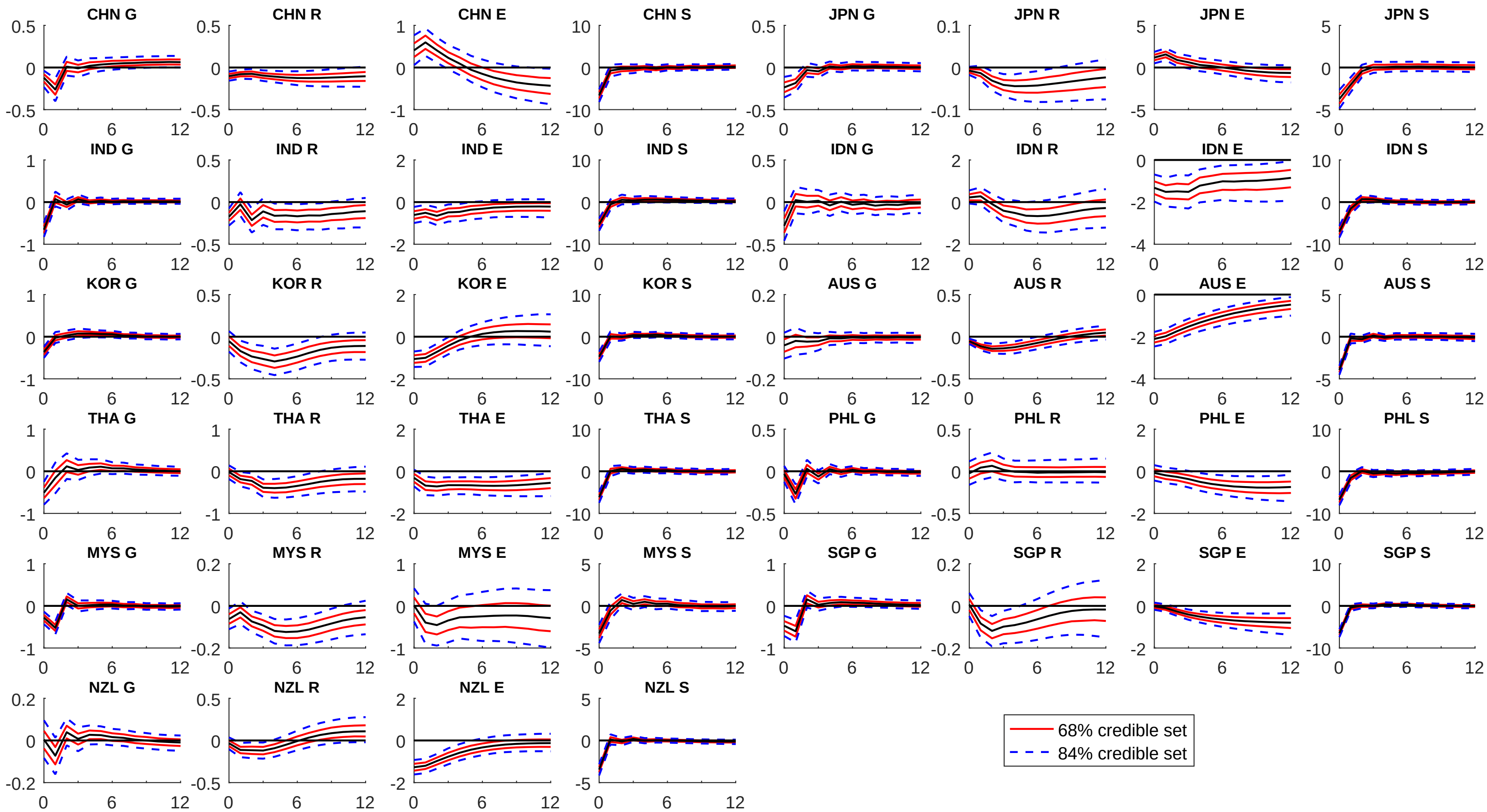


Figure A.7: Impulse Response Functions to a One Standard Deviation Financial Uncertainty Shock

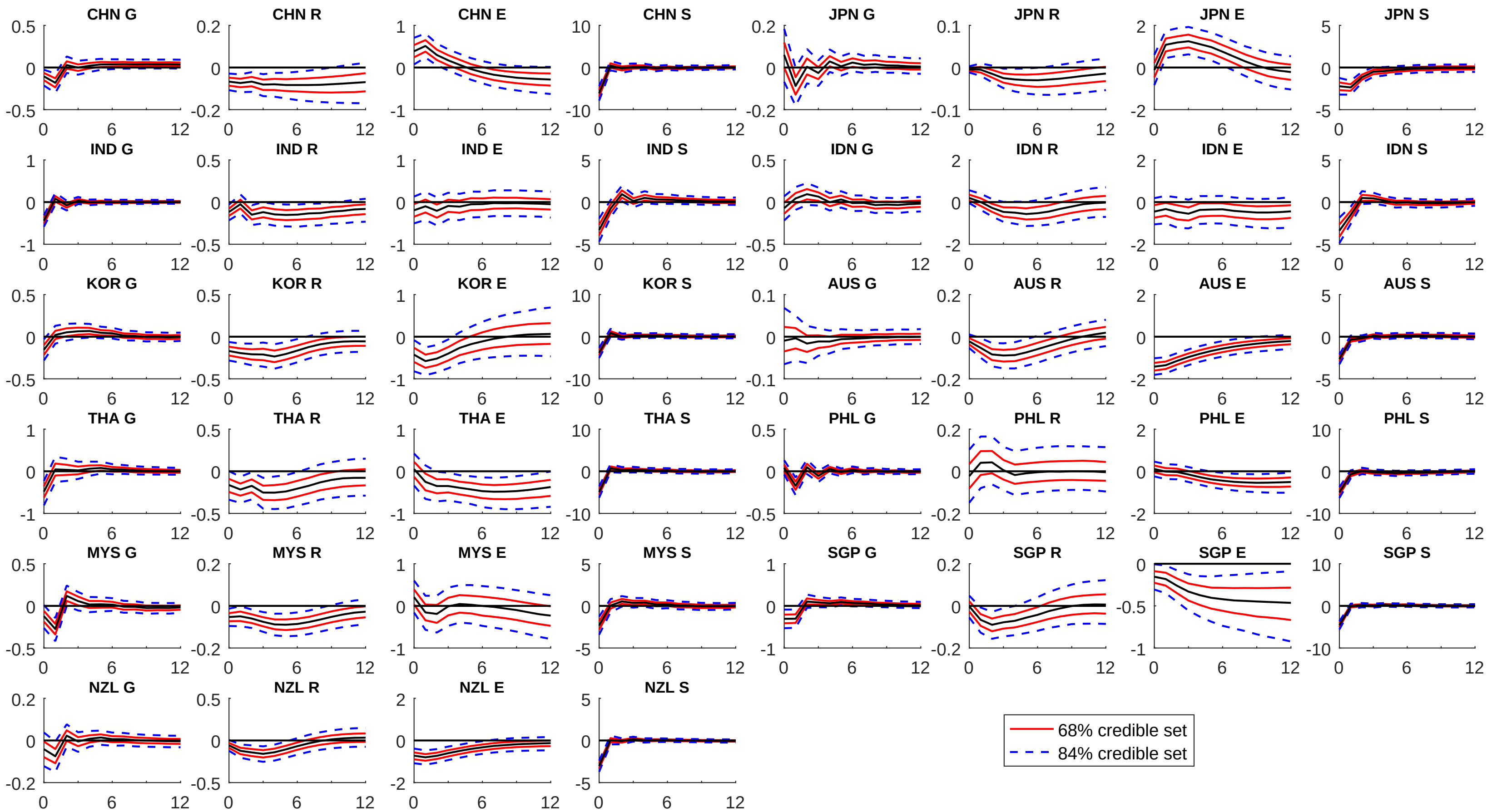
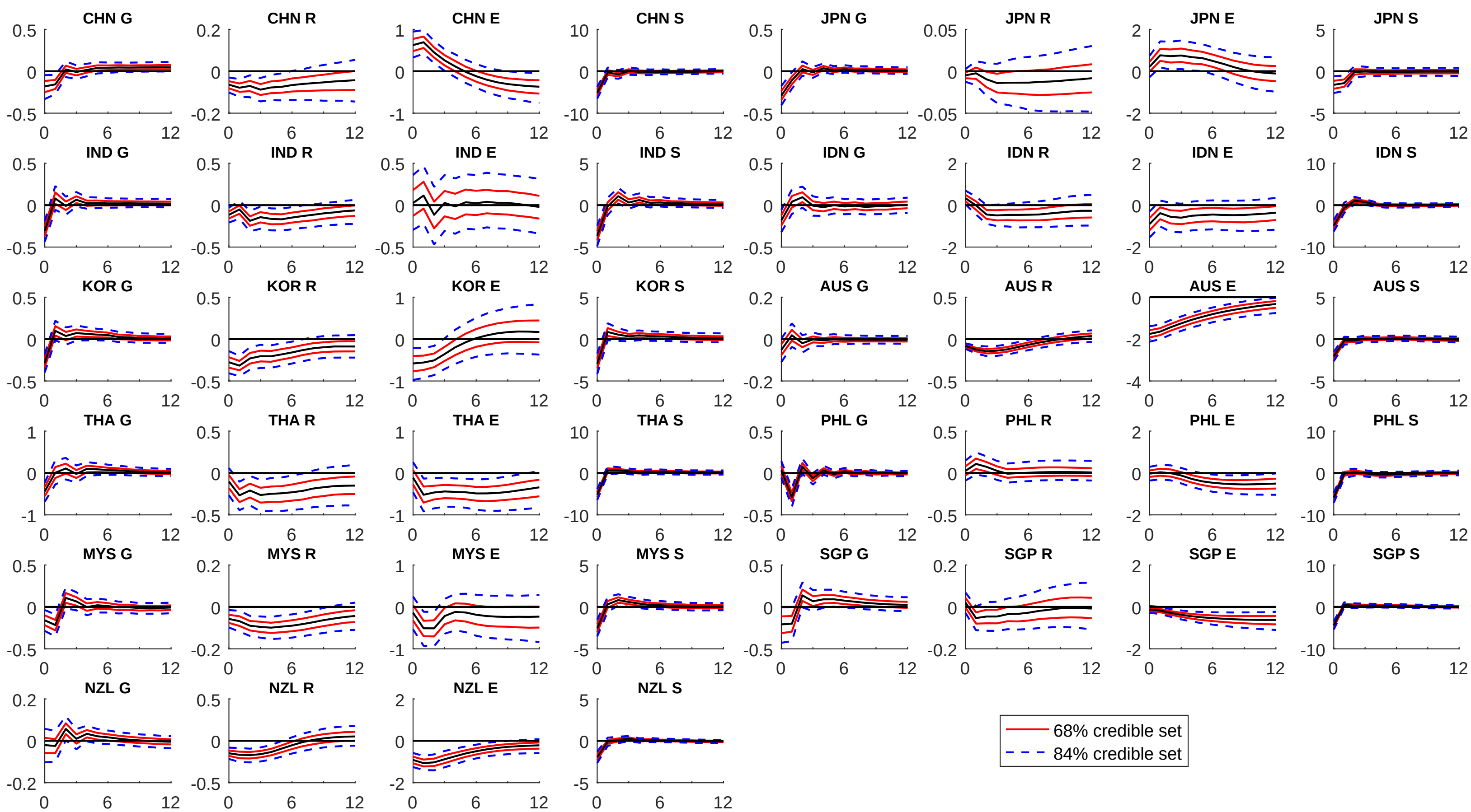


Figure A.8: Impulse Response Functions to a One Standard Deviation Real Uncertainty Shock



A.3.2 Response of AP countries to Adverse Regional and Domestic Shocks

Figure A.9: Impulse Response Functions to a One Standard Deviation China GDP Growth Shock

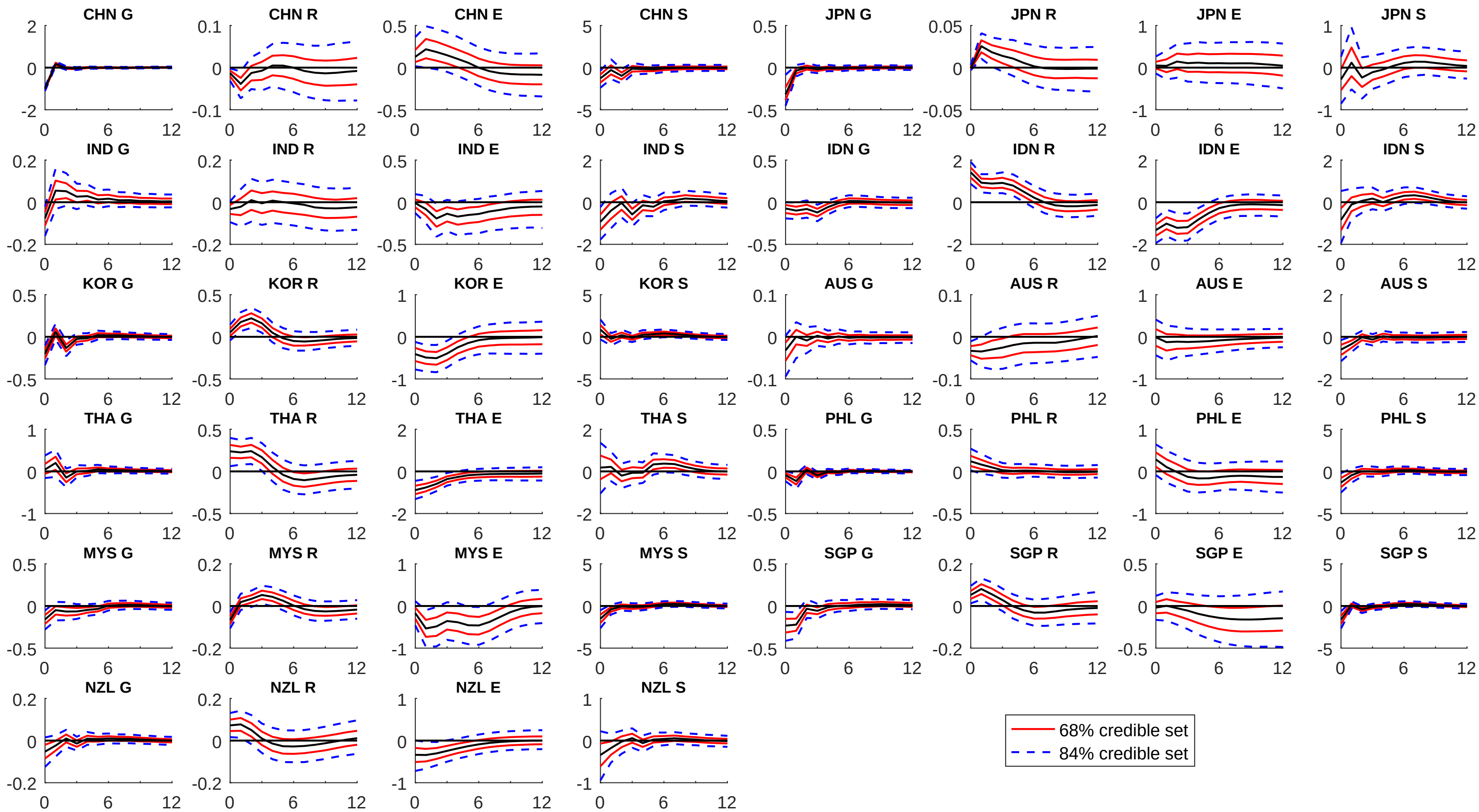


Figure A.10: Impulse Response Functions to a One Standard Deviation Japan GDP Growth Shock

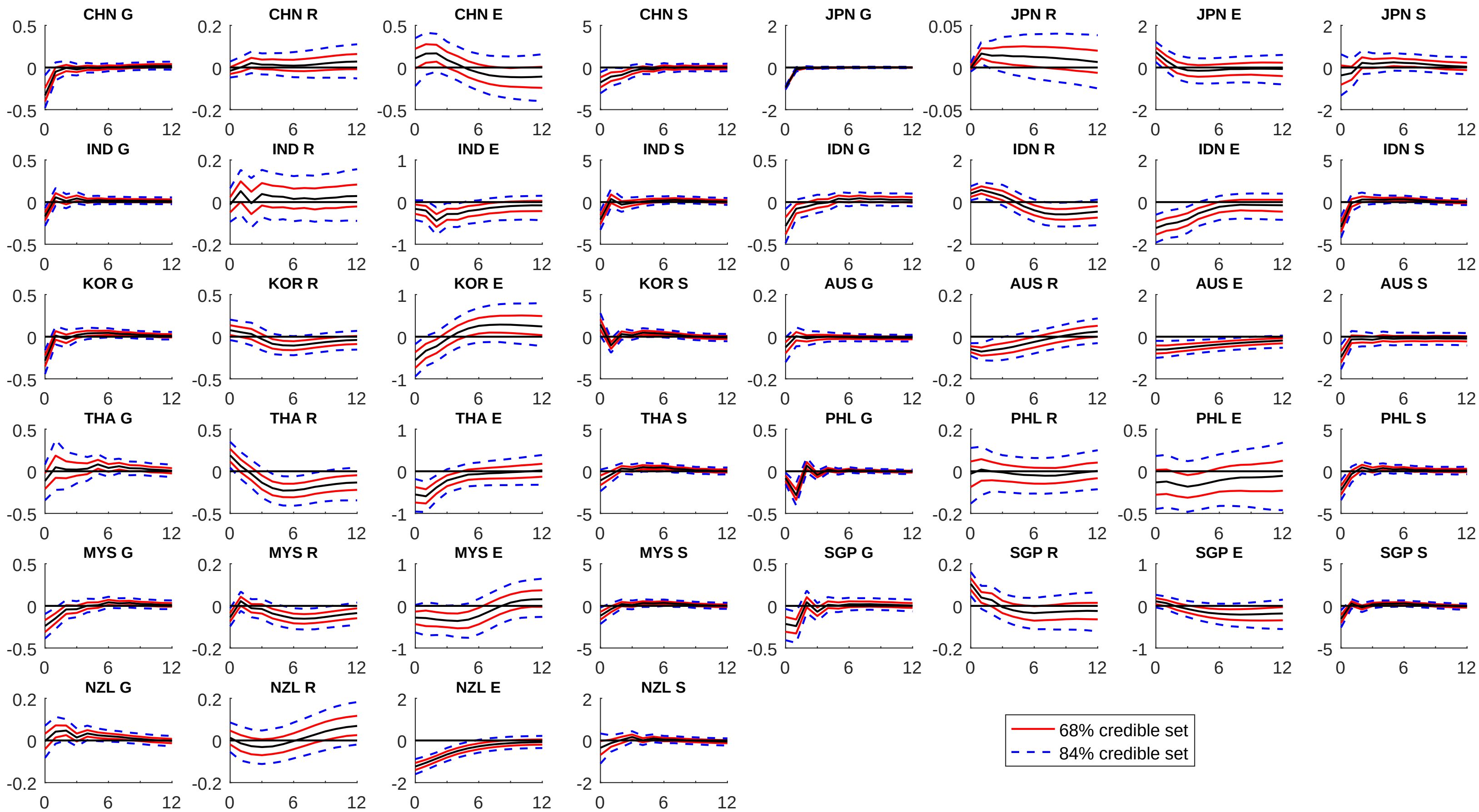


Figure A.11: Impulse Response Functions to a One Standard Deviation India GDP Growth Shock

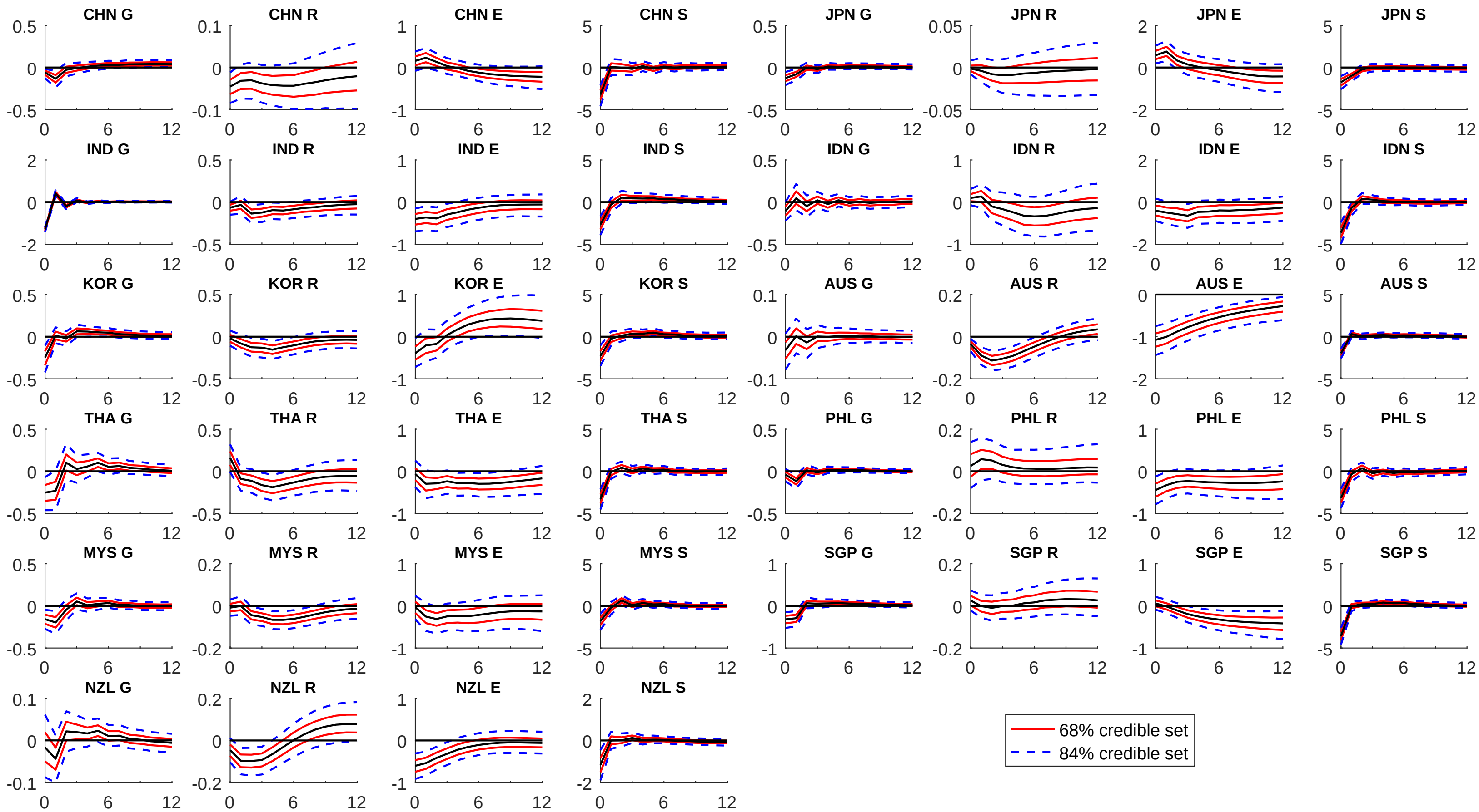


Figure A.12: Impulse Response Functions to a One Standard Deviation Indonesia GDP Growth Shock

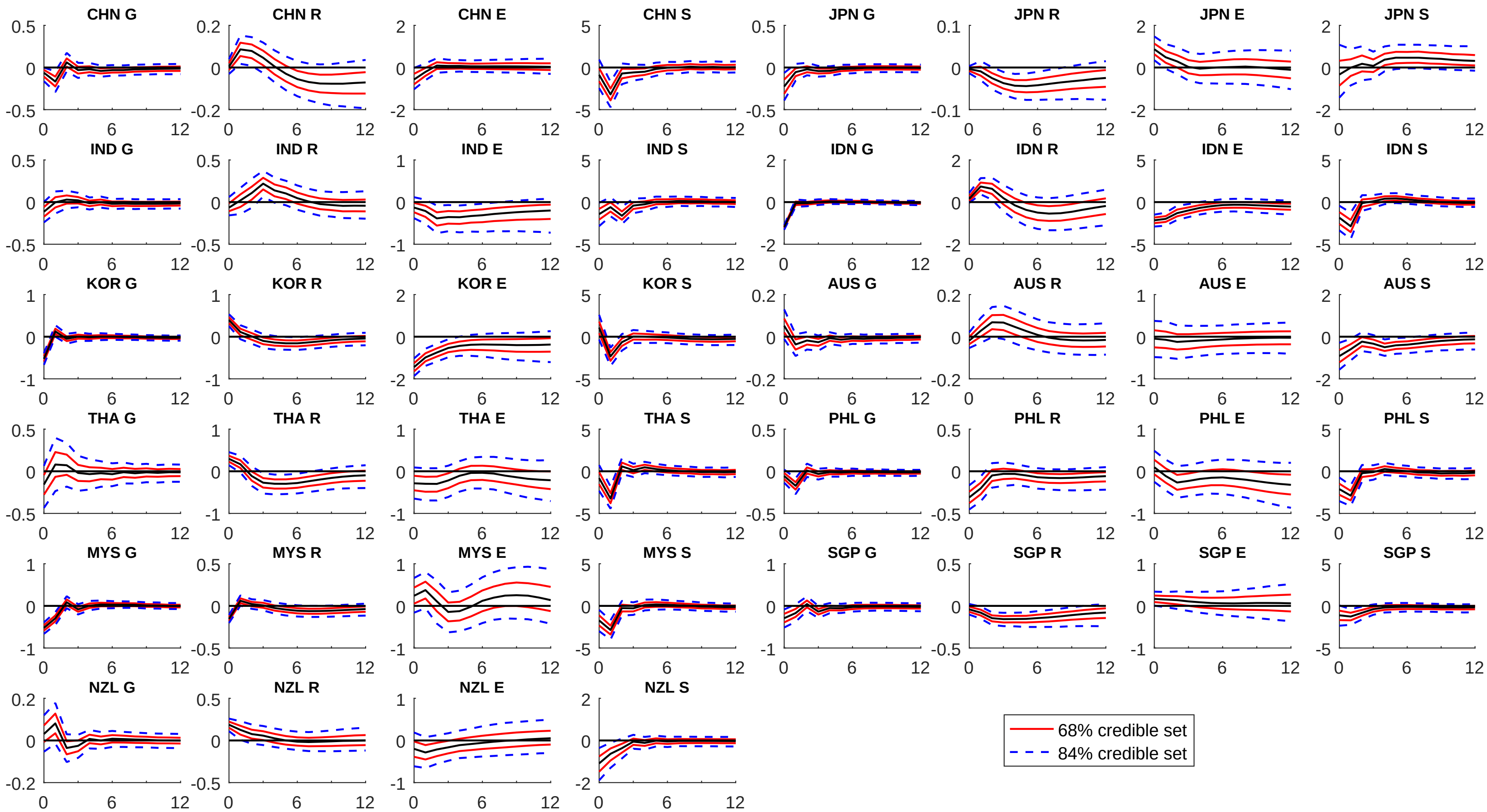


Figure A.13: Impulse Response Functions to a One Standard Deviation Korea GDP Growth Shock

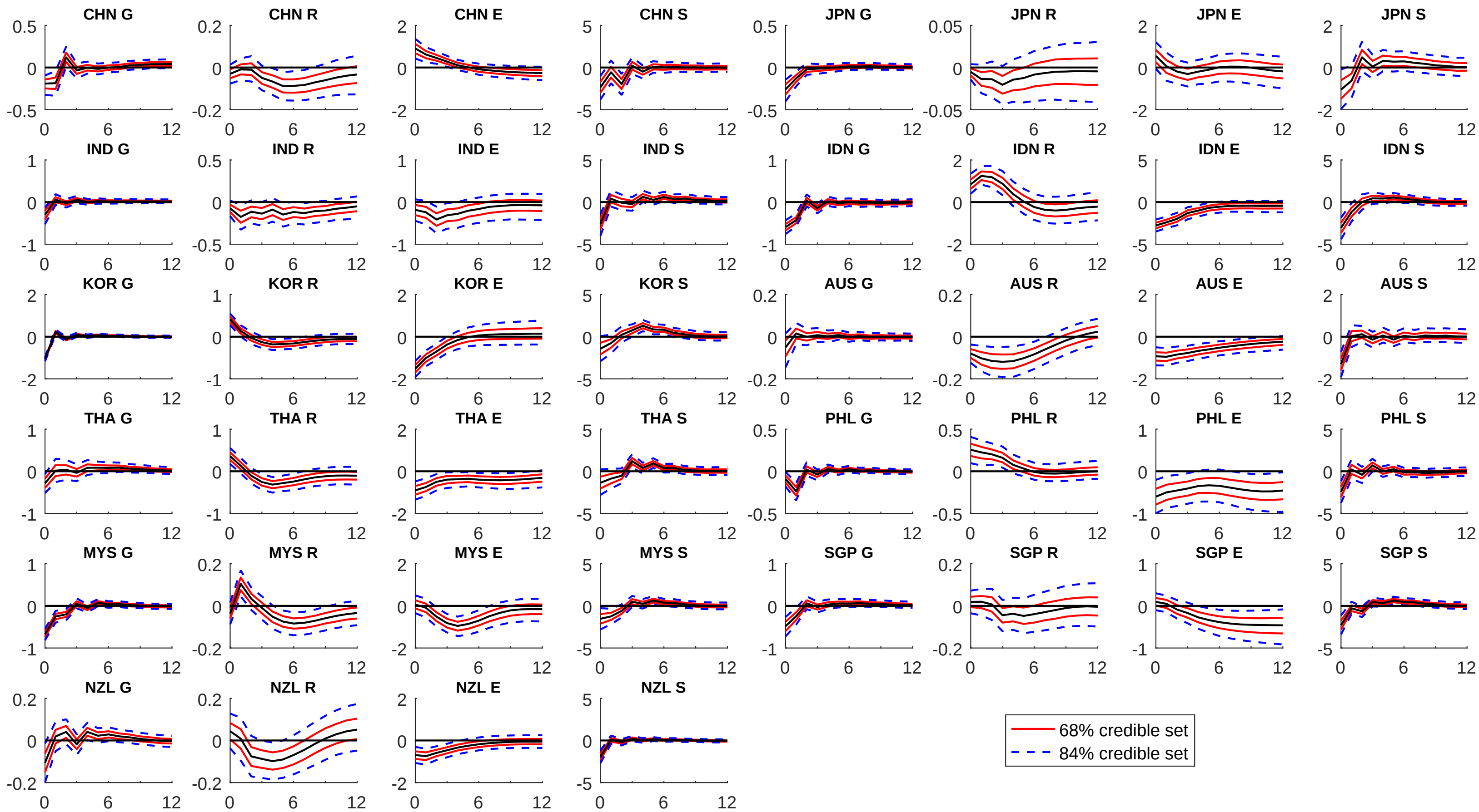


Figure A.14: Impulse Response Functions to a One Standard Deviation Australia GDP Growth Shock

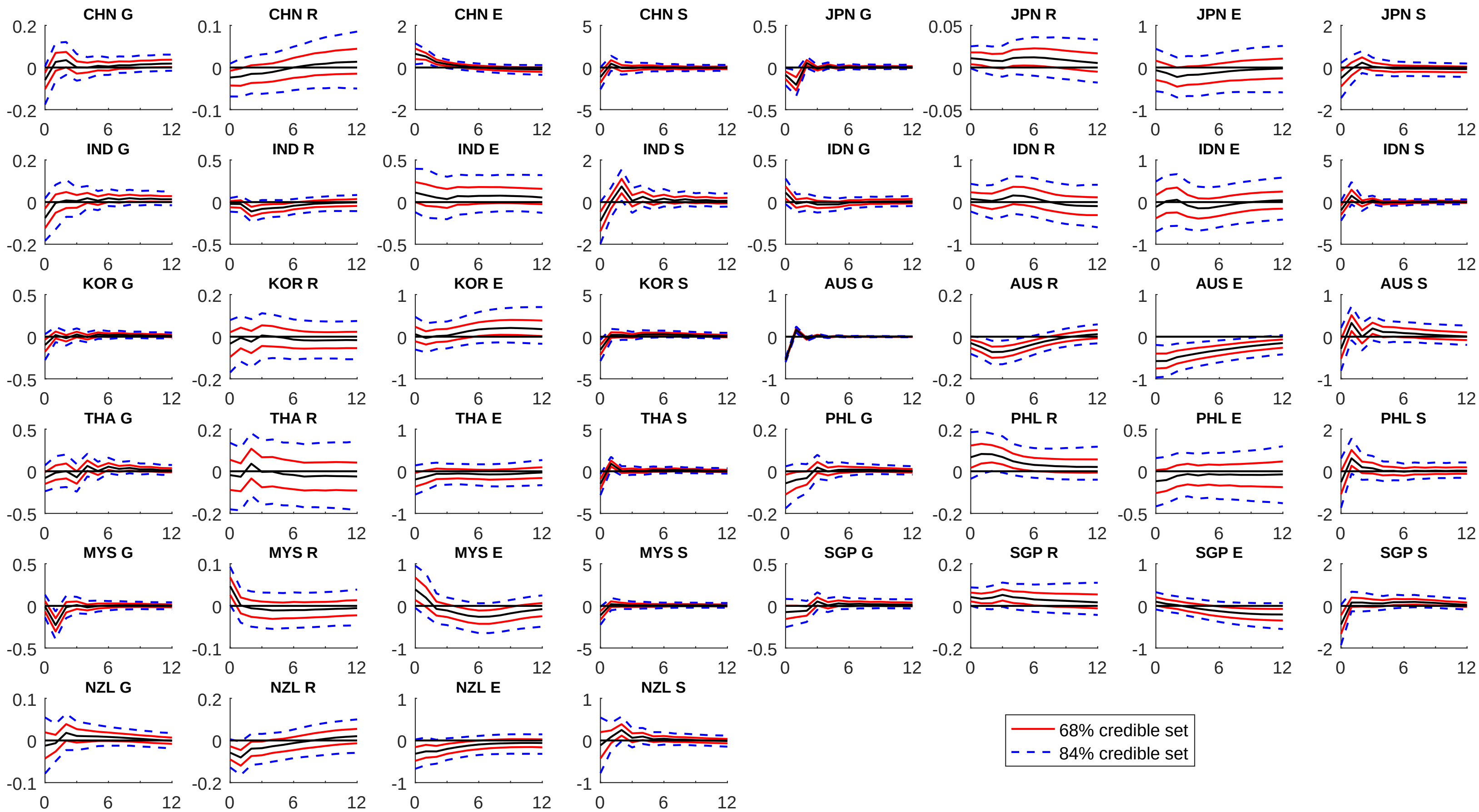


Figure A.15: Impulse Response Functions to a One Standard Deviation Thailand GDP Growth Shock

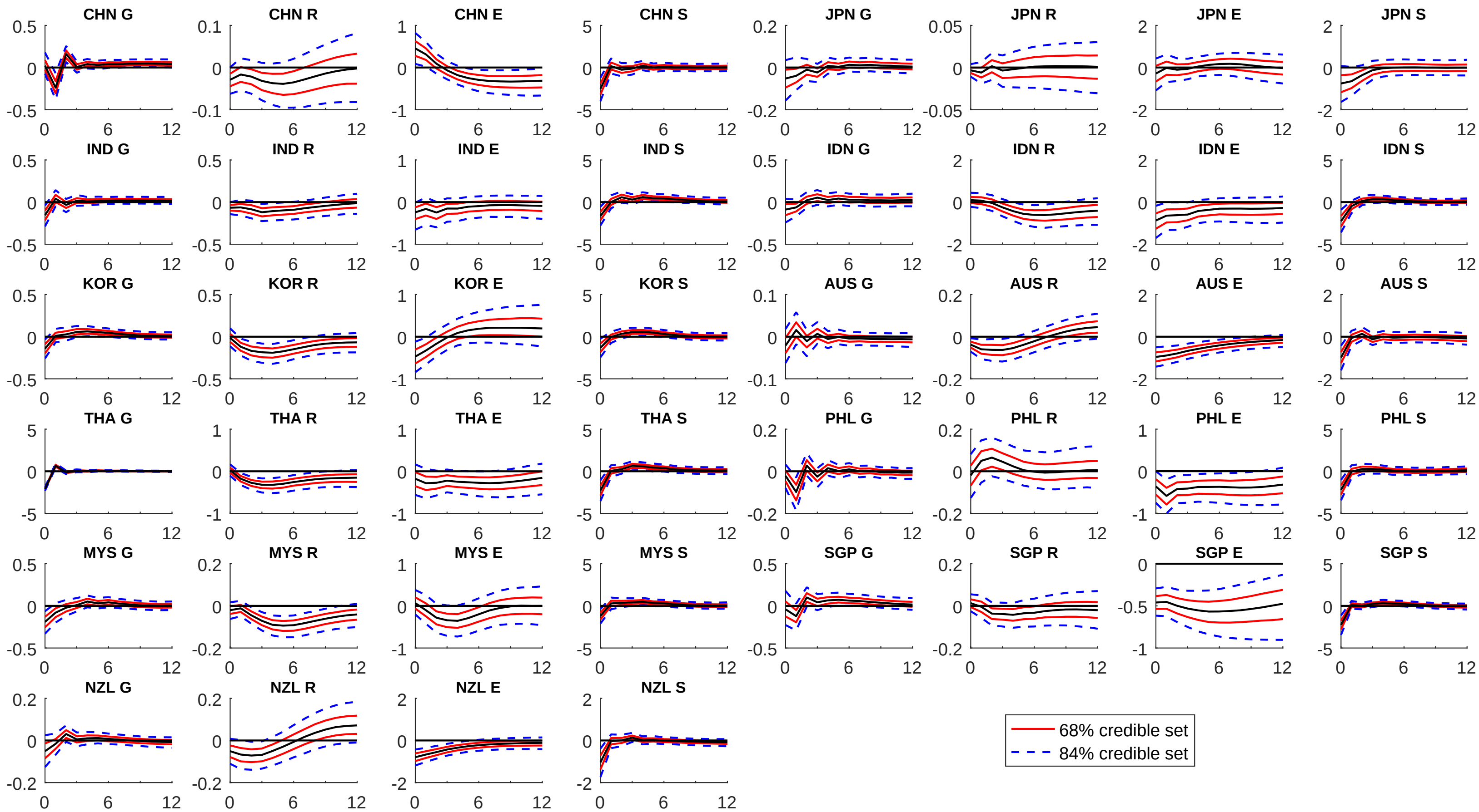


Figure A.16: Impulse Response Functions to a One Standard Deviation Philippines GDP Growth Shock

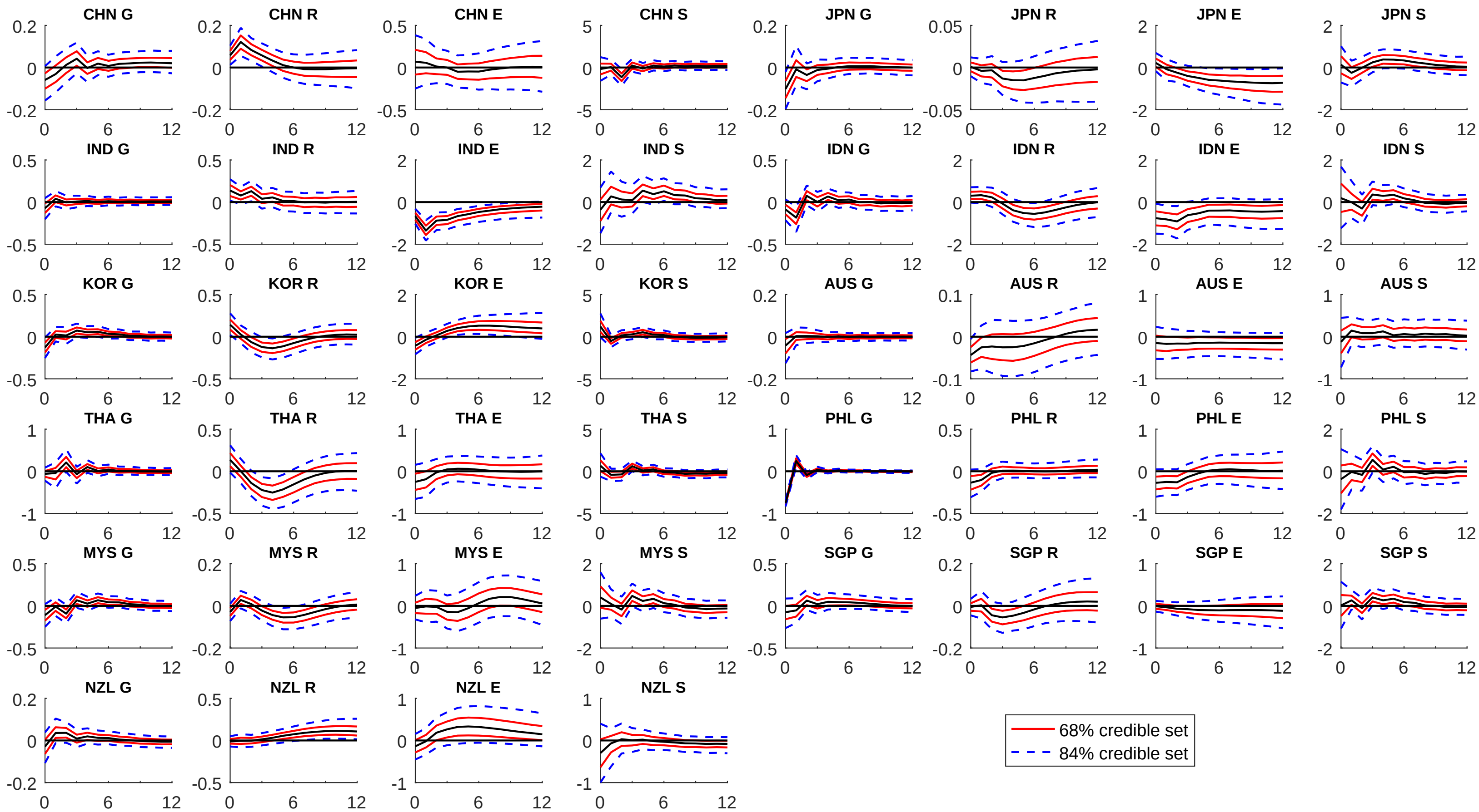


Figure A.17: Impulse Response Functions to a One Standard Deviation Malaysia GDP Growth Shock

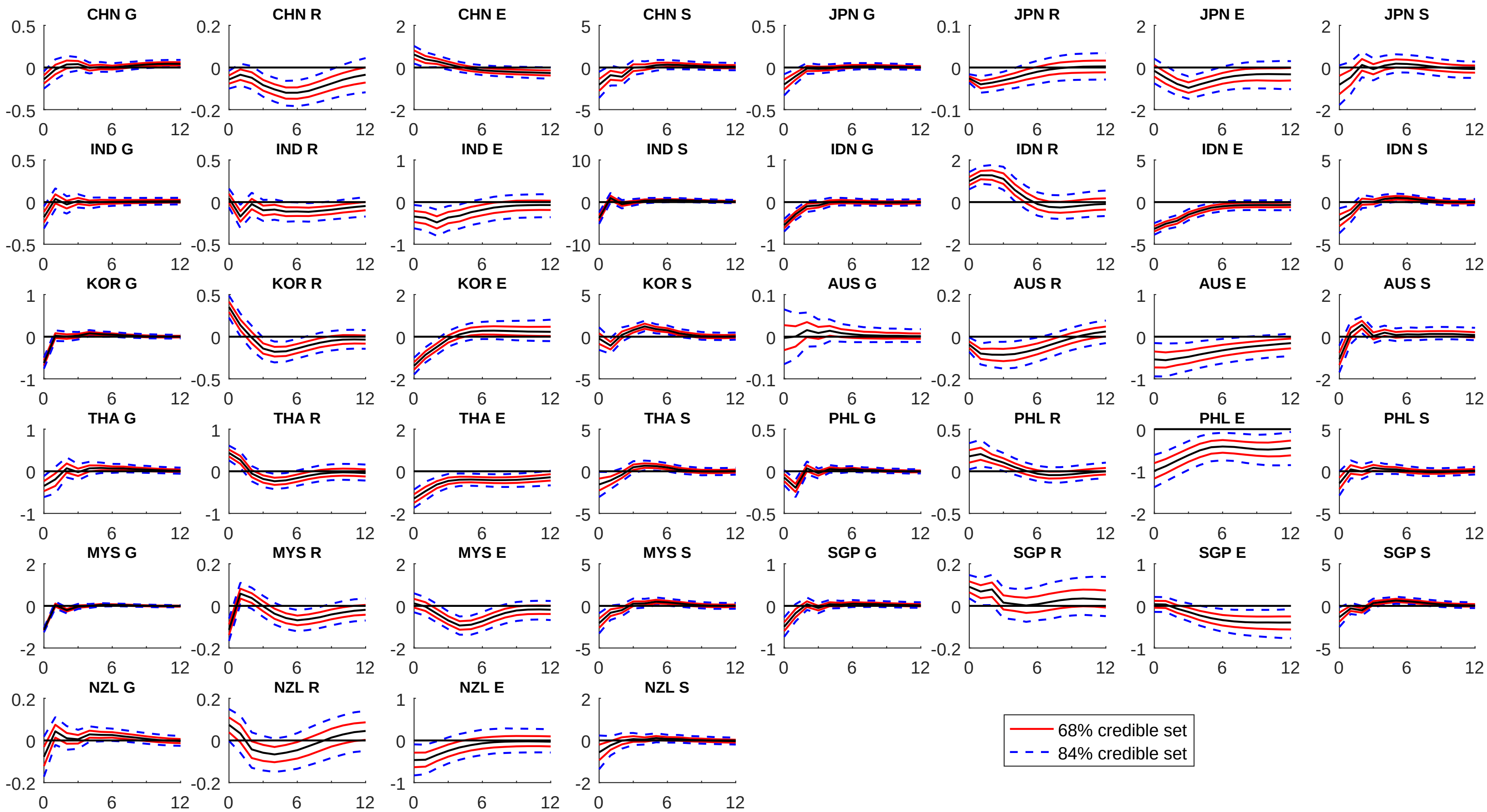


Figure A.18: Impulse Response Functions to a One Standard Deviation Singapore GDP Growth Shock

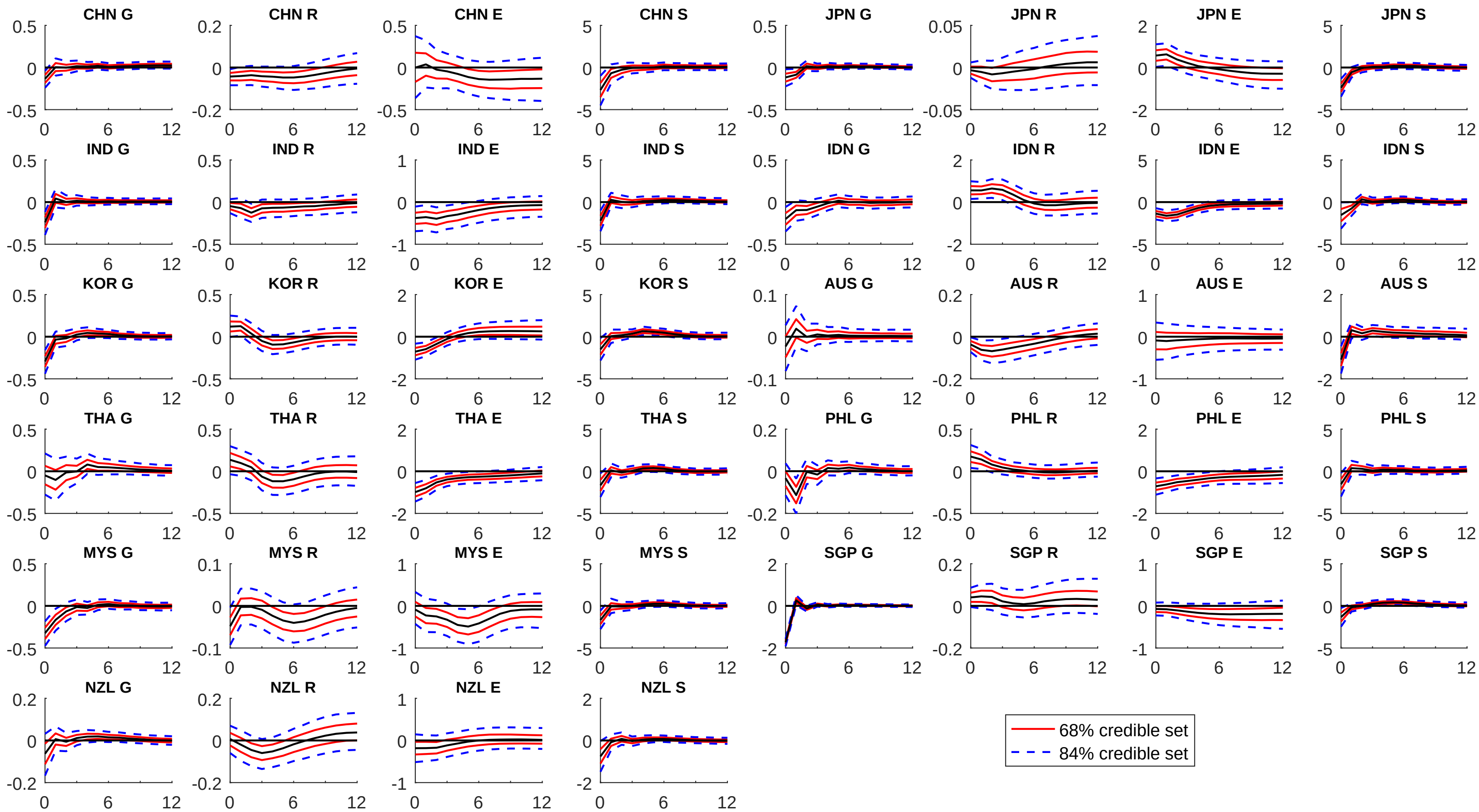


Figure A.19: Impulse Response Functions to a One Standard Deviation New Zealand GDP Growth Shock

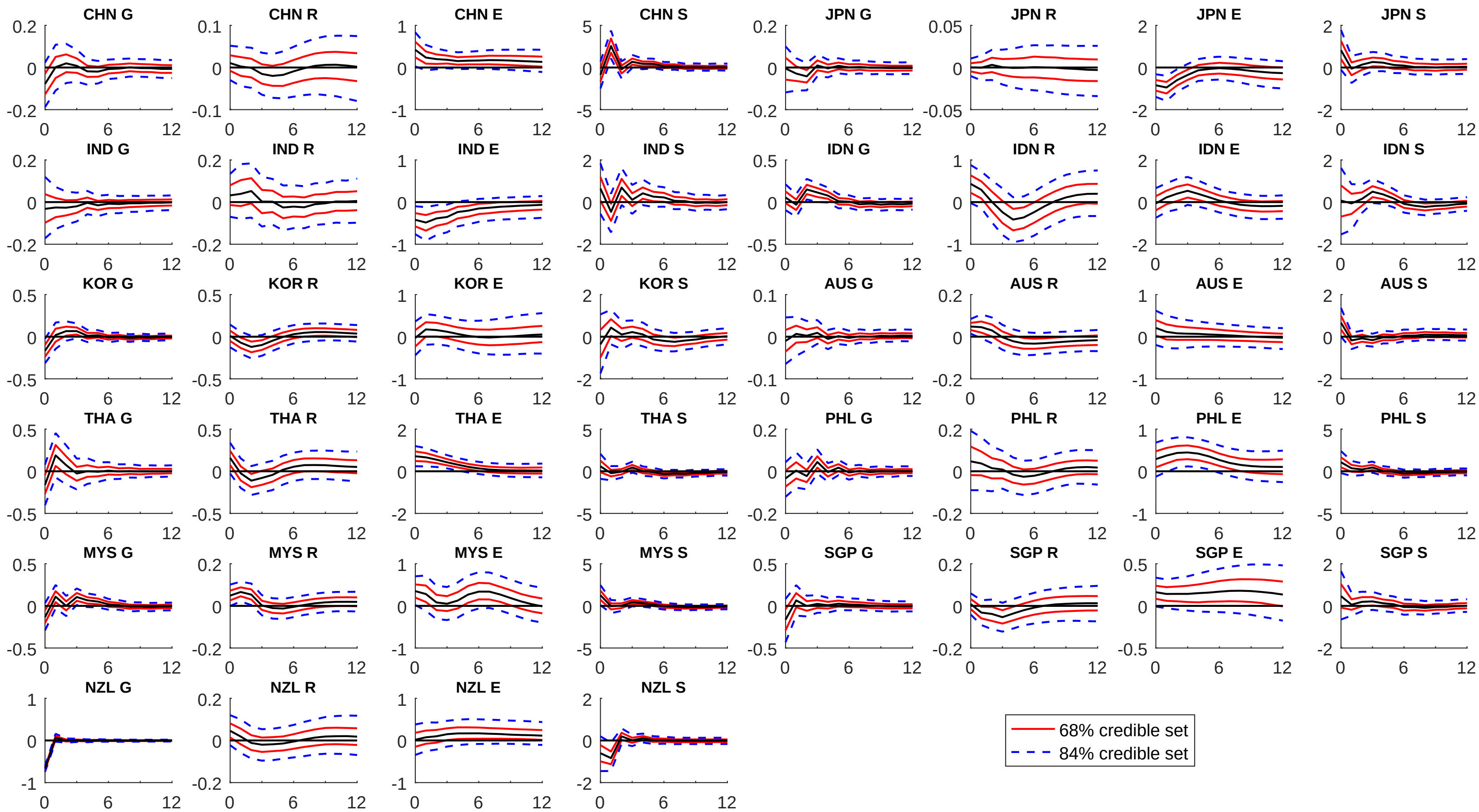


Figure A.20: Impulse Response Functions to a One Standard Deviation China Monetary Policy Shock

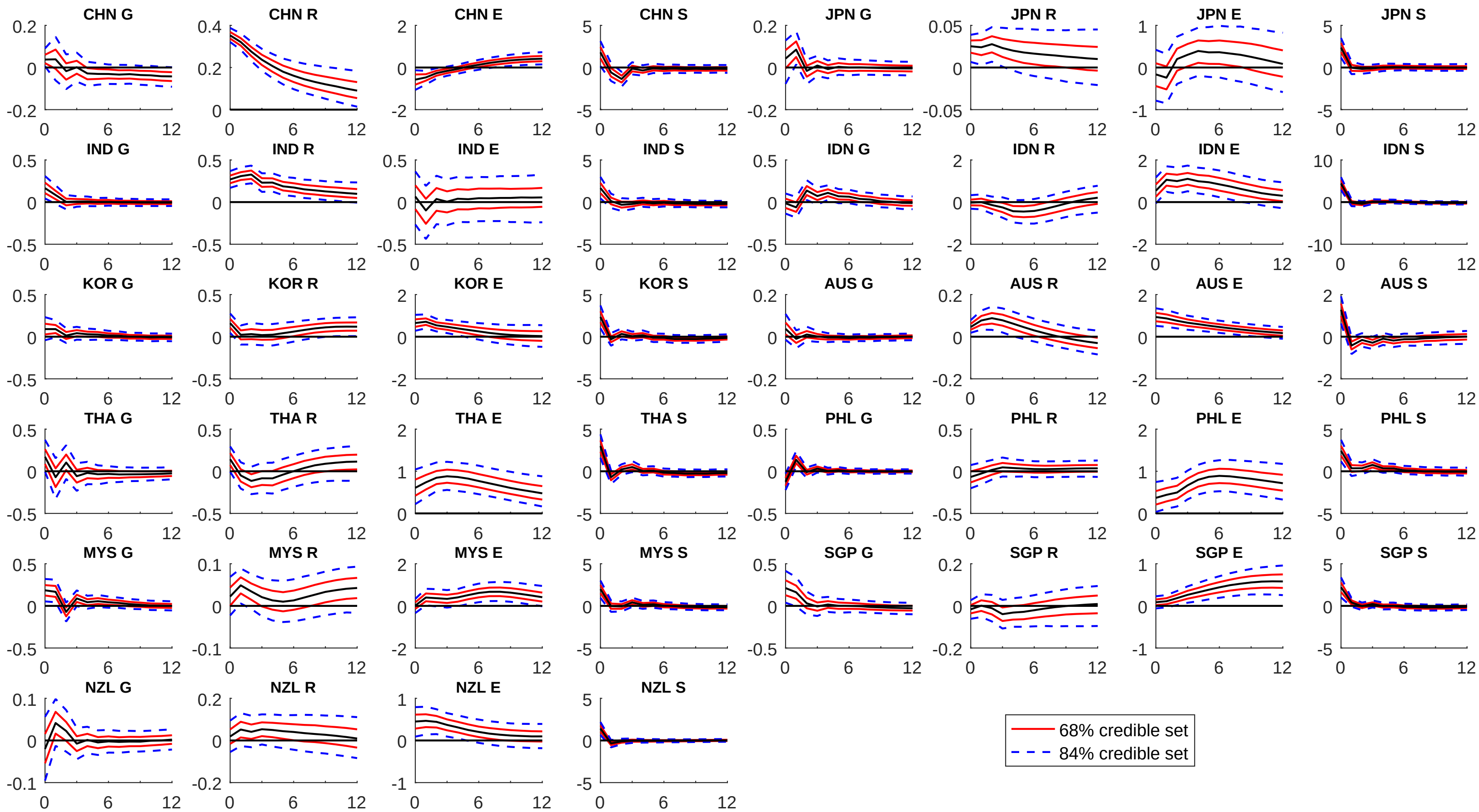


Figure A.21: Impulse Response Functions to a One Standard Deviation Japan Monetary Policy Shock

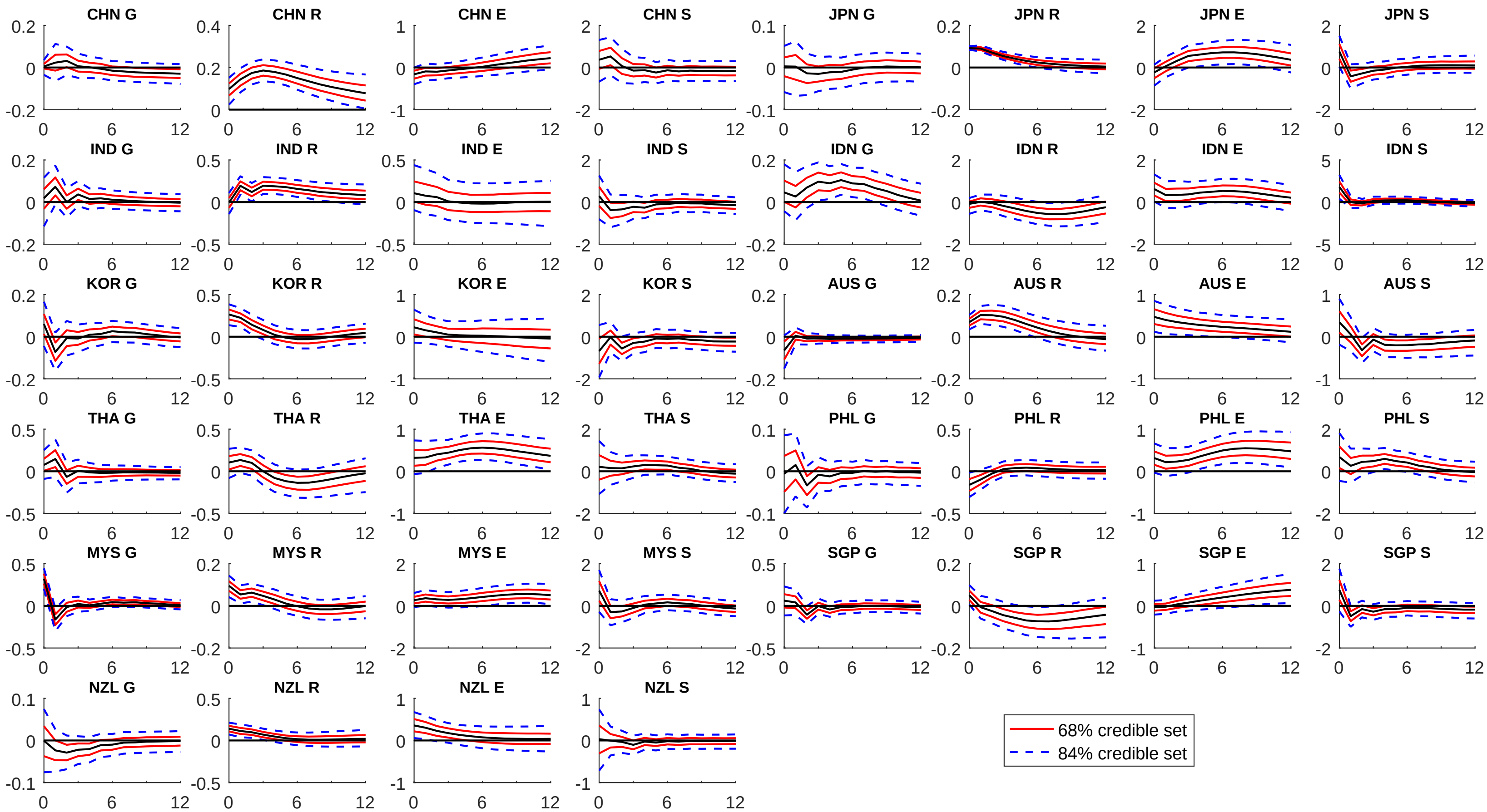


Figure A.22: Impulse Response Functions to a One Standard Deviation India Monetary Policy Shock

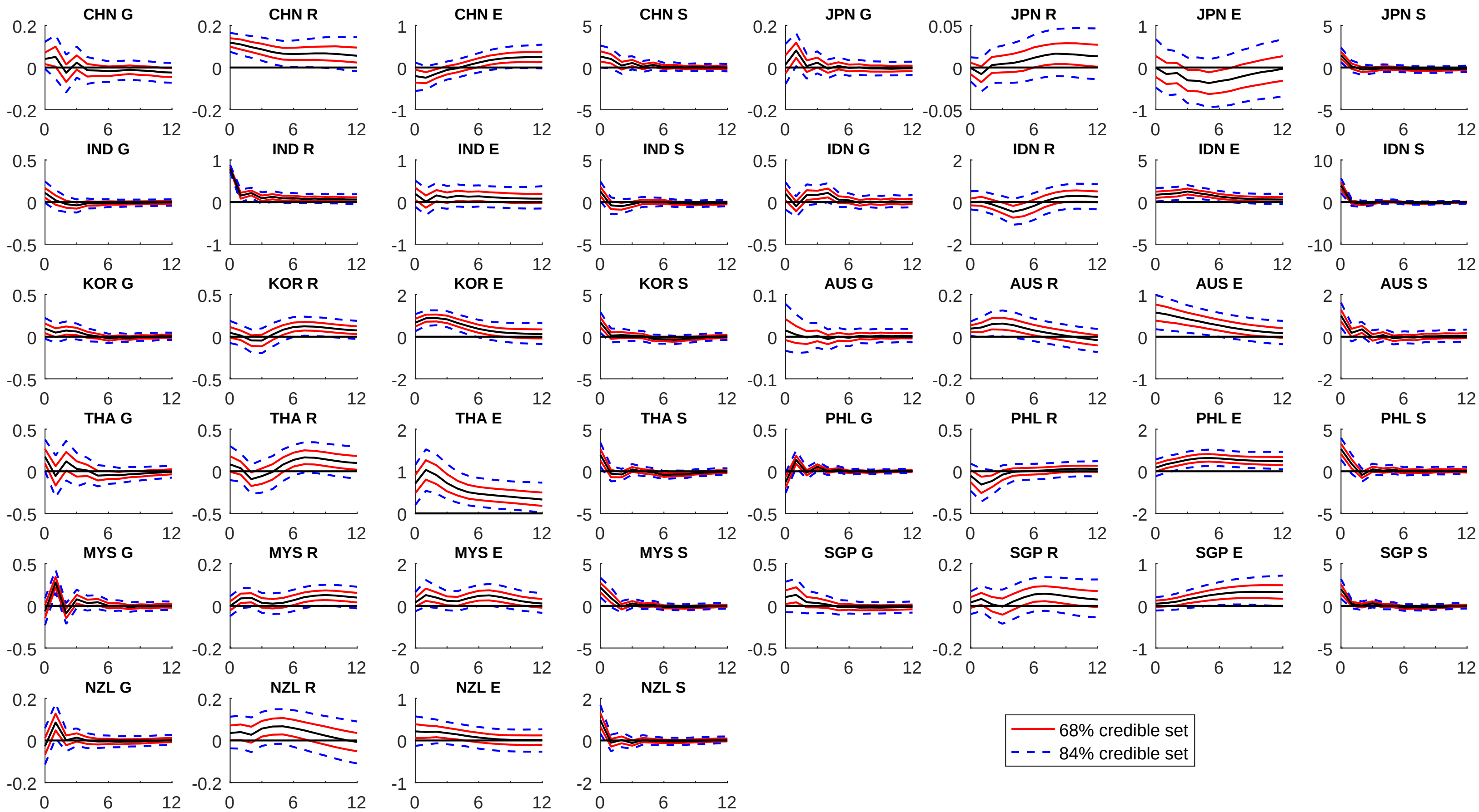


Figure A.23: Impulse Response Functions to a One Standard Deviation Indonesia Monetary Policy Shock

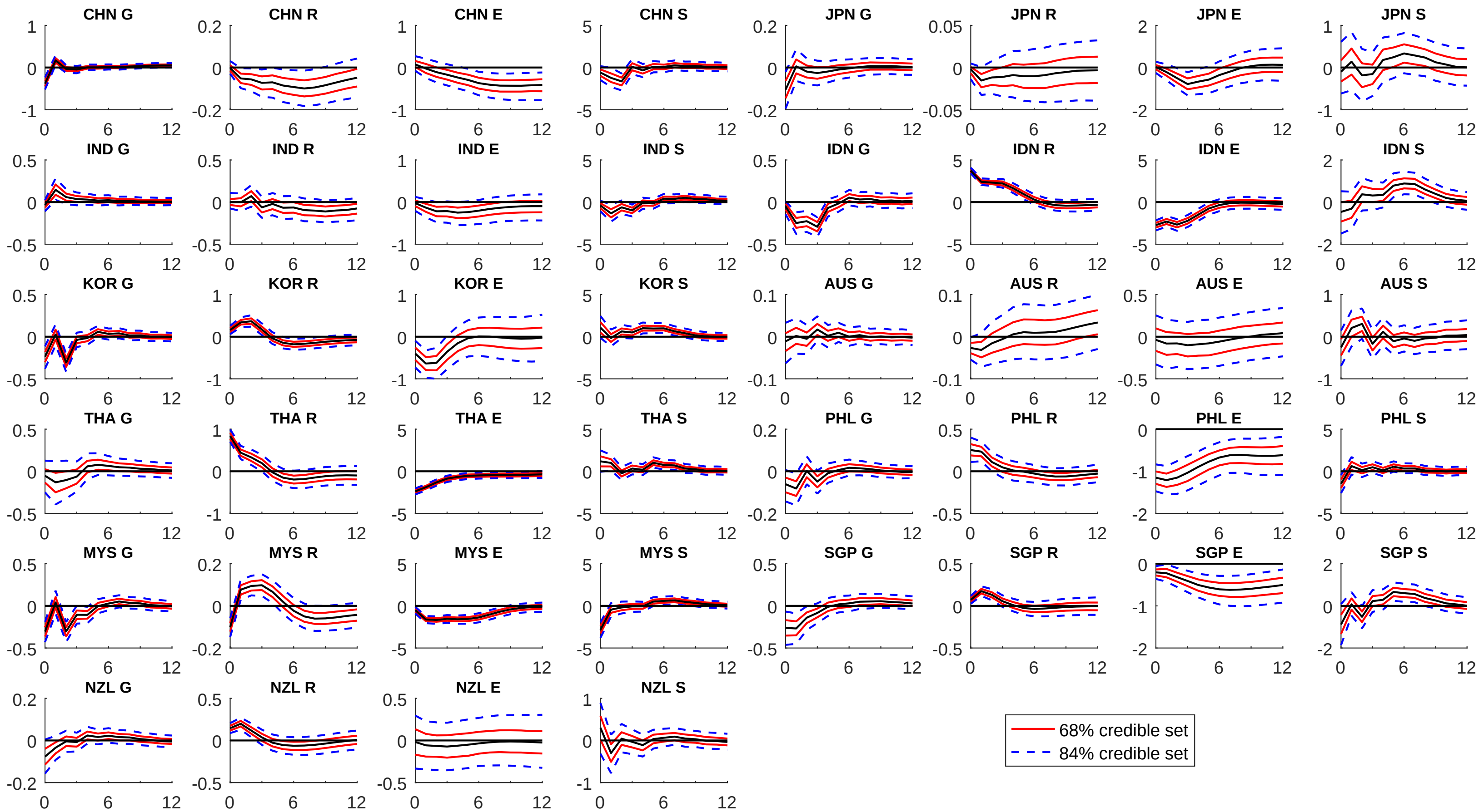


Figure A.24: Impulse Response Functions to a One Standard Deviation Korea Monetary Policy Shock

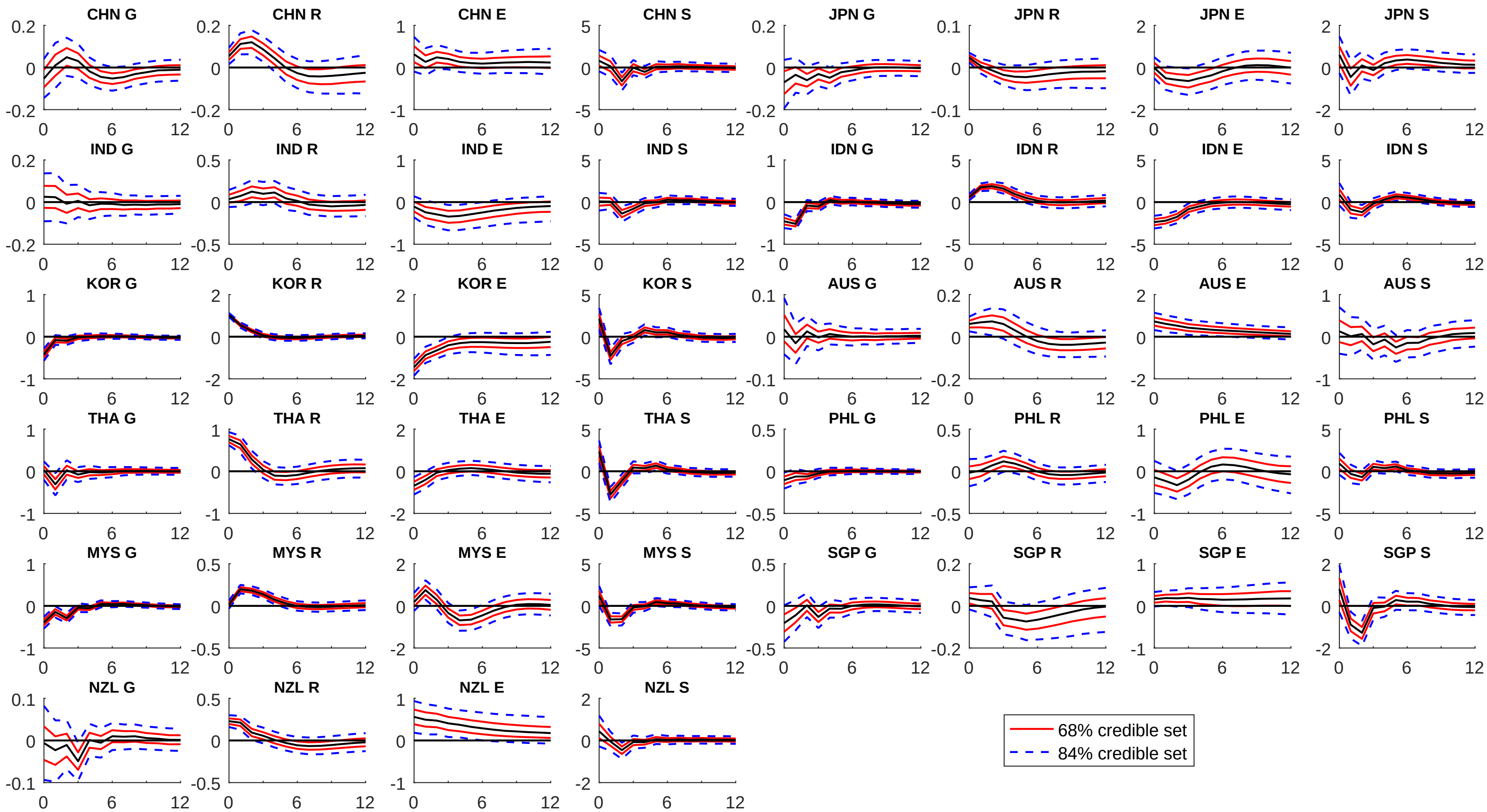


Figure A.25: Impulse Response Functions to a One Standard Deviation Australia Monetary Policy Shock

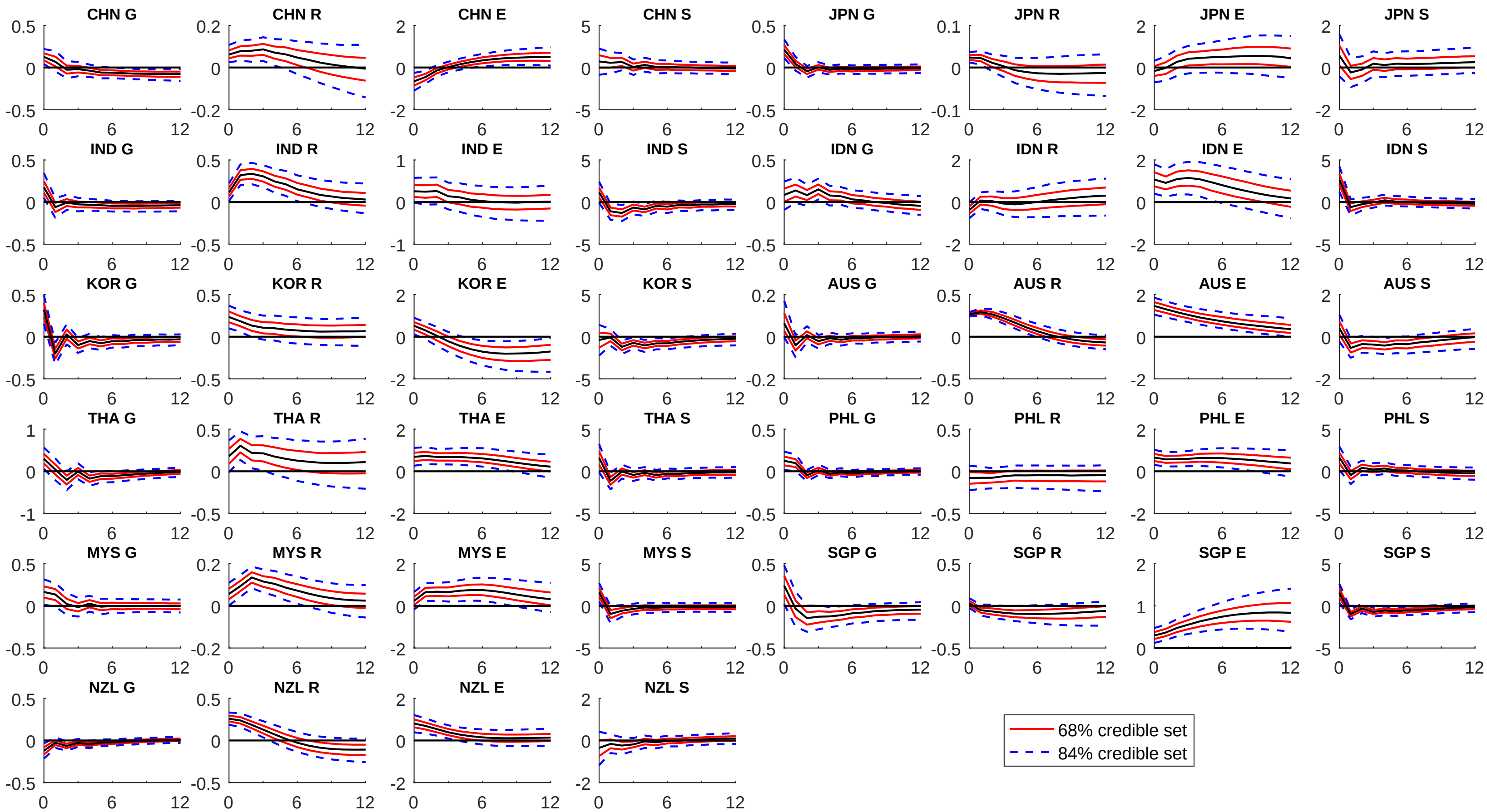


Figure A.26: Impulse Response Functions to a One Standard Deviation Thailand Monetary Policy Shock

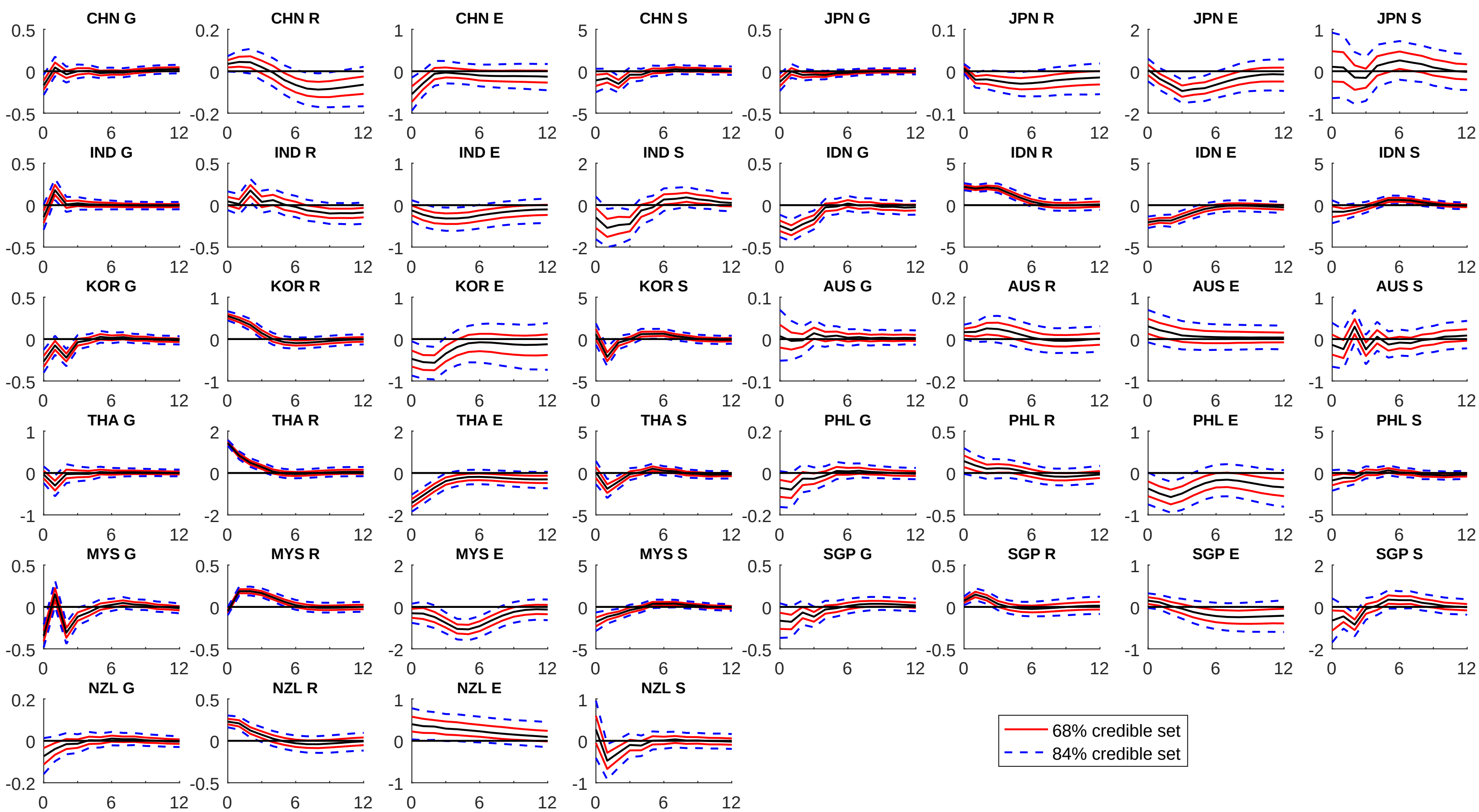


Figure A.27: Impulse Response Functions to a One Standard Deviation Philippines Monetary Policy Shock

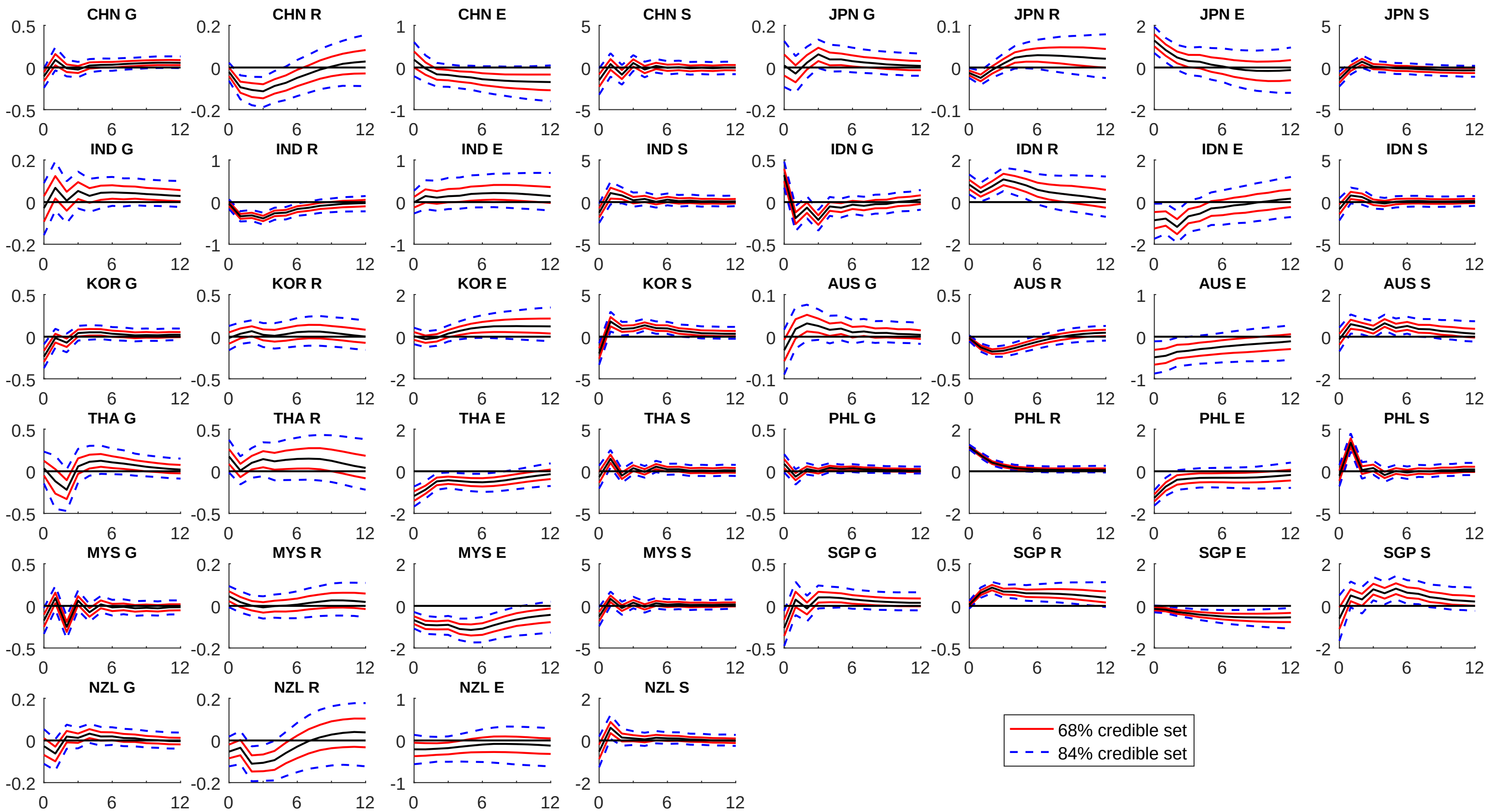


Figure A.28: Impulse Response Functions to a One Standard Deviation Malaysia Monetary Policy Shock

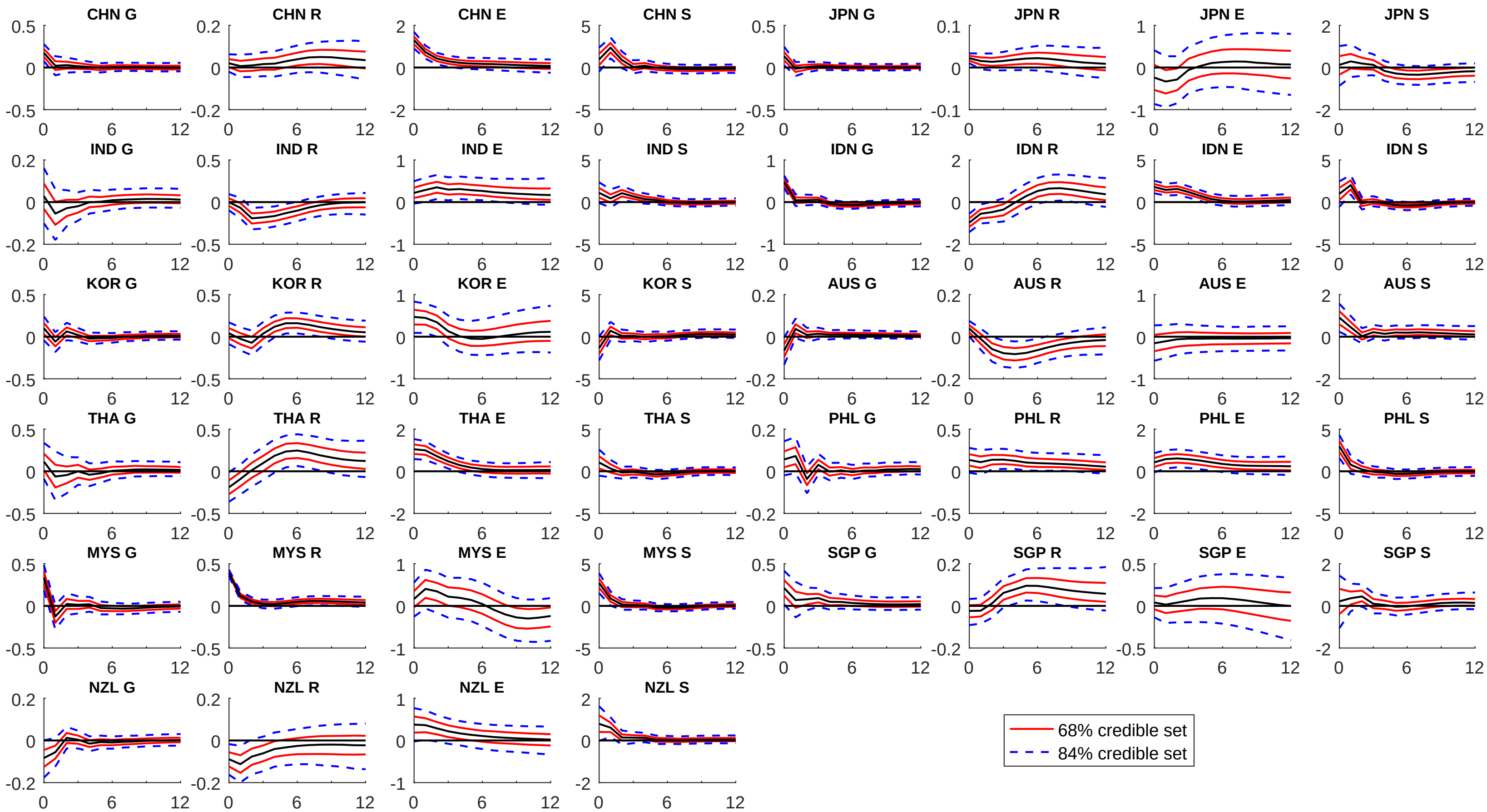


Figure A.29: Impulse Response Functions to a One Standard Deviation Singapore Monetary Policy Shock

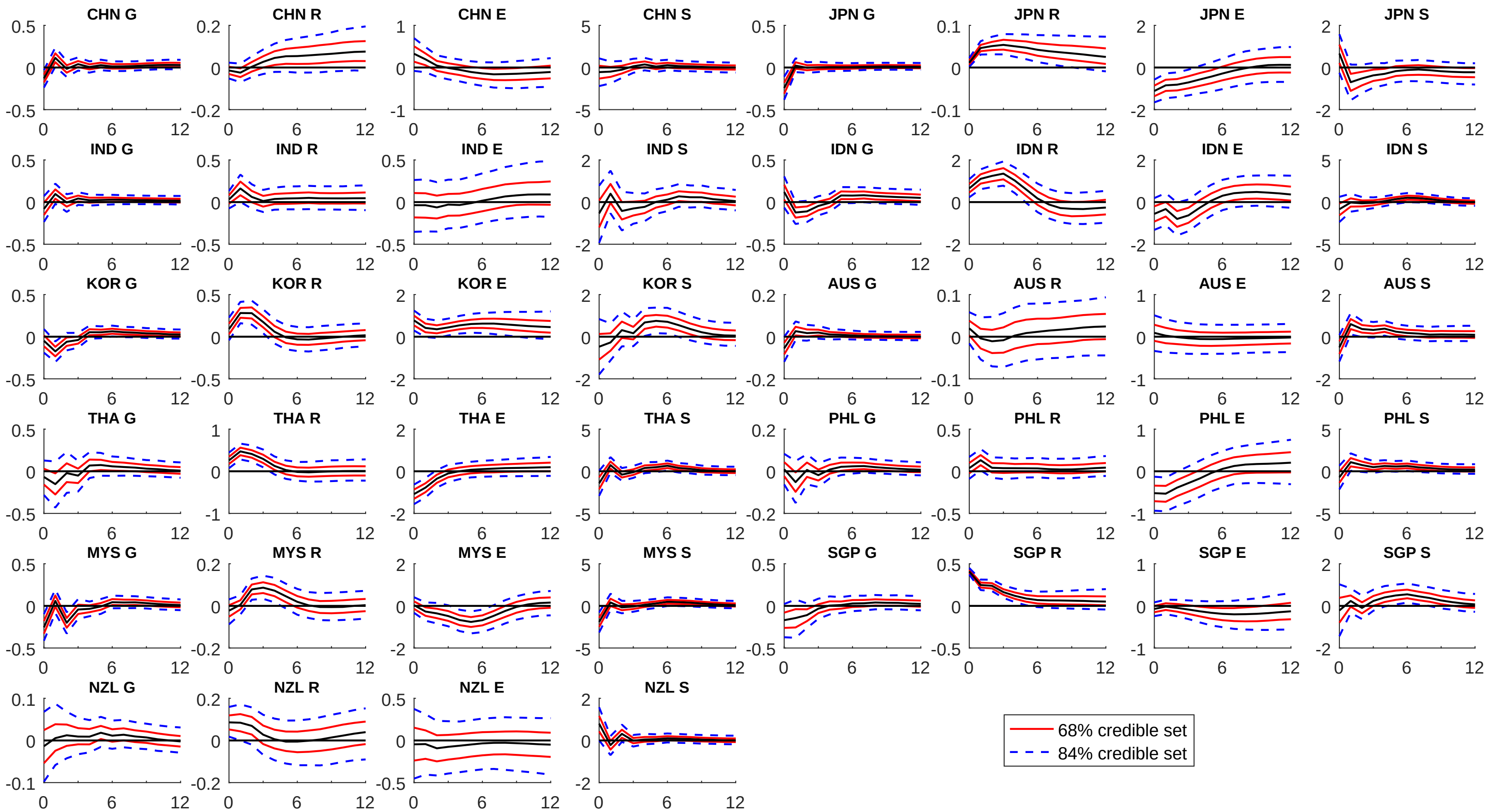


Figure A.30: Impulse Response Functions to a One Standard Deviation New Zealand Monetary Policy Shock

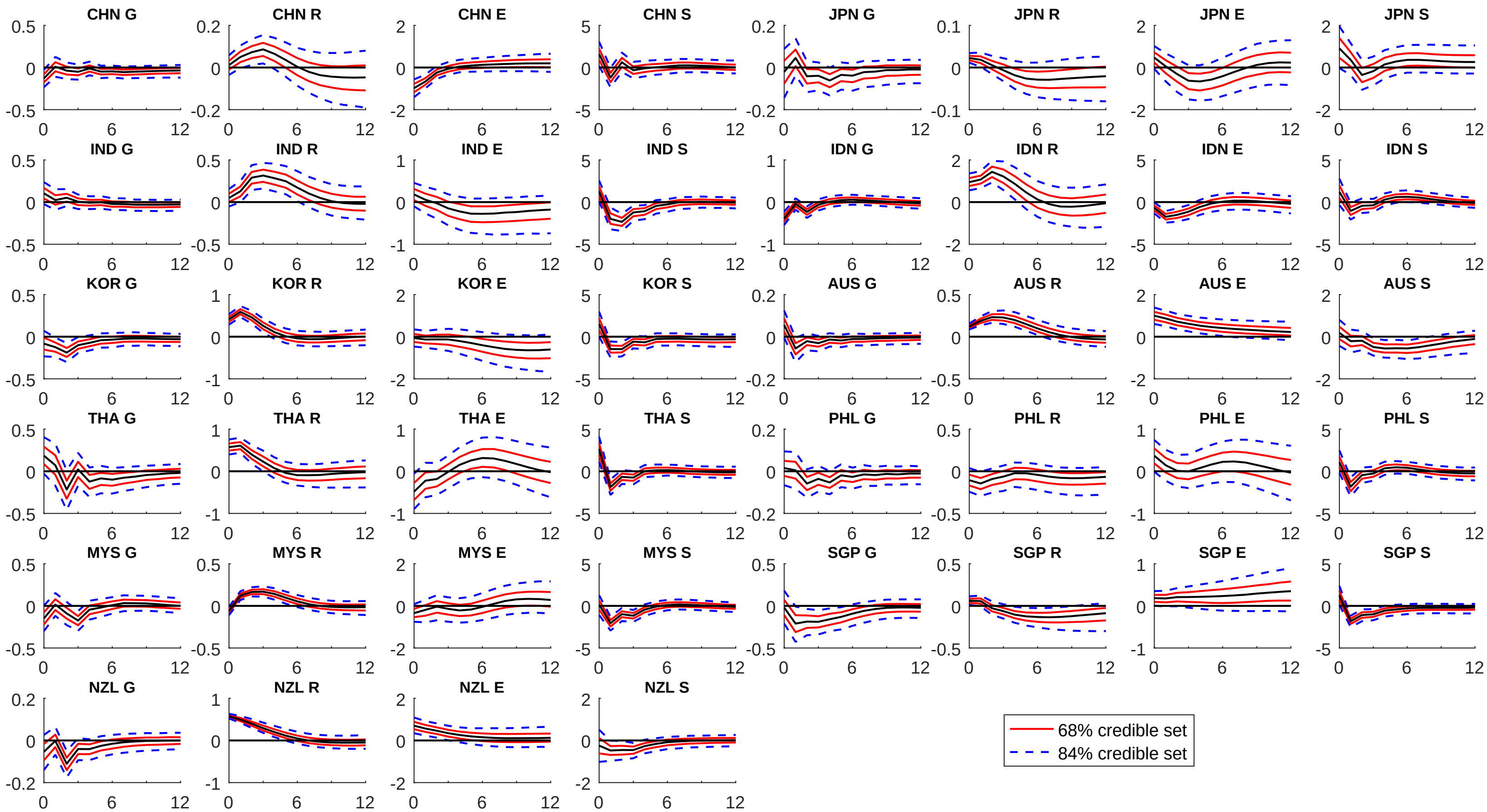


Figure A.31: Impulse Response Functions to a One Standard Deviation China Exchange Rate Shock

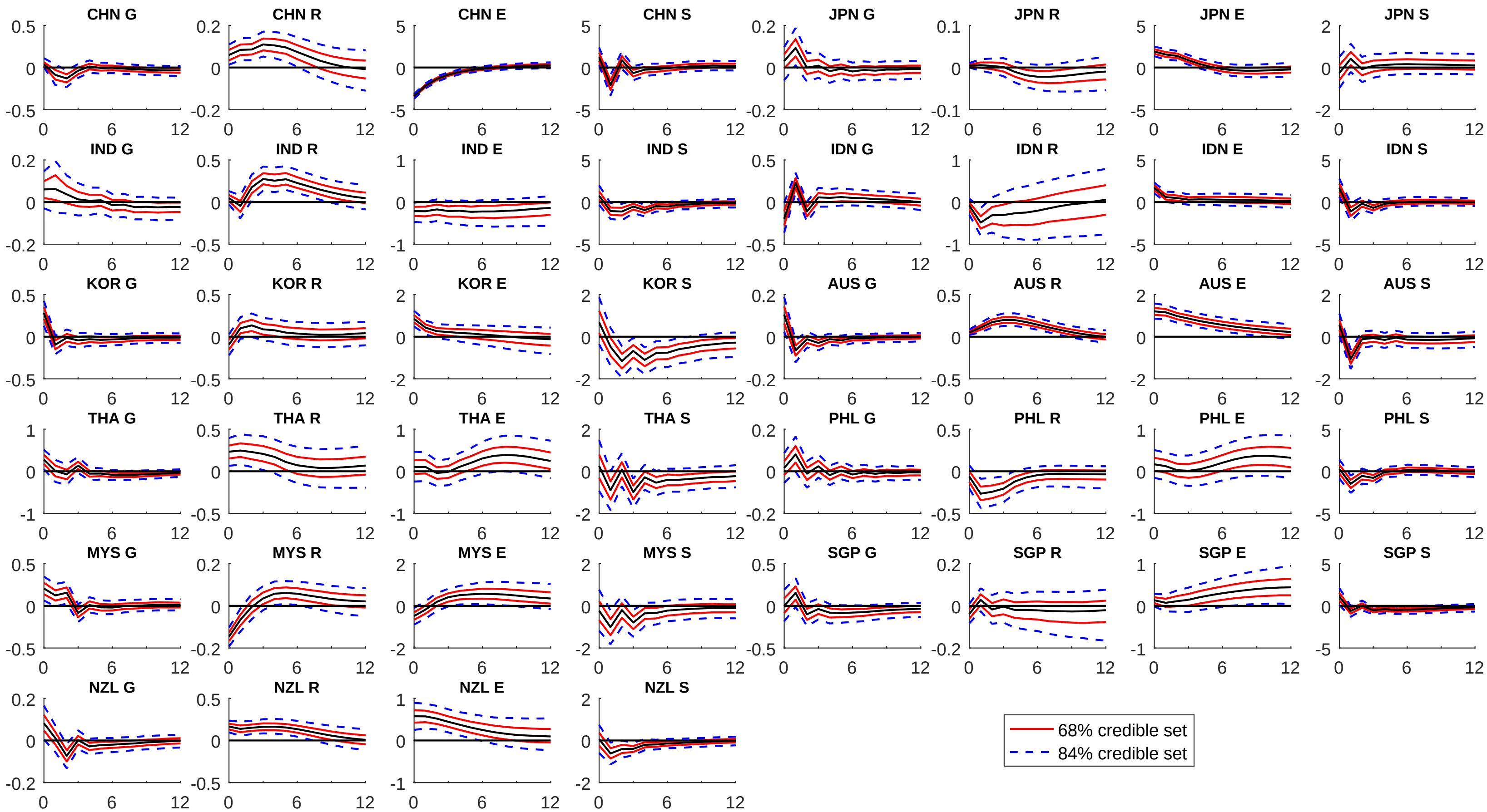


Figure A.32: Impulse Response Functions to a One Standard Deviation Japan Exchange Rate Shock

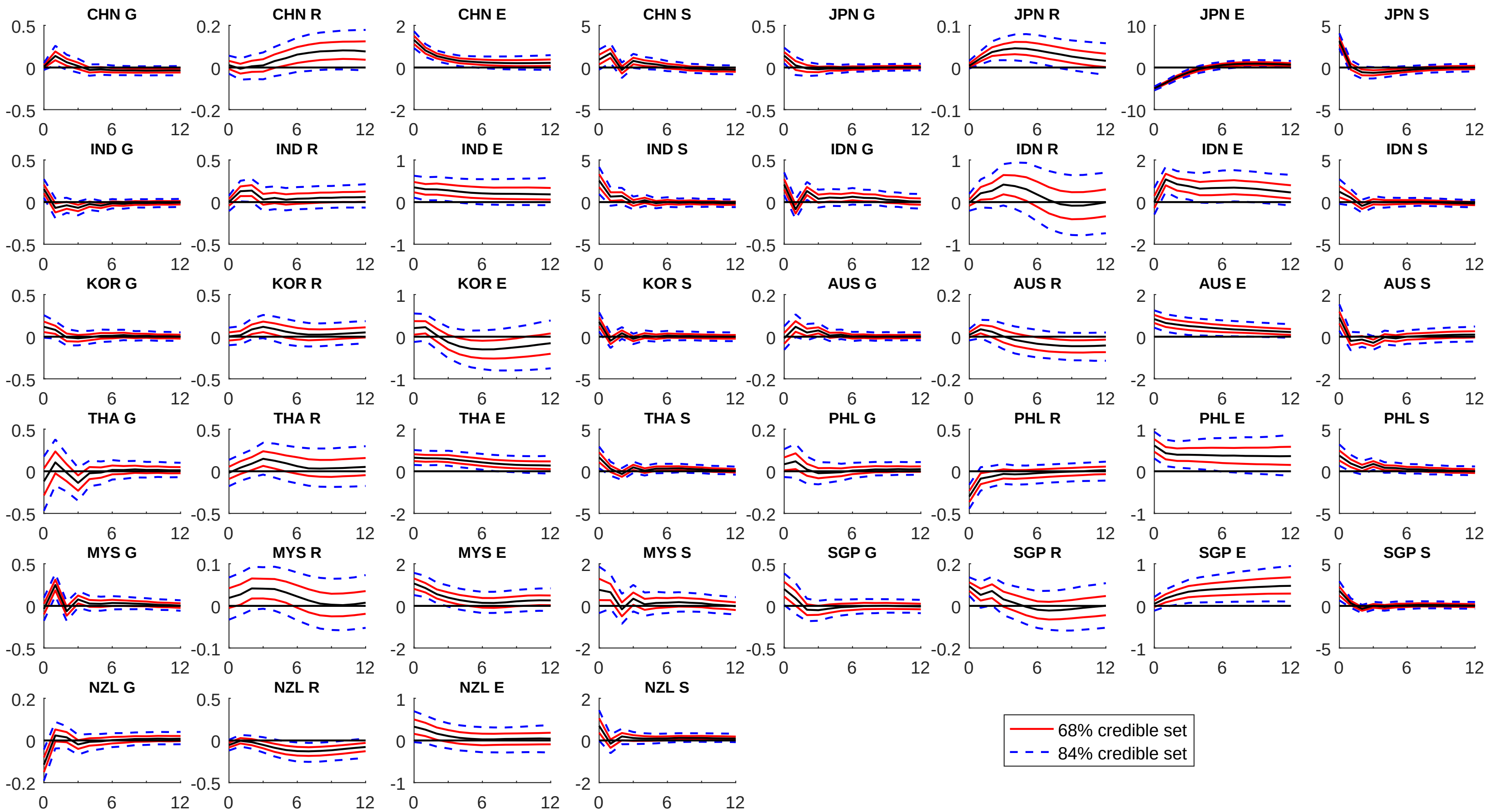


Figure A.33: Impulse Response Functions to a One Standard Deviation Japan Exchange Rate Shock

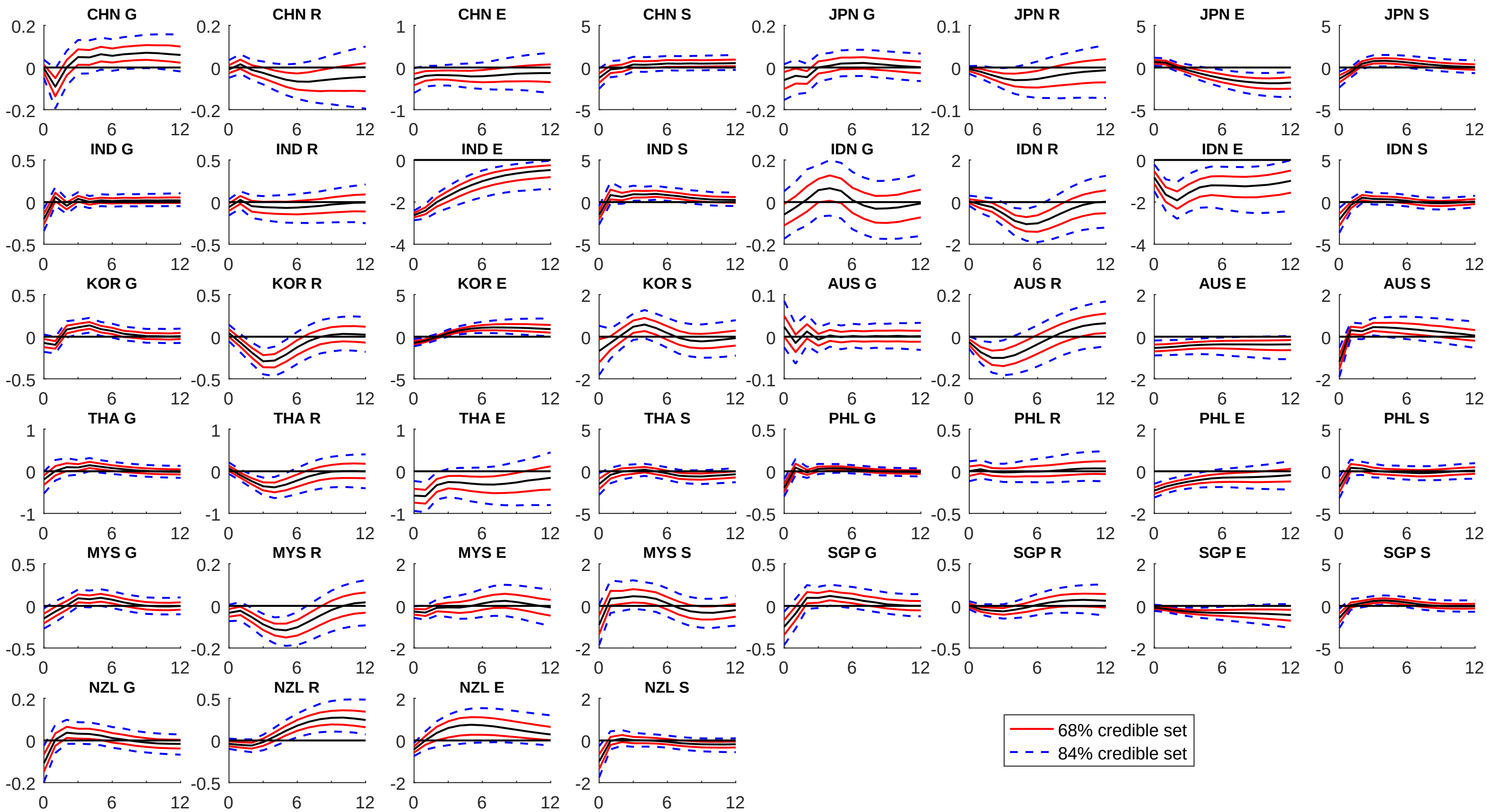


Figure A.34: Impulse Response Functions to a One Standard Deviation Indonesia Exchange Rate Shock

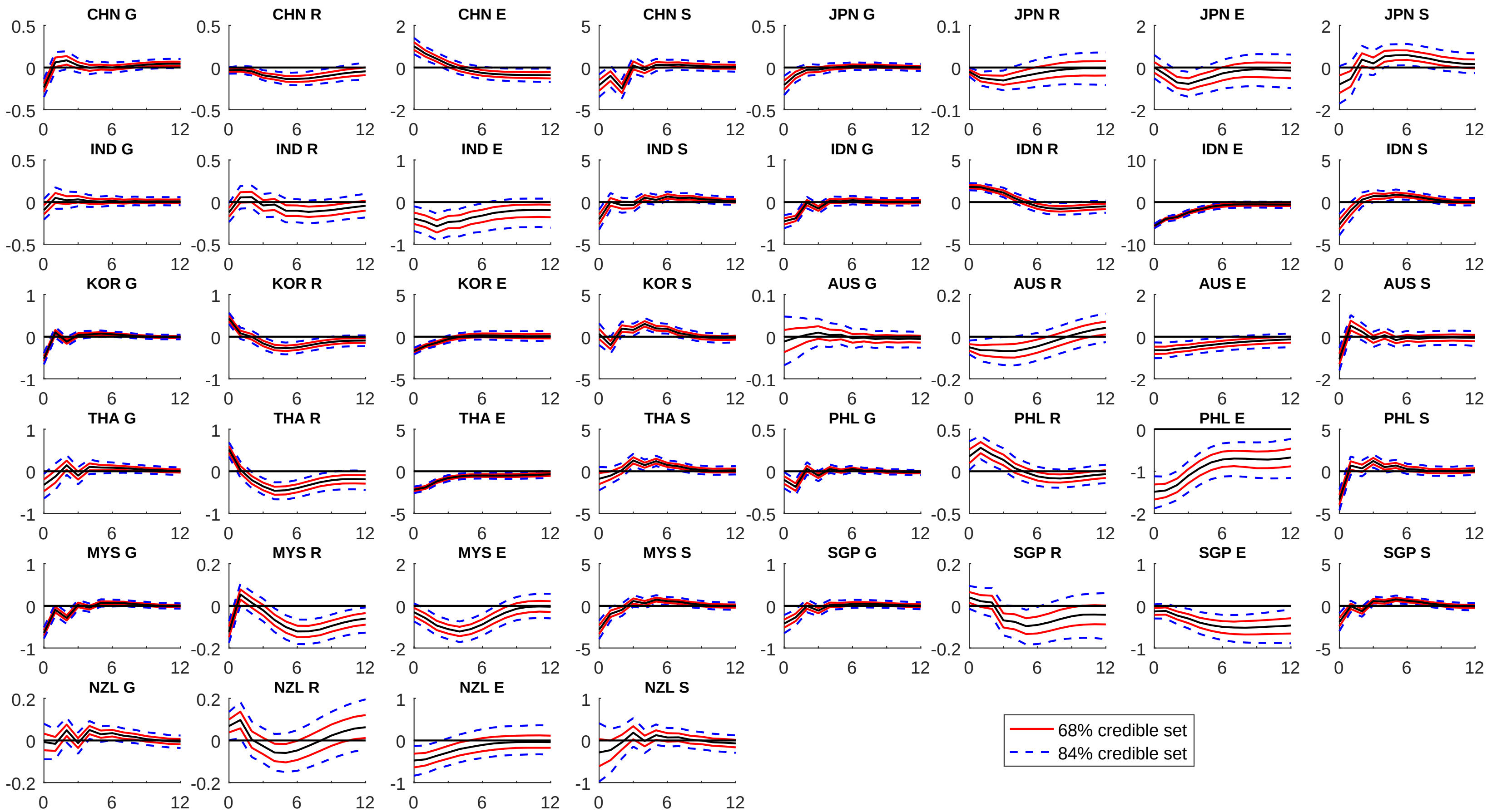


Figure A.35: Impulse Response Functions to a One Standard Deviation Korea Exchange Rate Shock

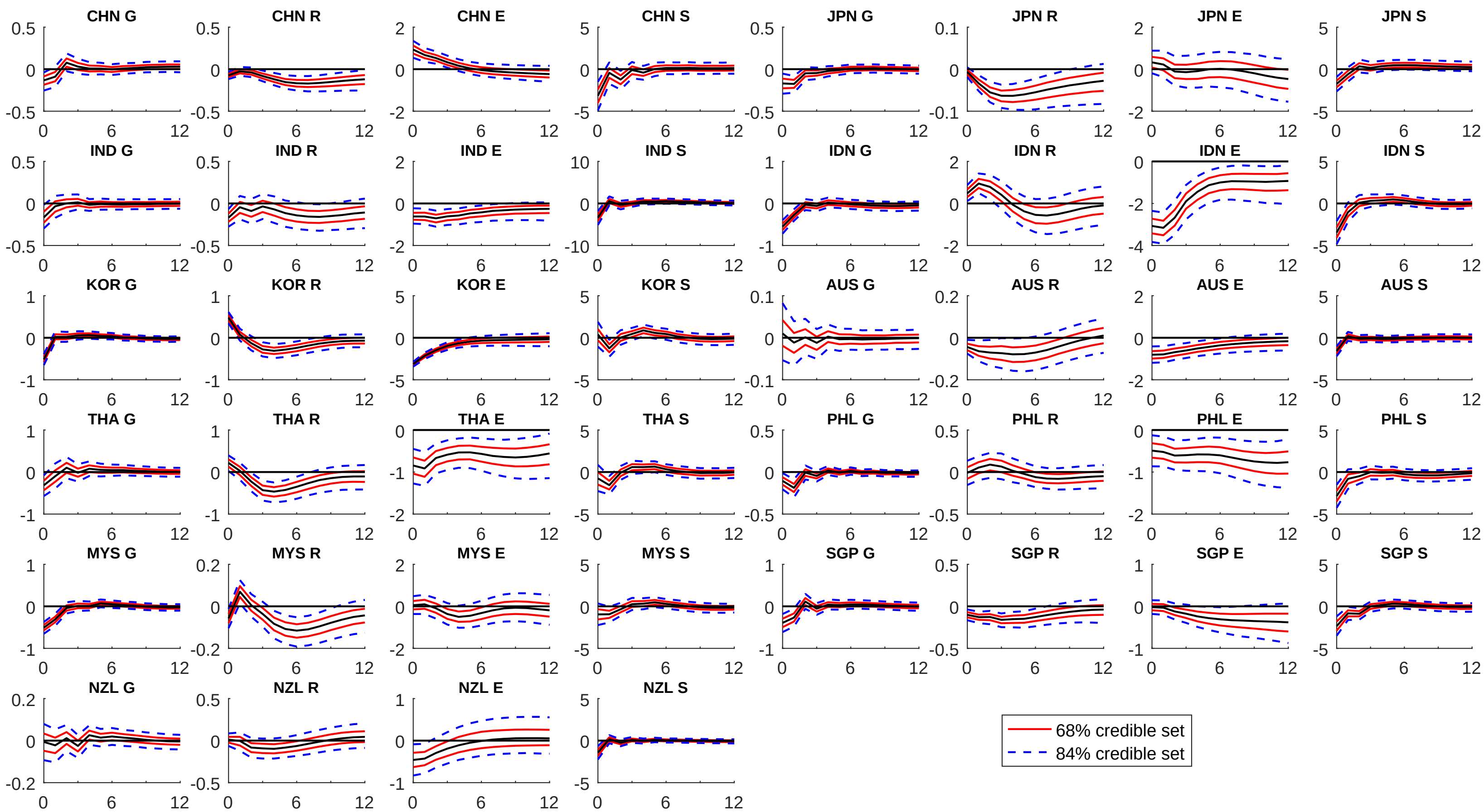


Figure A.36: Impulse Response Functions to a One Standard Deviation Australia Exchange Rate Shock

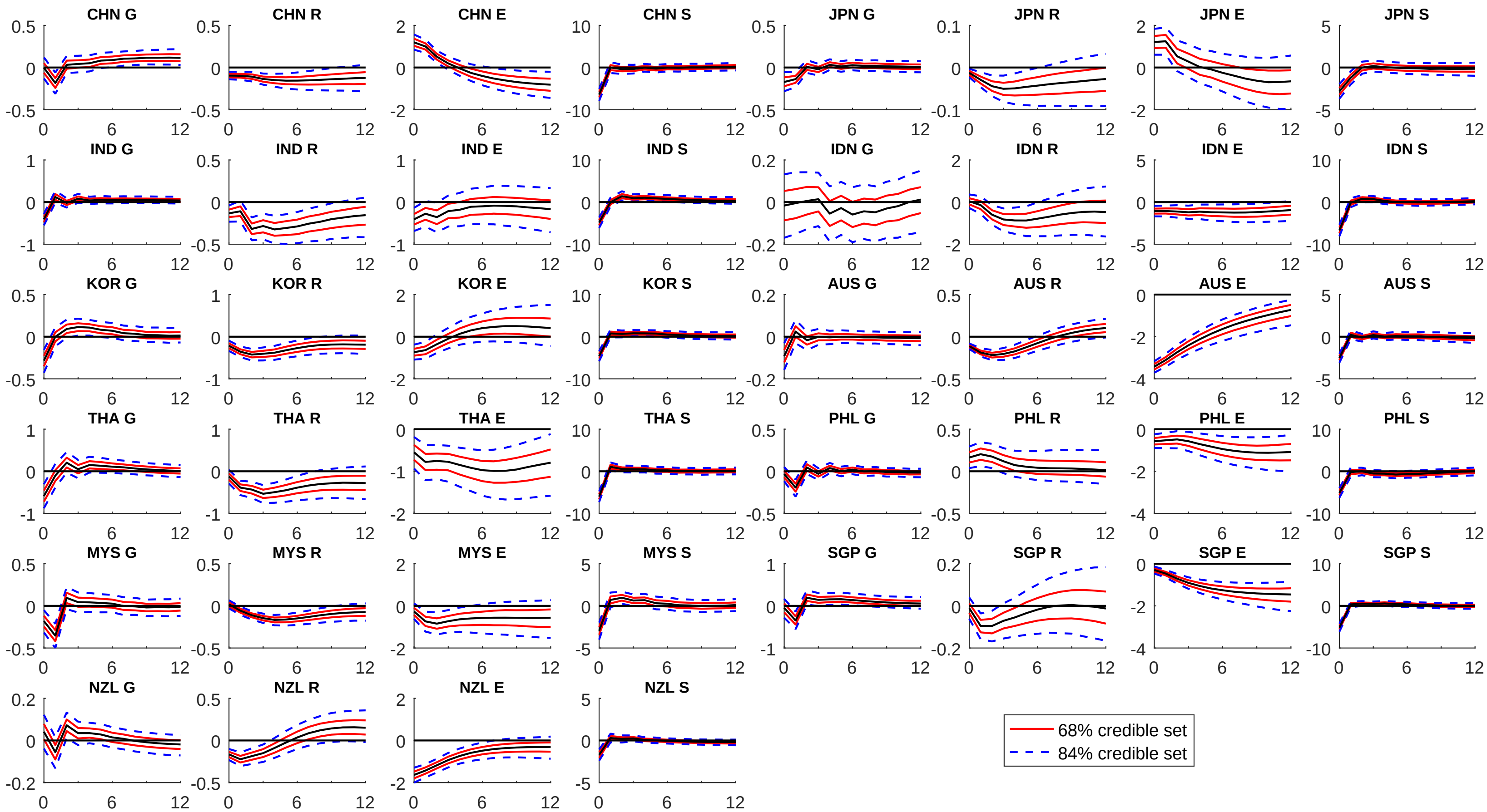


Figure A.37: Impulse Response Functions to a One Standard Deviation Thailand Exchange Rate Shock

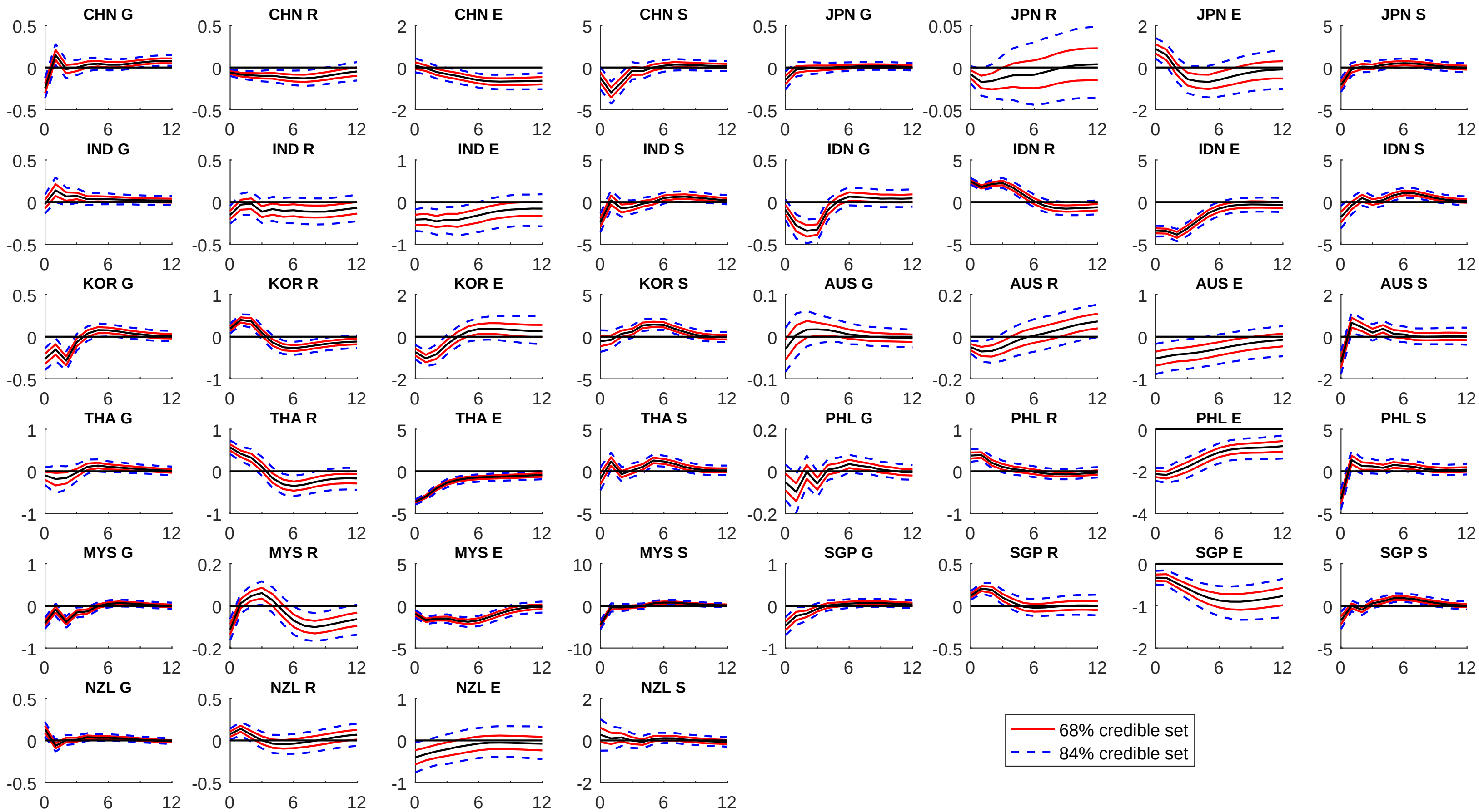


Figure A.38: Impulse Response Functions to a One Standard Deviation Philippines Exchange Rate Shock

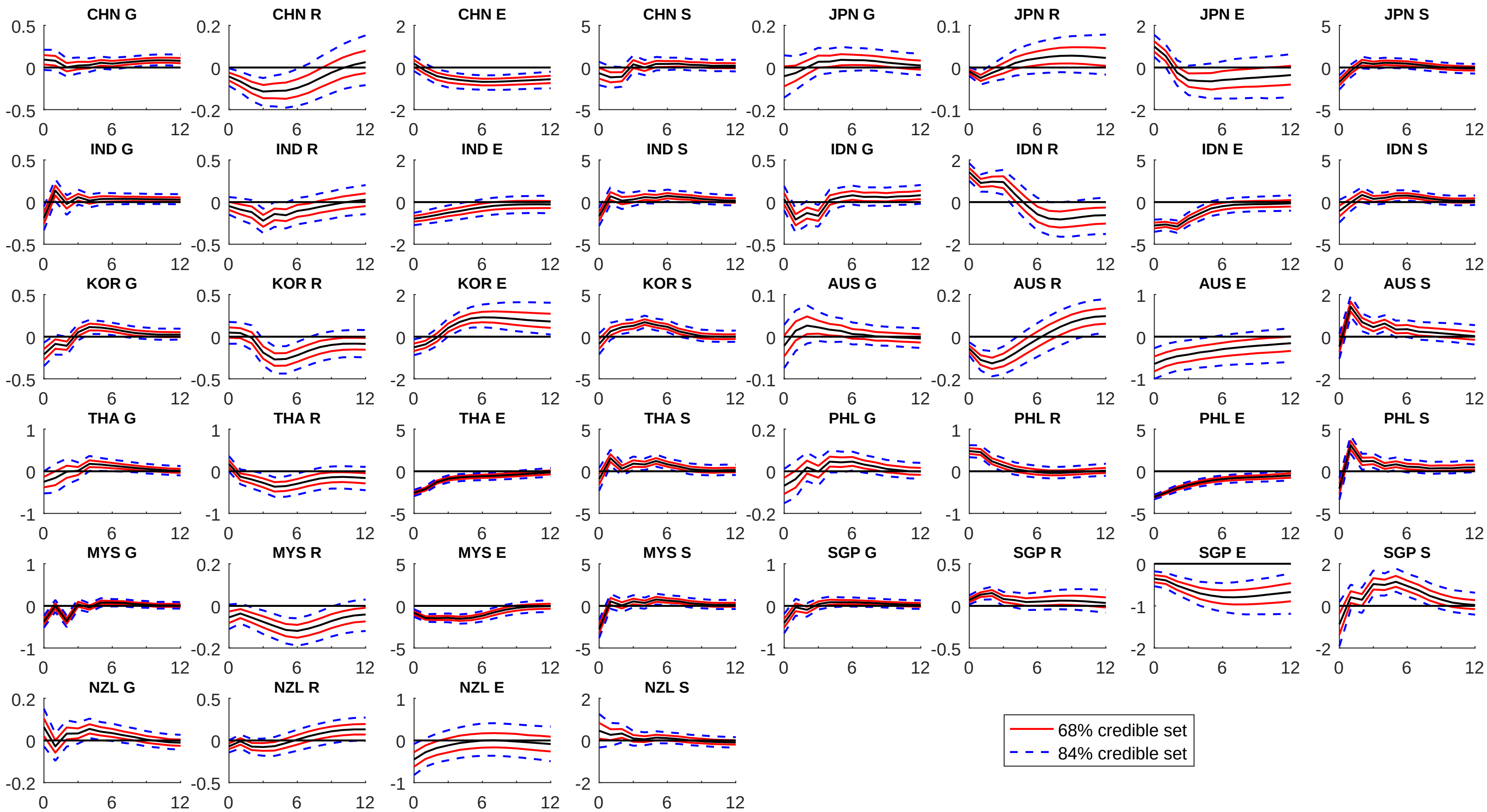


Figure A.39: Impulse Response Functions to a One Standard Deviation Malaysia Exchange Rate Shock

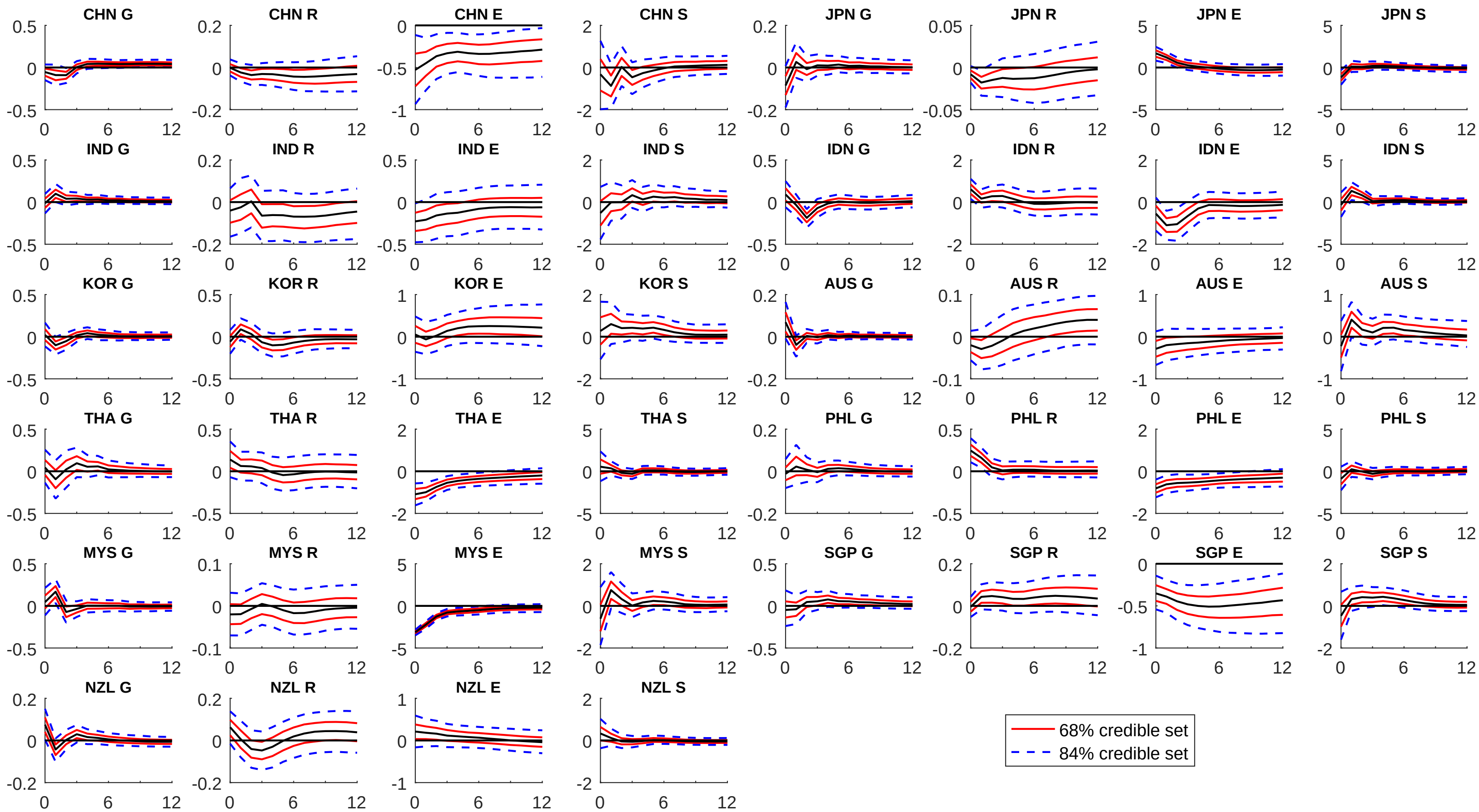


Figure A.40: Impulse Response Functions to a One Standard Deviation Singapore Exchange Rate Shock

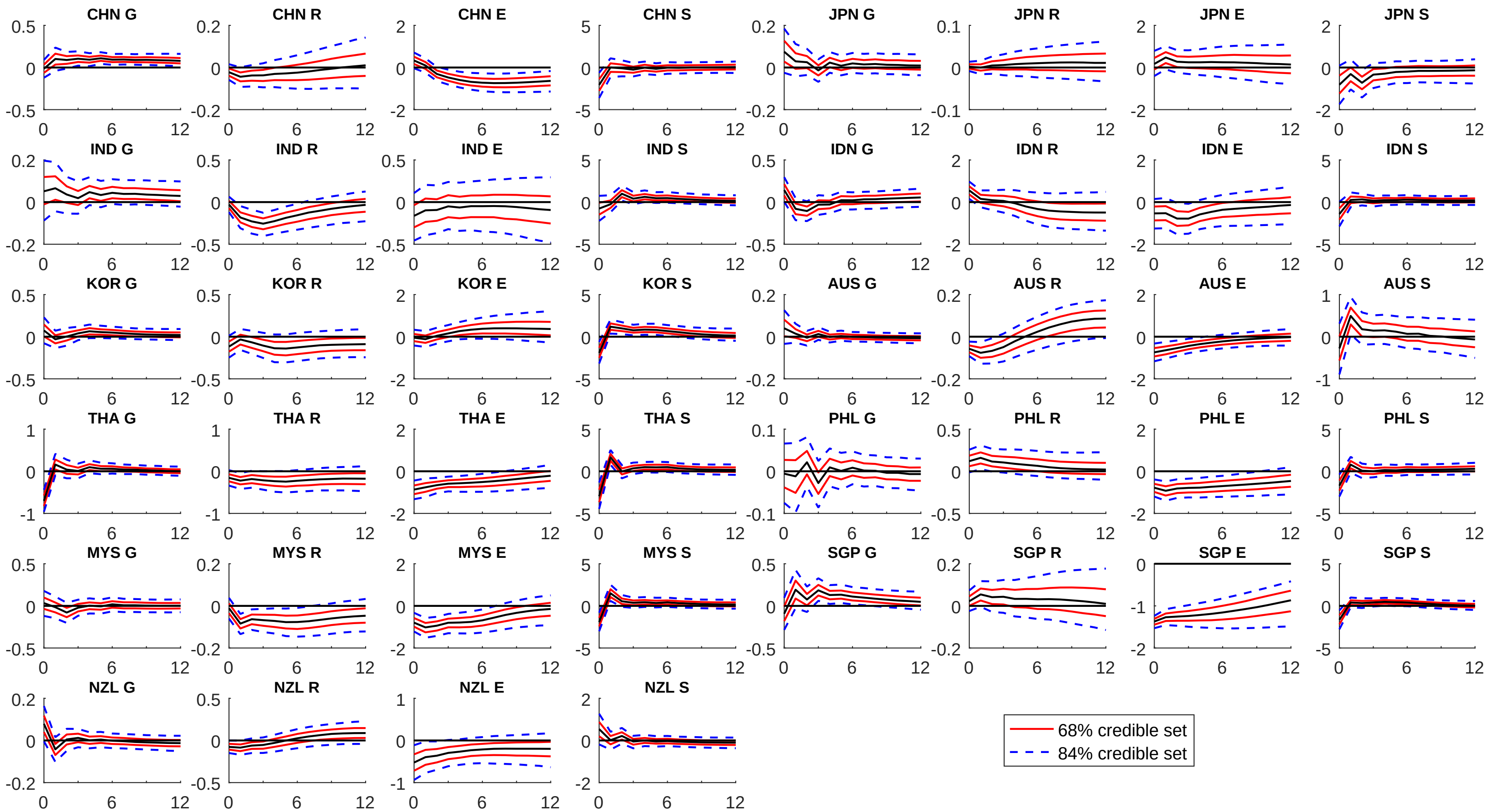


Figure A.41: Impulse Response Functions to a One Standard Deviation New Zealand Exchange Rate Shock

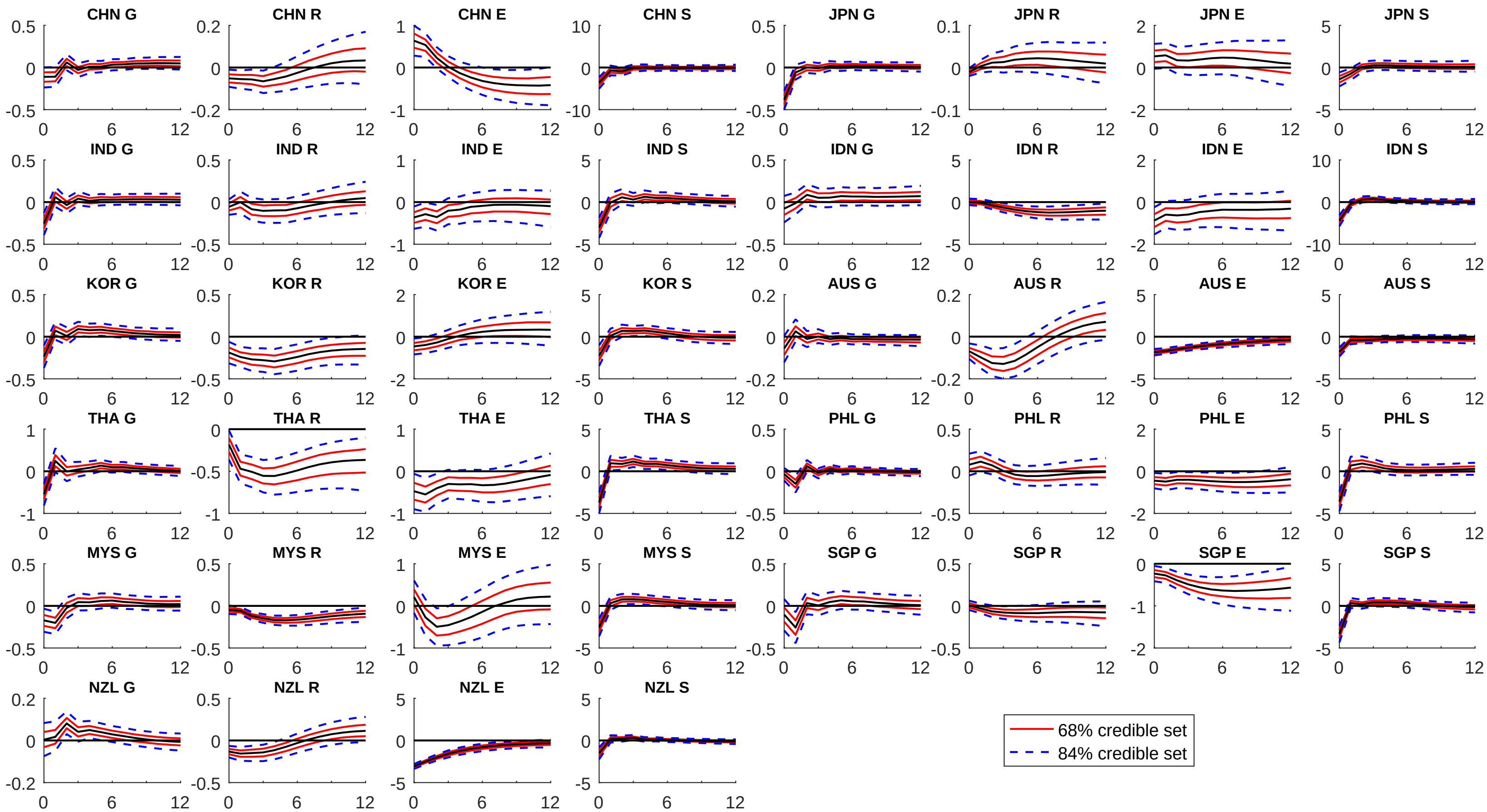


Figure A.42: Impulse Response Functions to a One Standard Deviation China Stock Price Growth Shock

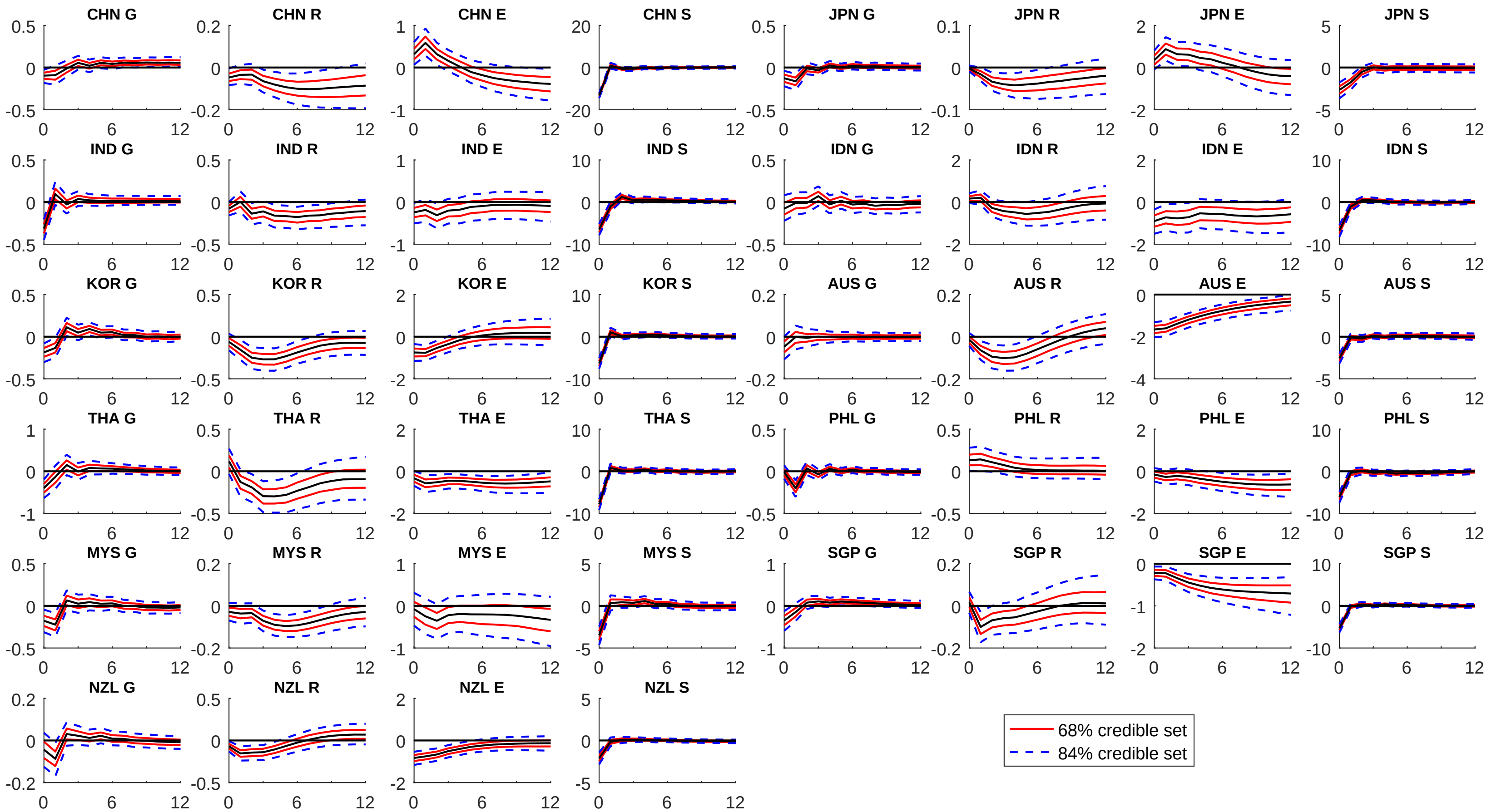


Figure A.43: Impulse Response Functions to a One Standard Deviation Japan Stock Price Growth Shock

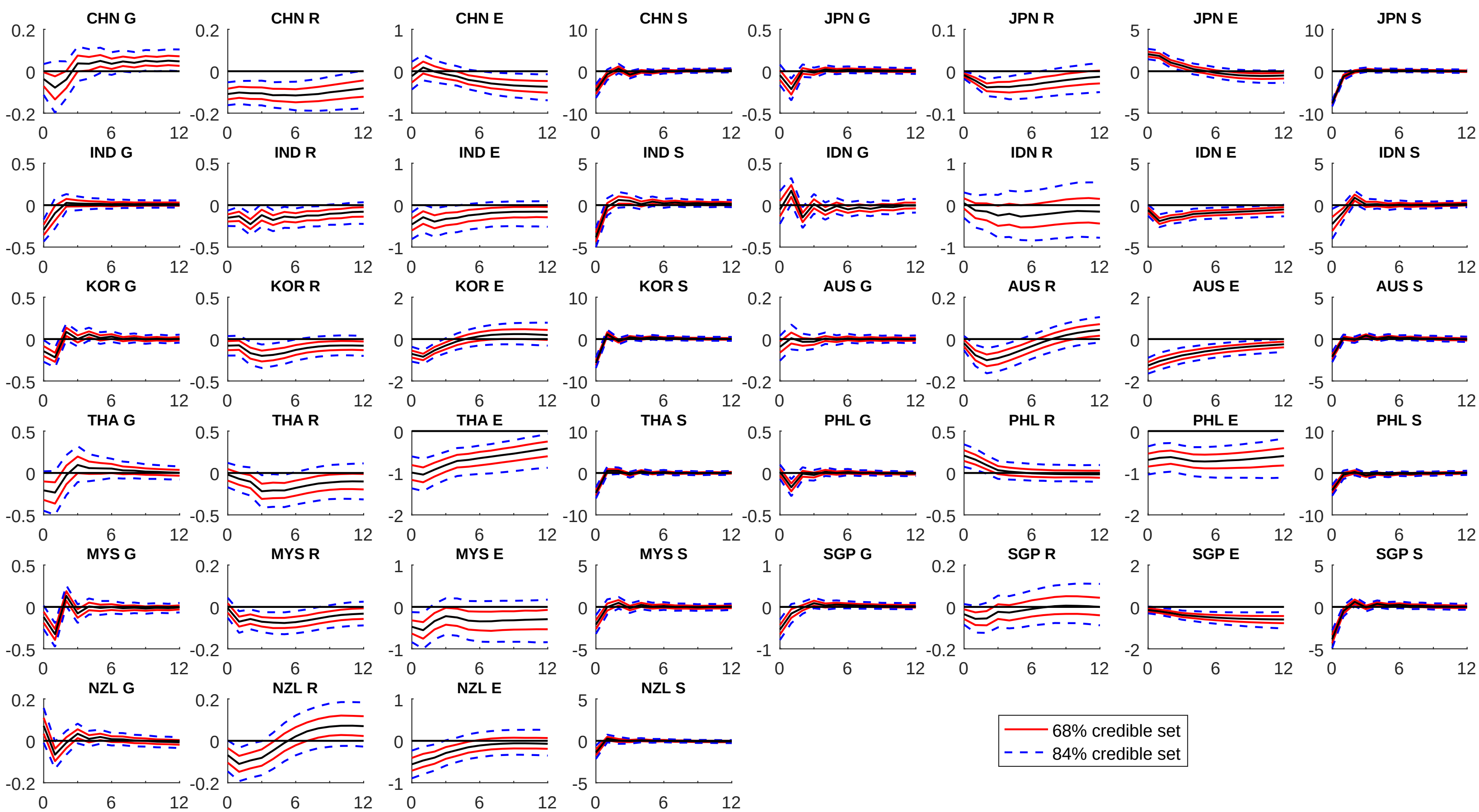


Figure A.44: Impulse Response Functions to a One Standard Deviation India Stock Price Growth Shock

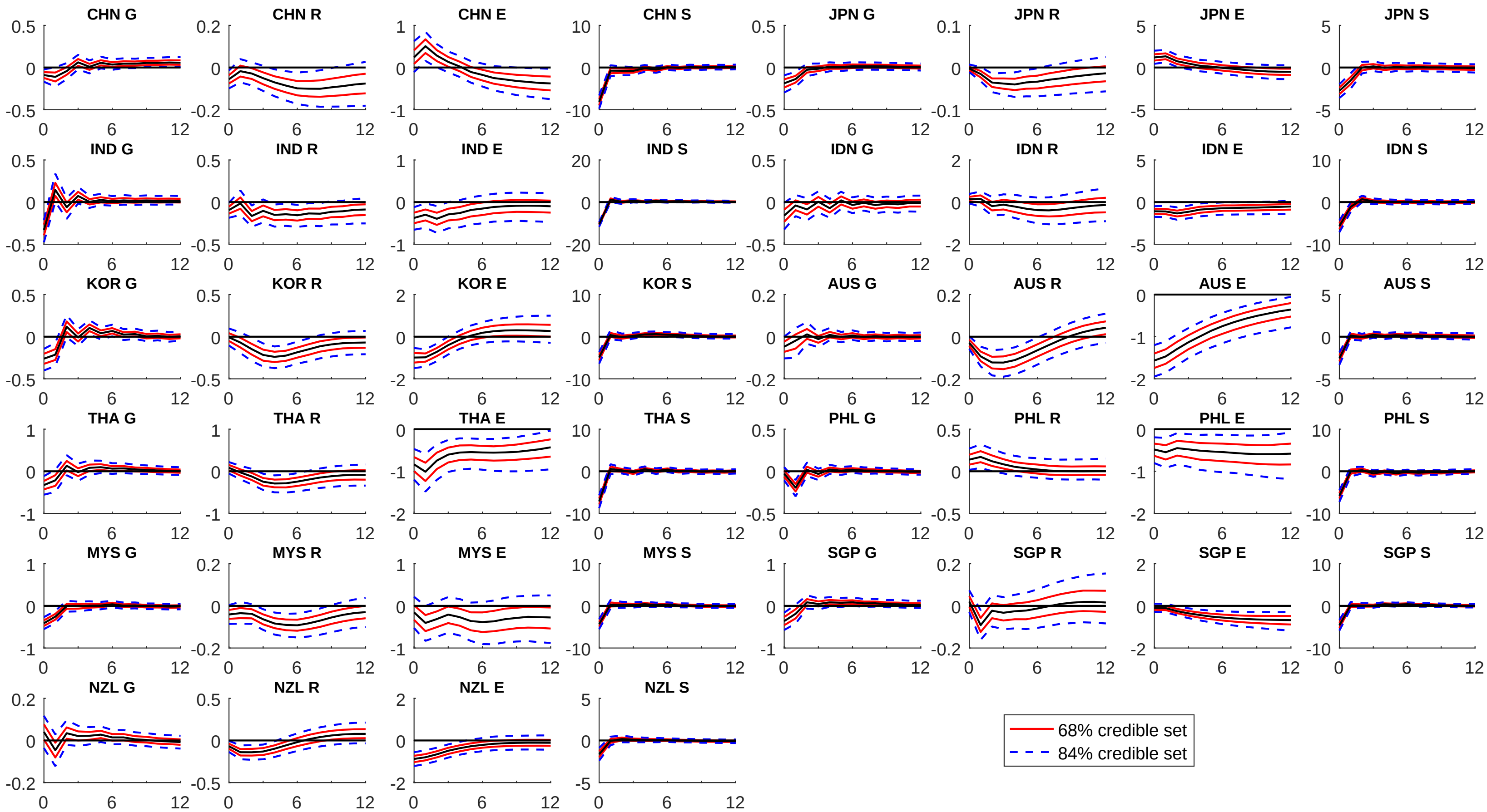


Figure A.45: Impulse Response Functions to a One Standard Deviation Indonesia Stock Price Growth Shock

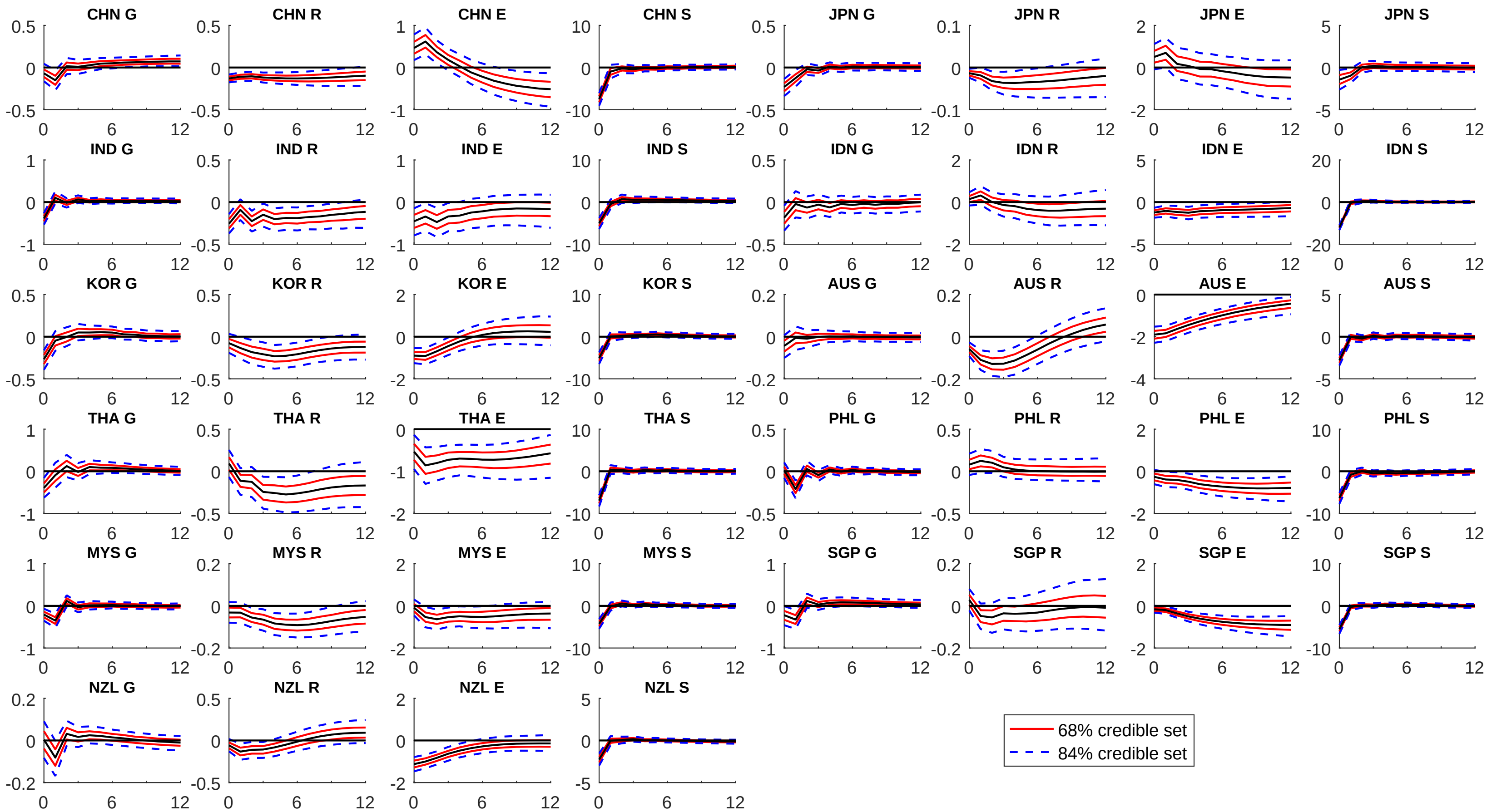


Figure A.46: Impulse Response Functions to a One Standard Deviation Korea Stock Price Growth Shock

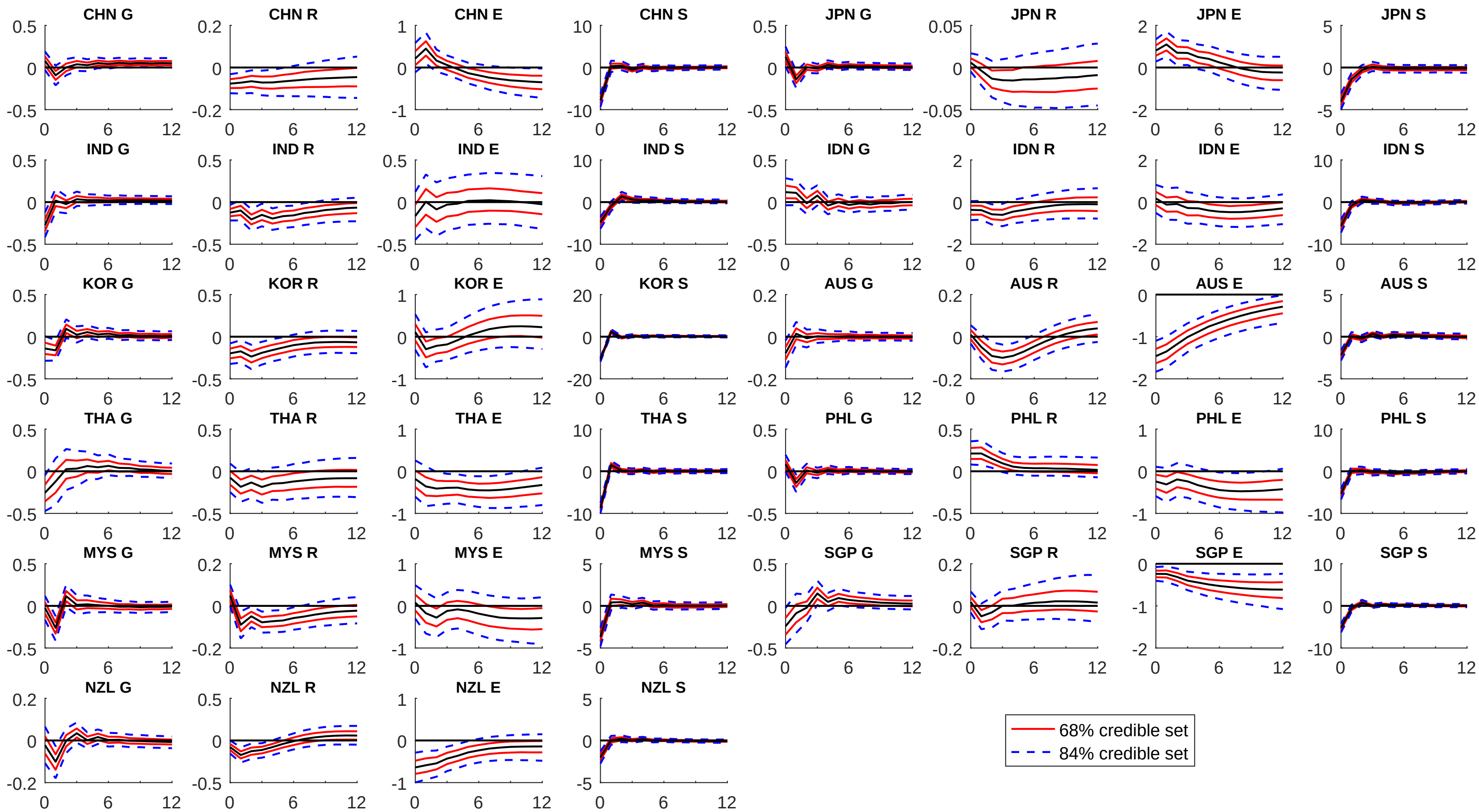


Figure A.47: Impulse Response Functions to a One Standard Deviation Australia Stock Price Growth Shock

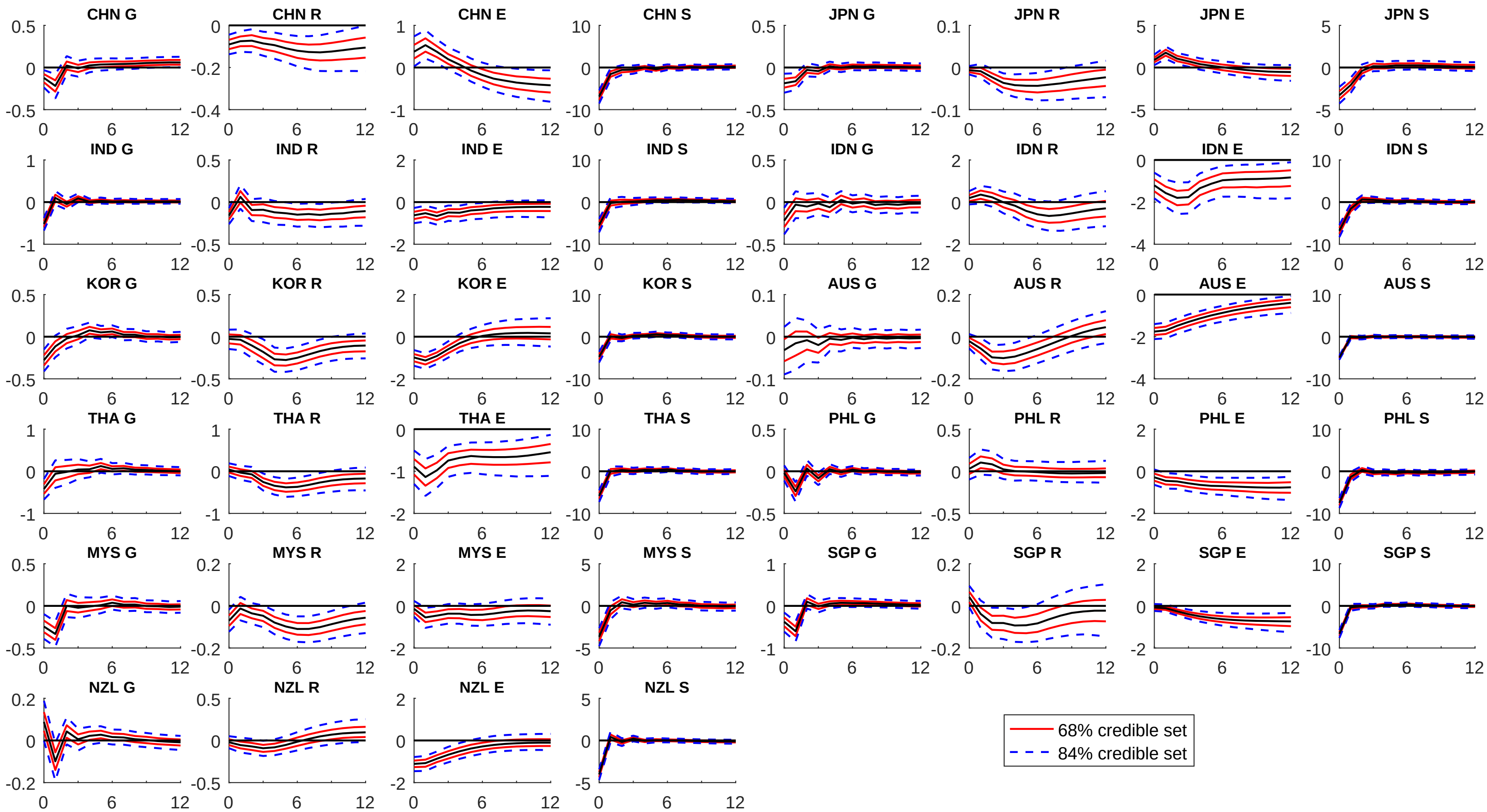


Figure A.48: Impulse Response Functions to a One Standard Deviation Thailand Stock Price Growth Shock

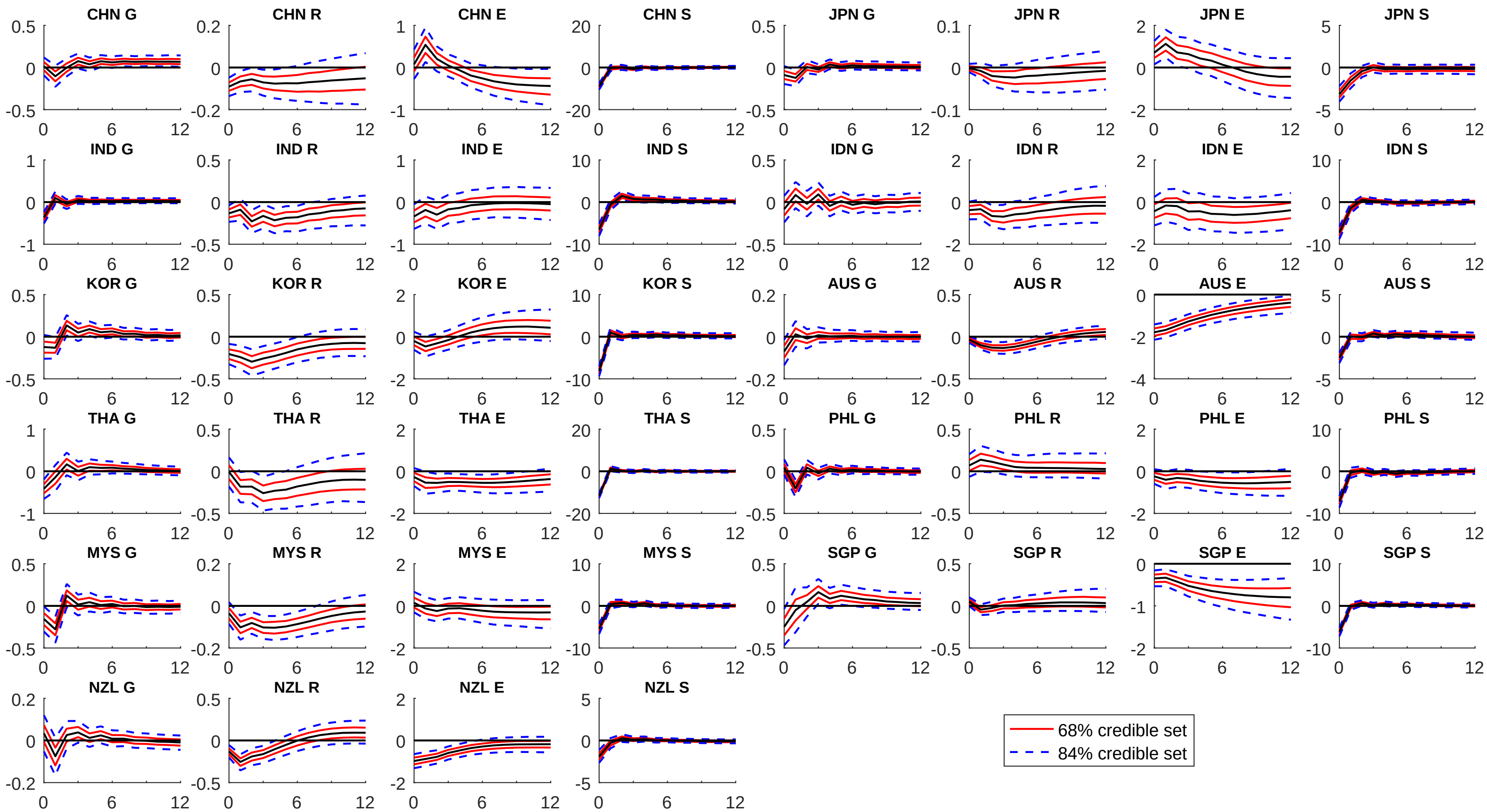


Figure A.49: Impulse Response Functions to a One Standard Deviation Philippines Stock Price Growth Shock

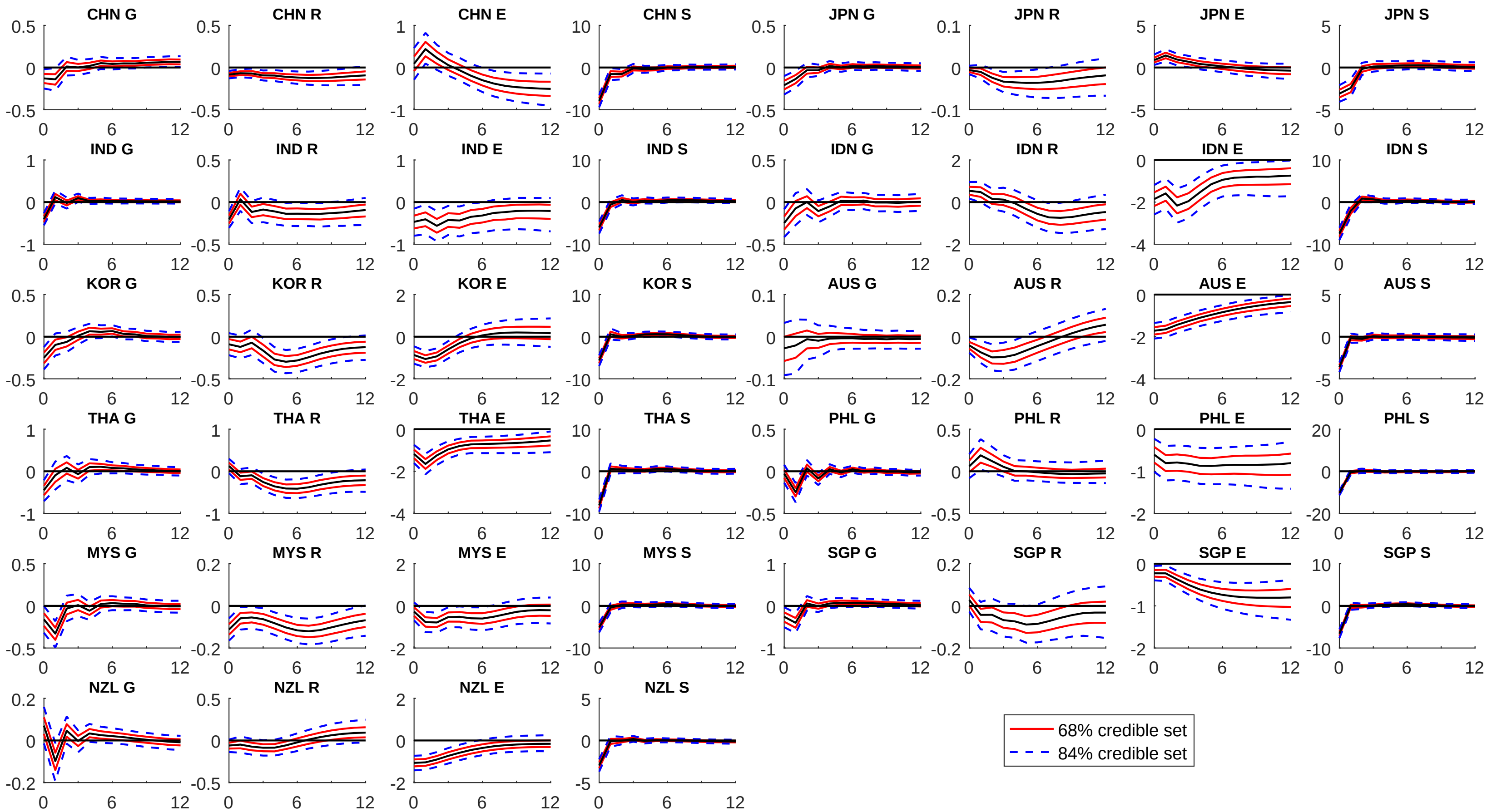


Figure A.50: Impulse Response Functions to a One Standard Deviation Malaysia Stock Price Growth Shock

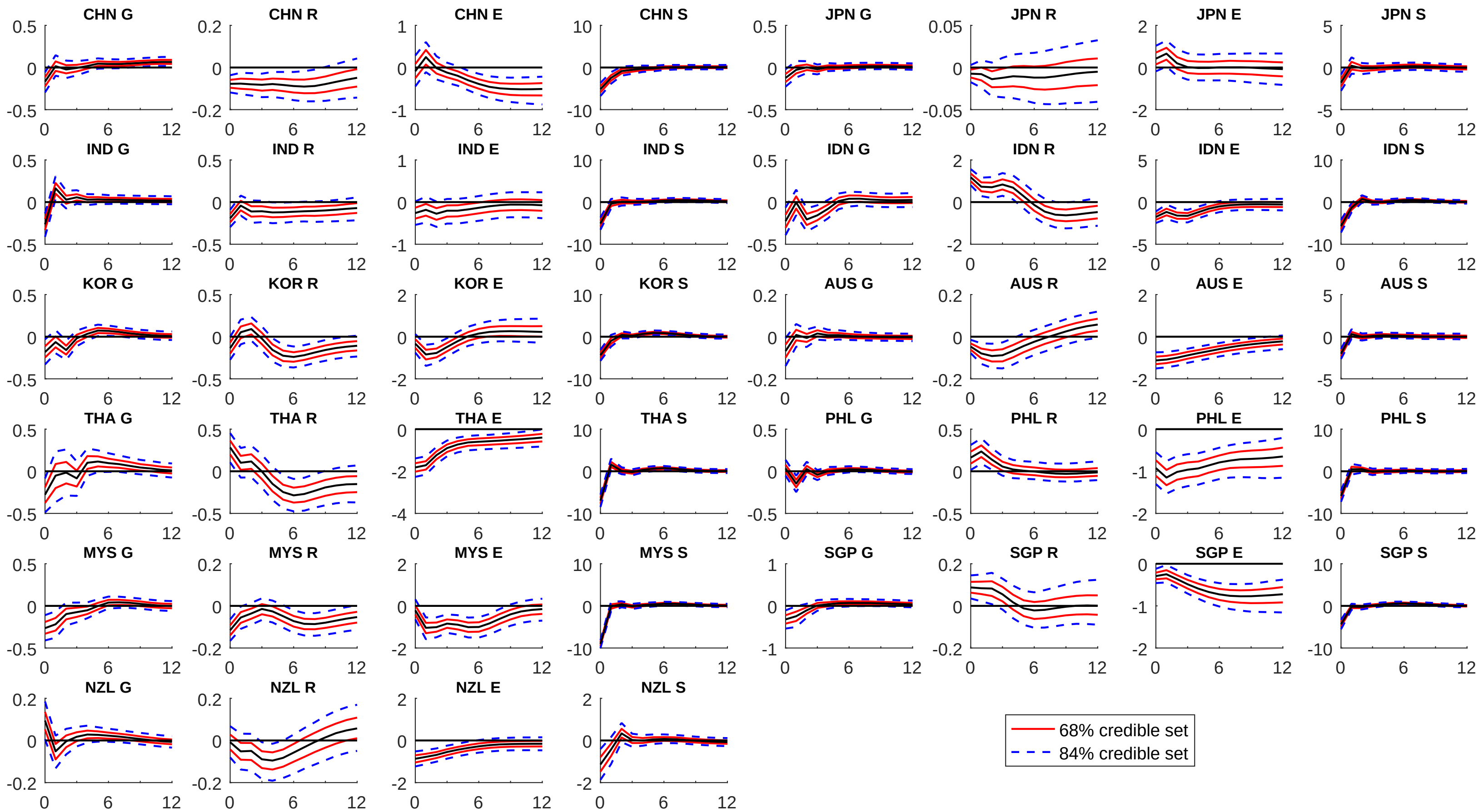


Figure A.51: Impulse Response Functions to a One Standard Deviation Singapore Stock Price Growth Shock

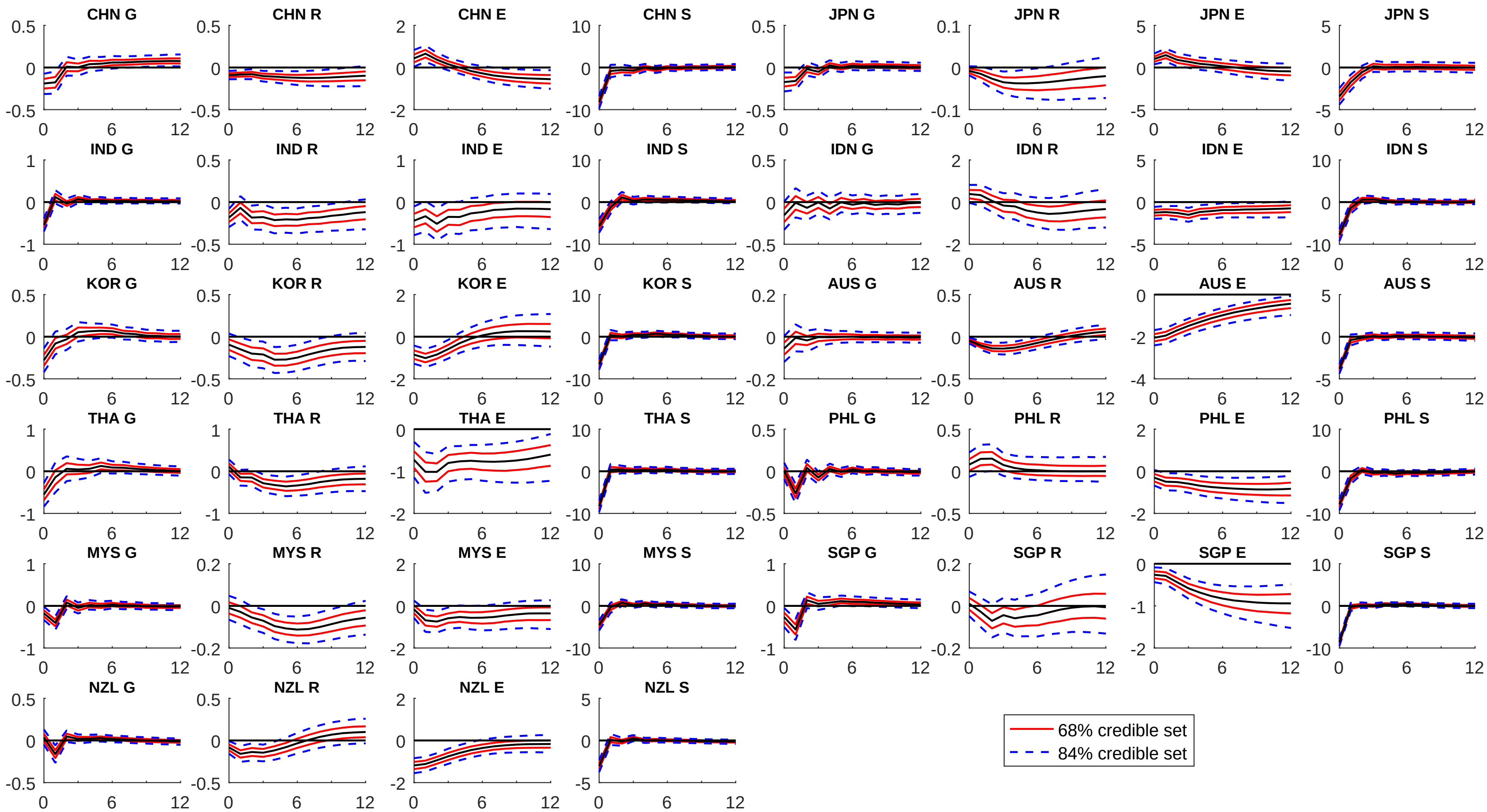
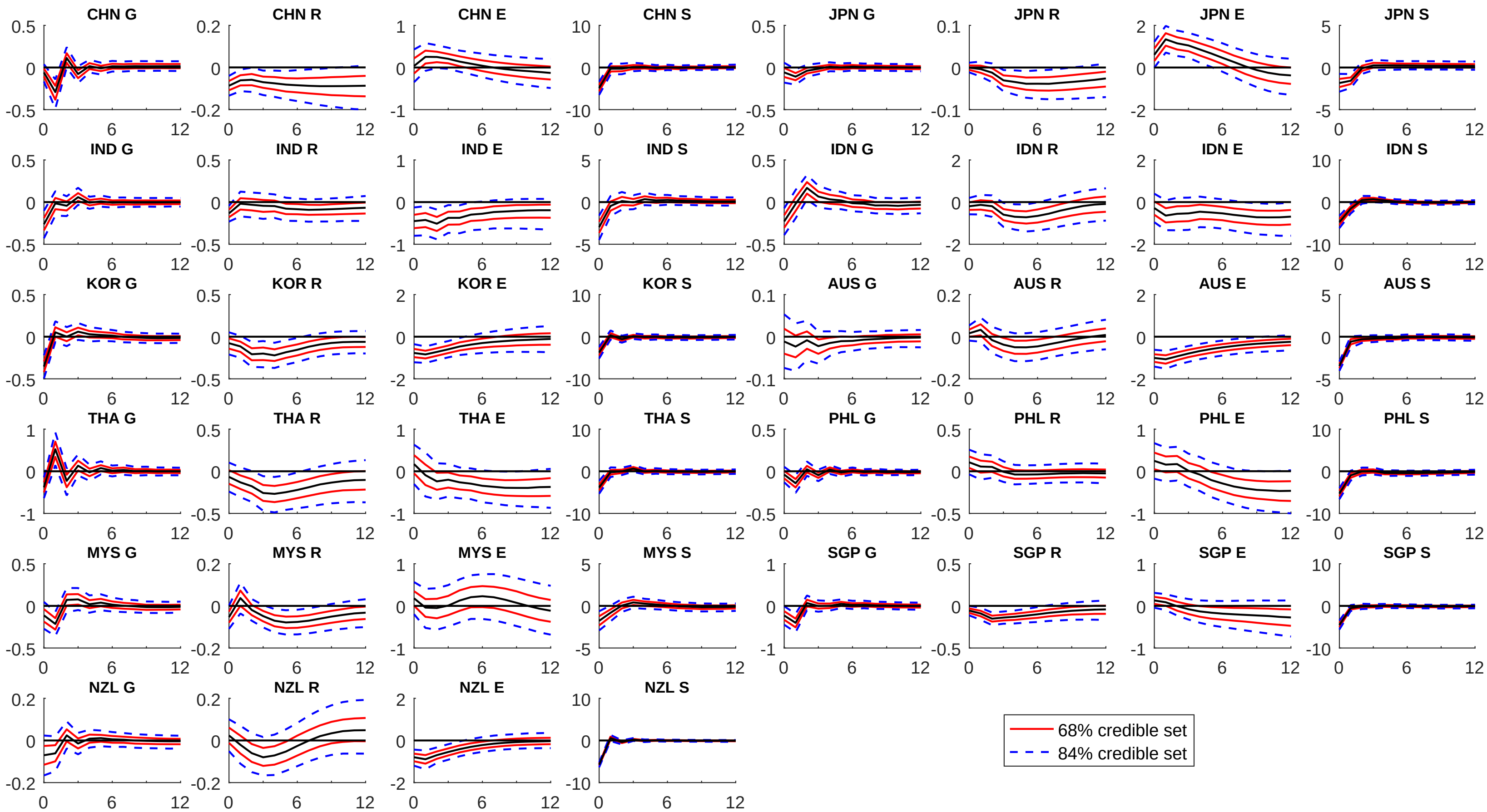
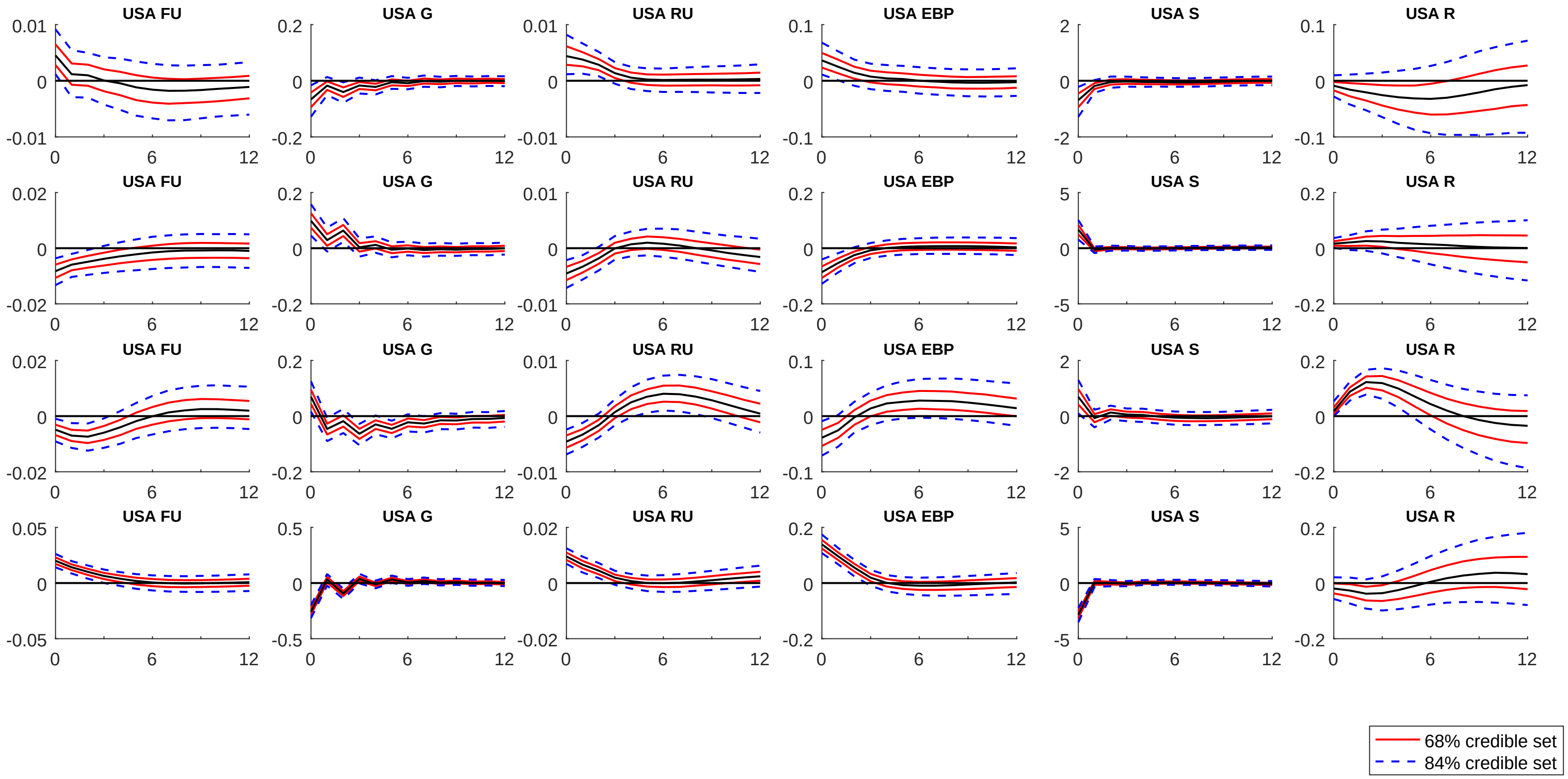


Figure A.52: Impulse Response Functions to a One Standard Deviation New Zealand Stock Price Growth Shock



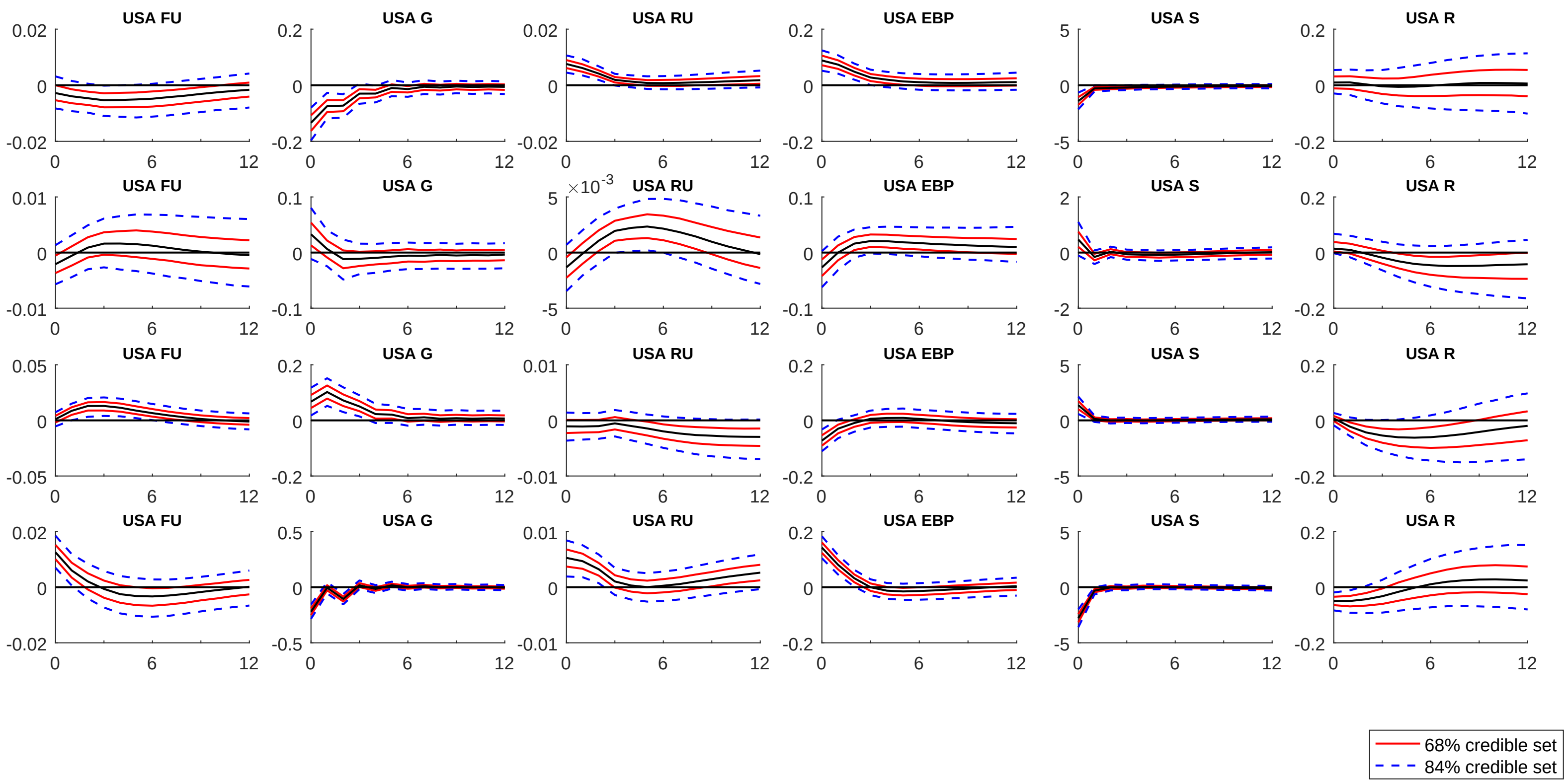
A.3.3 Response of US to Adverse AP Shocks

Figure A.53: Impulse Response Functions to a One Standard Deviation Shock in each Chinese Variable



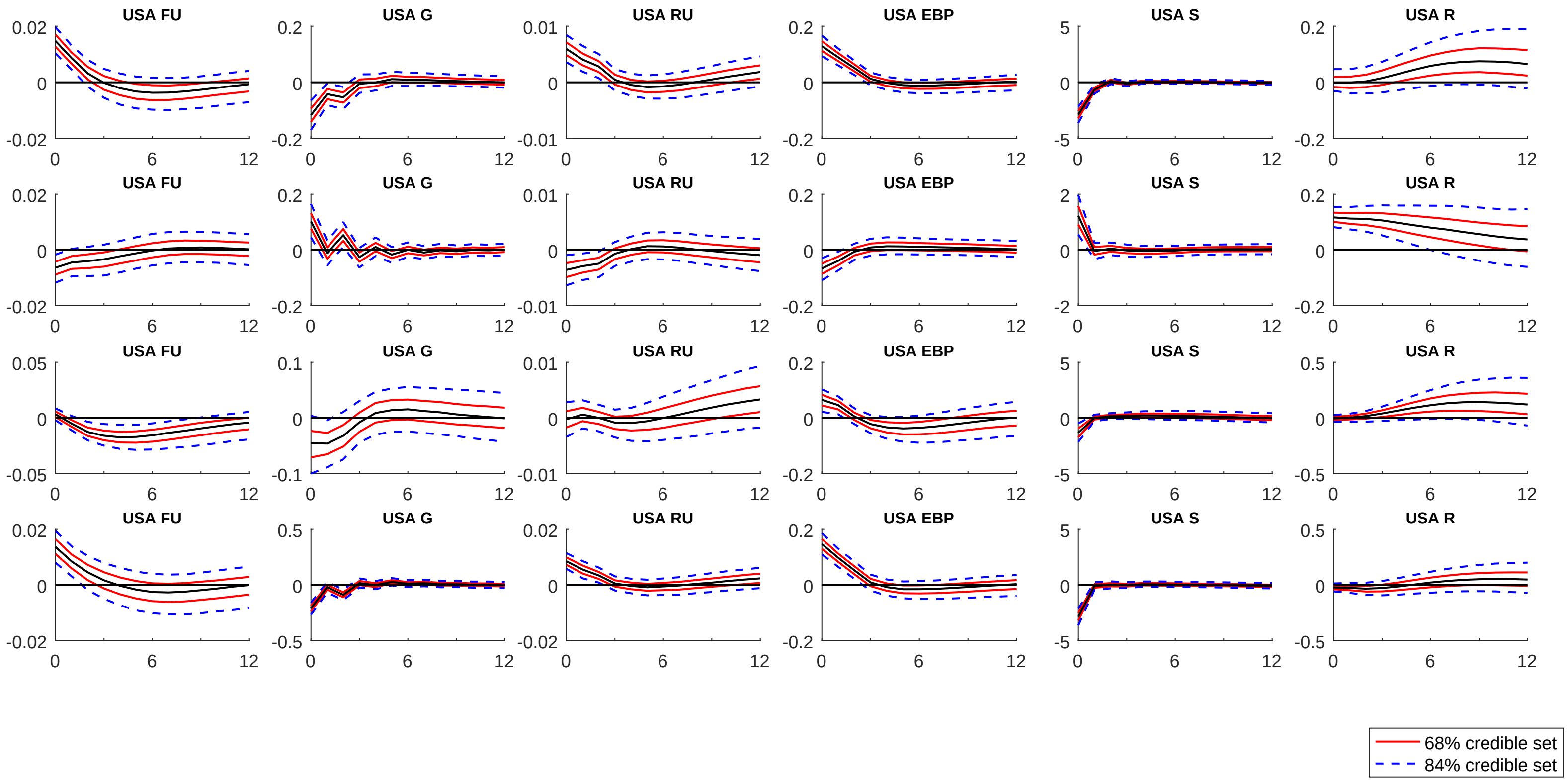
Note: From top to bottom, US impulse response functions to a deterioration in economic conditions, a monetary contraction, an increase in international competitiveness and a deterioration in financial markets.

Figure A.54: Impulse Response Functions to a One Standard Deviation Shock in each Japanese Variable



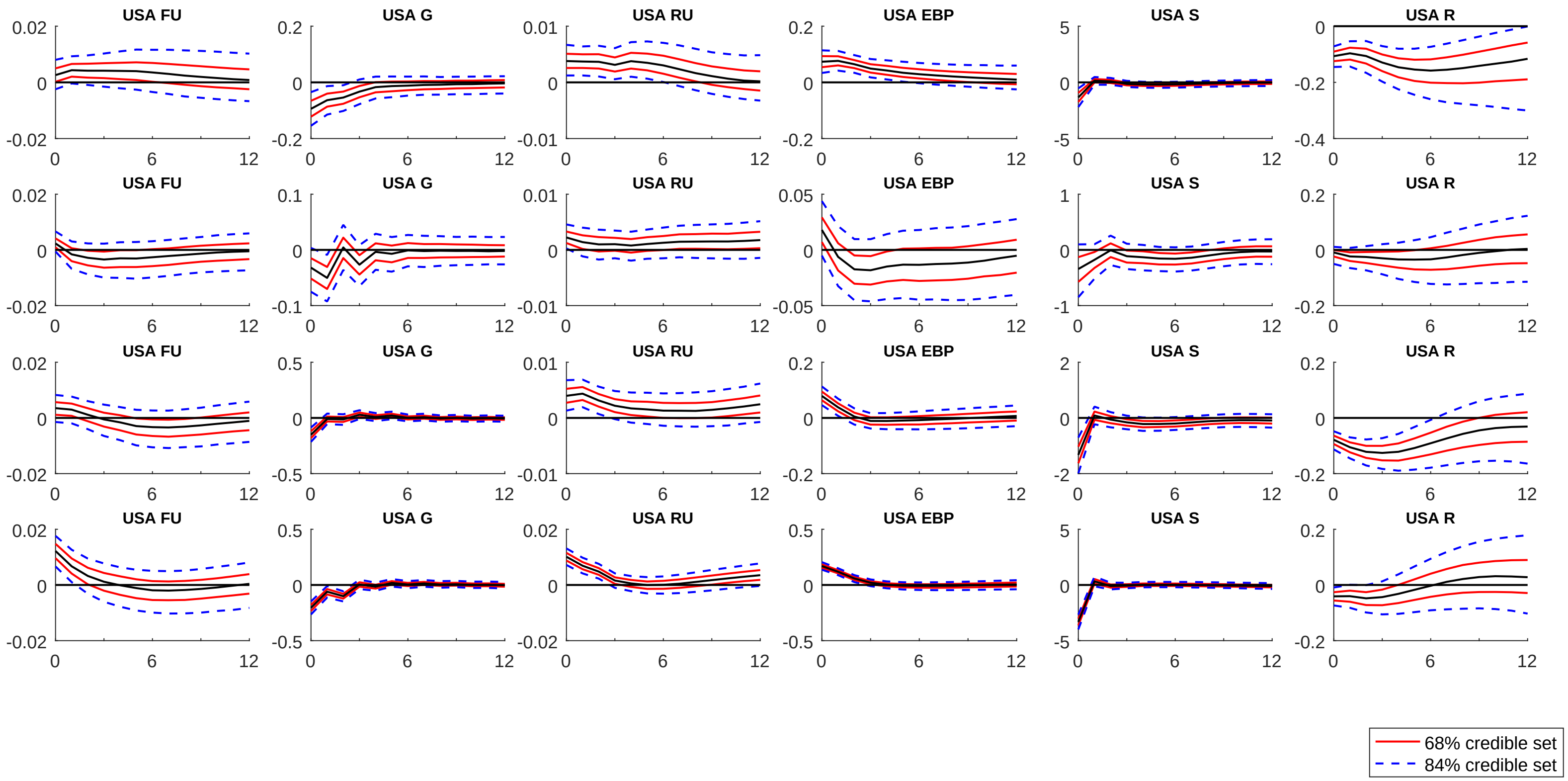
Note: From top to bottom, US impulse response functions to a deterioration in economic conditions, a monetary contraction, an increase in international competitiveness and a deterioration in financial markets.

Figure A.55: Impulse Response Functions to a One Standard Deviation Shock in each Indian Variable



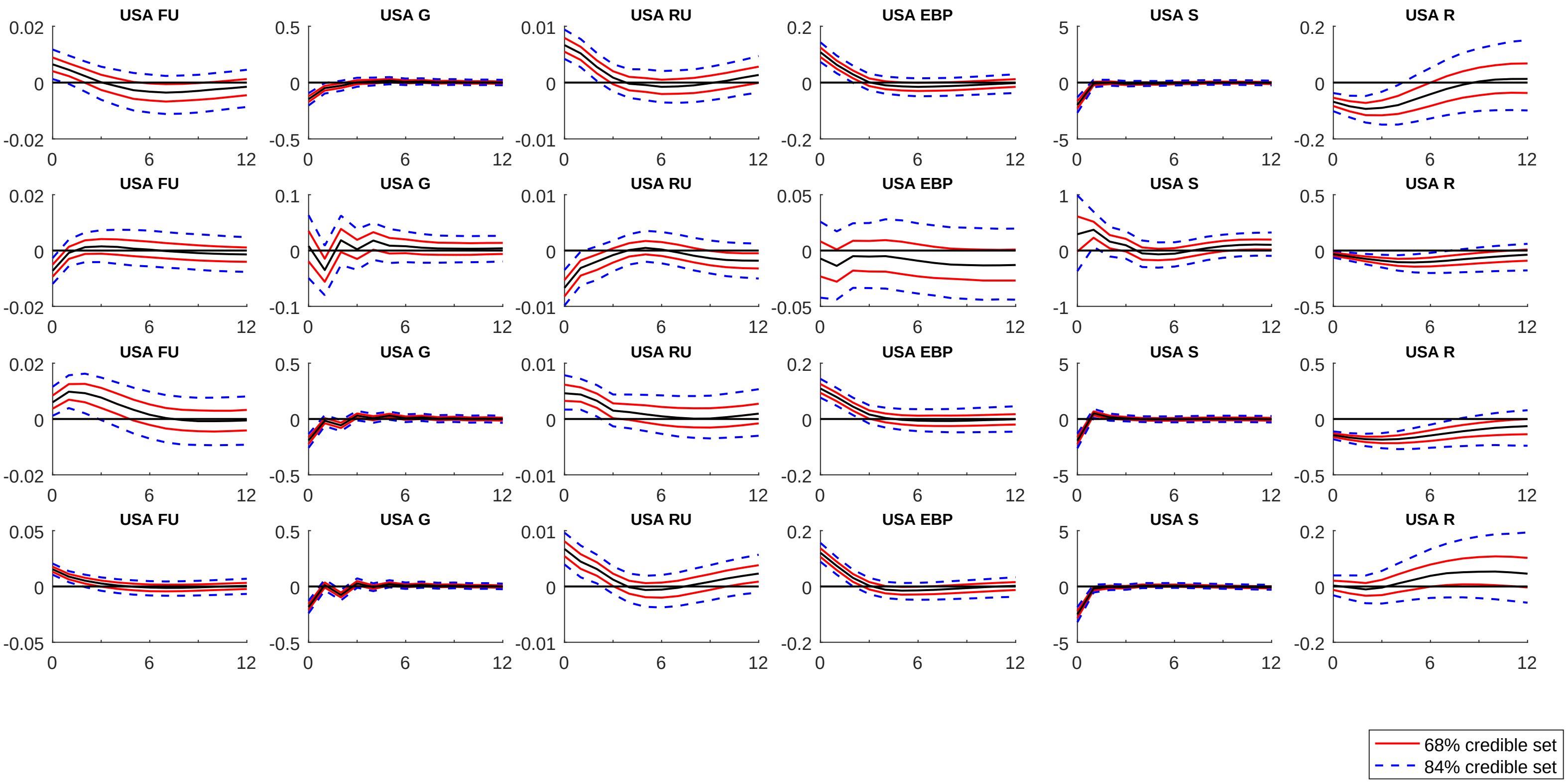
Note: From top to bottom, US impulse response functions to a deterioration in economic conditions, a monetary contraction, an increase in international competitiveness and a deterioration in financial markets.

Figure A.56: Impulse Response Functions to a One Standard Deviation Shock in each Indonesian Variable



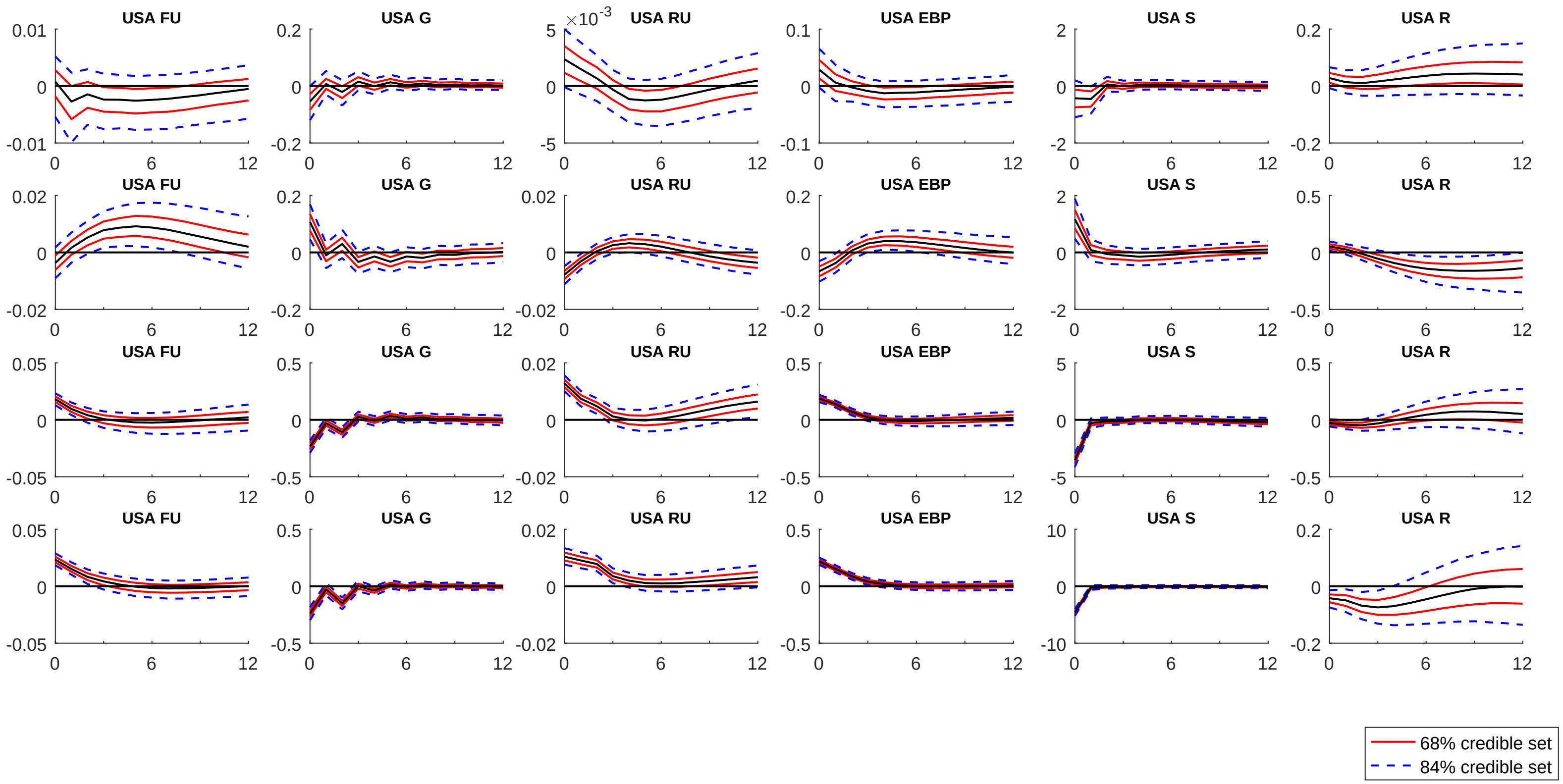
Note: From top to bottom, US impulse response functions to a deterioration in economic conditions, a monetary contraction, an increase in international competitiveness and a deterioration in financial markets.

Figure A.57: Impulse Response Functions to a One Standard Deviation Shock in each Korean Variable



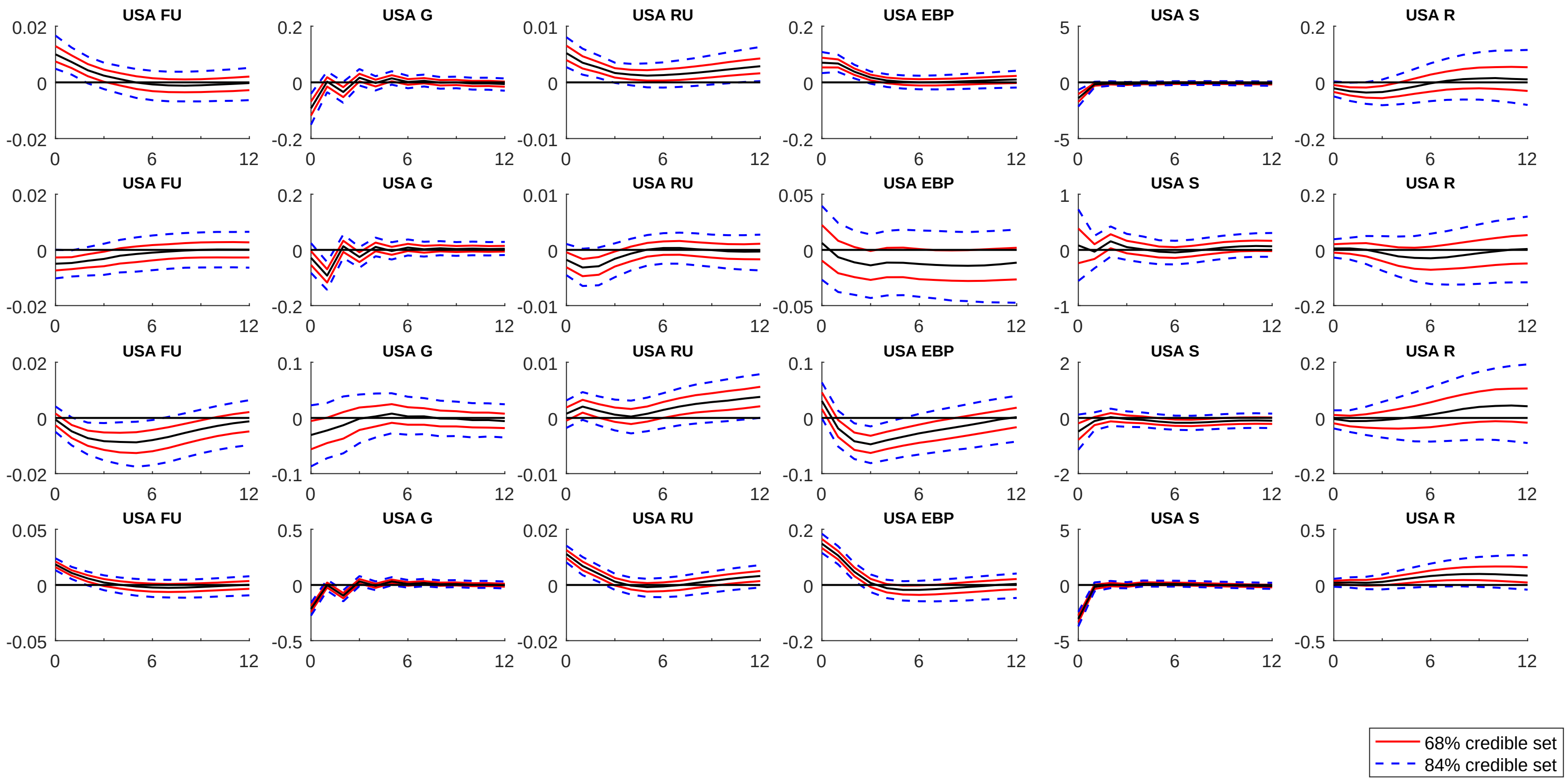
Note: From top to bottom, US impulse response functions to a deterioration in economic conditions, a monetary contraction, an increase in international competitiveness and a deterioration in financial markets.

Figure A.58: Impulse Response Functions to a One Standard Deviation Shock in each Australian Variable



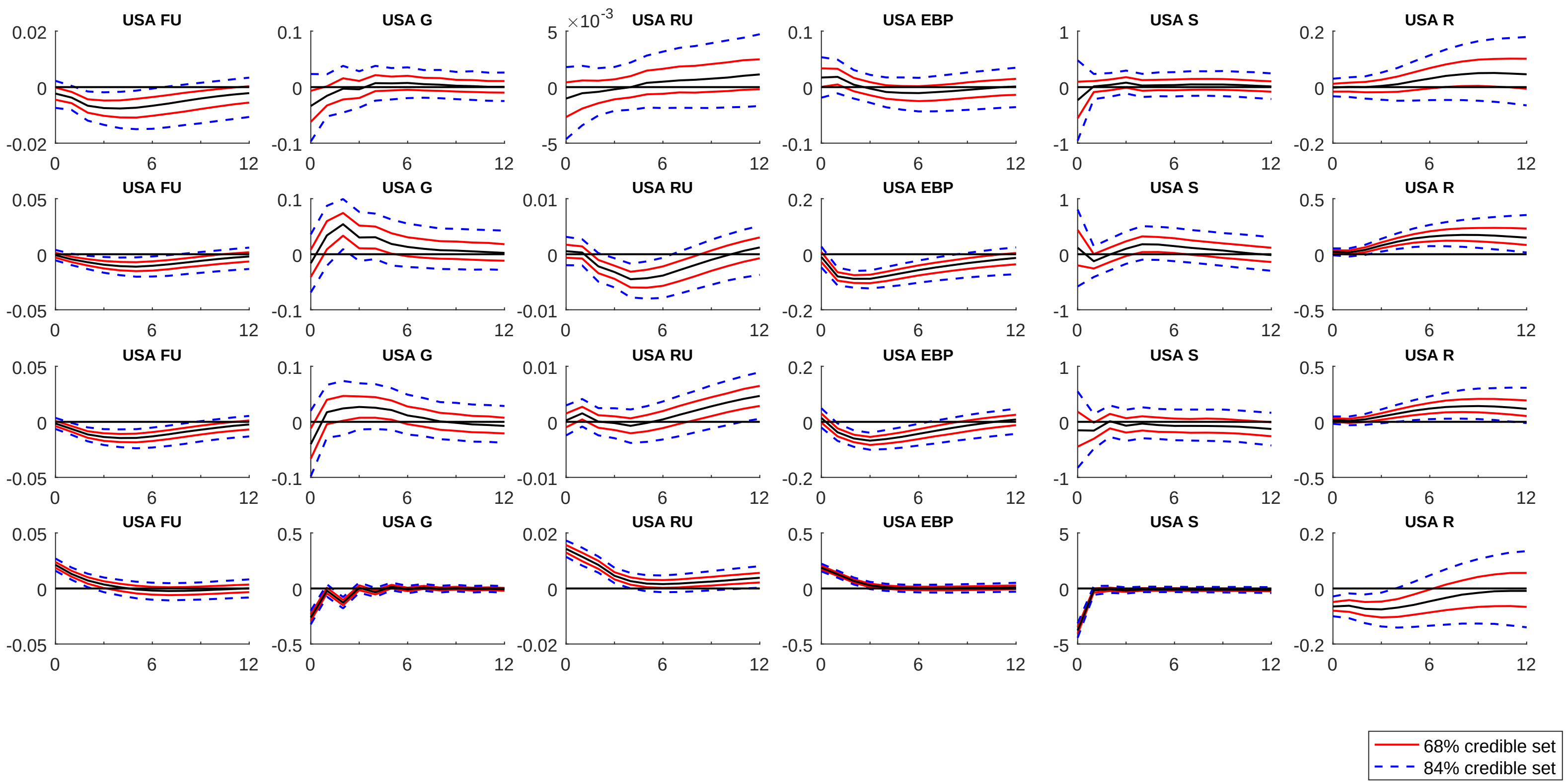
Note: From top to bottom, US impulse response functions to a deterioration in economic conditions, a monetary contraction, an increase in international competitiveness and a deterioration in financial markets.

Figure A.59: Impulse Response Functions to a One Standard Deviation Shock in each Thai Variable



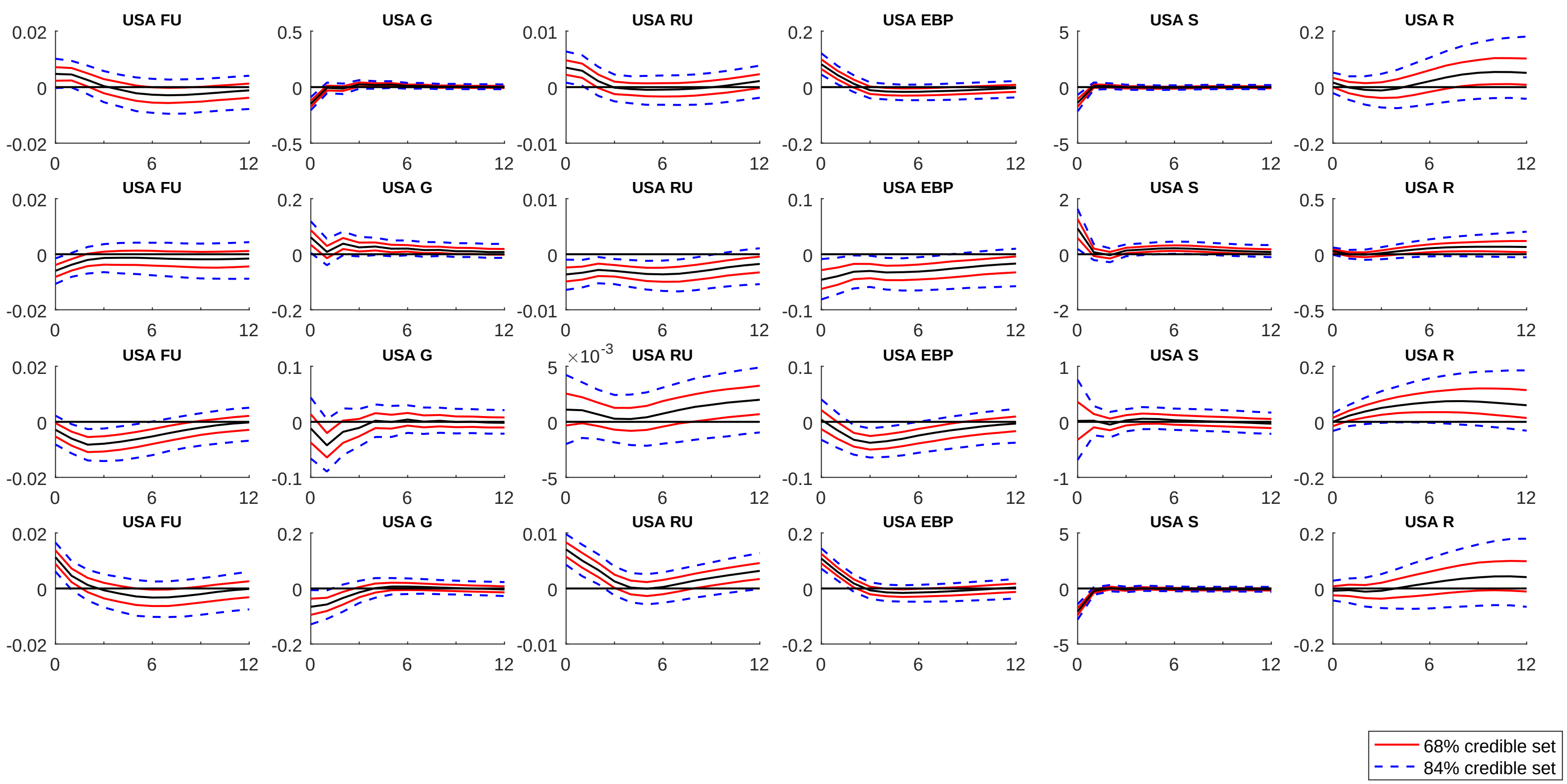
Note: From top to bottom, US impulse response functions to a deterioration in economic conditions, a monetary contraction, an increase in international competitiveness and a deterioration in financial markets.

Figure A.60: Impulse Response Functions to a One Standard Deviation Shock in each Philippine Variable



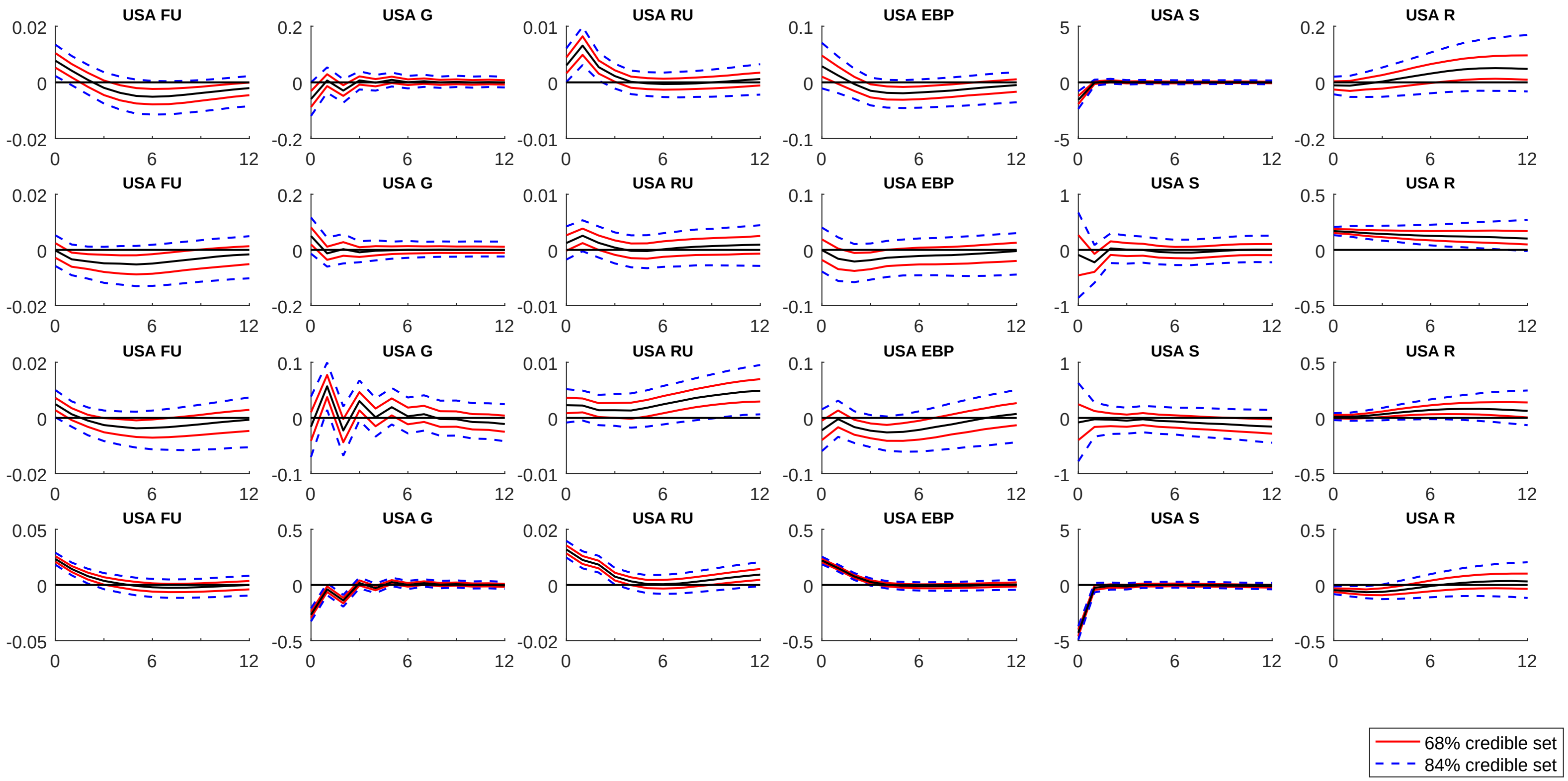
Note: From top to bottom, US impulse response functions to a deterioration in economic conditions, a monetary contraction, an increase in international competitiveness and a deterioration in financial markets.

Figure A.61: Impulse Response Functions to a One Standard Deviation Shock in each Malaysian Variable



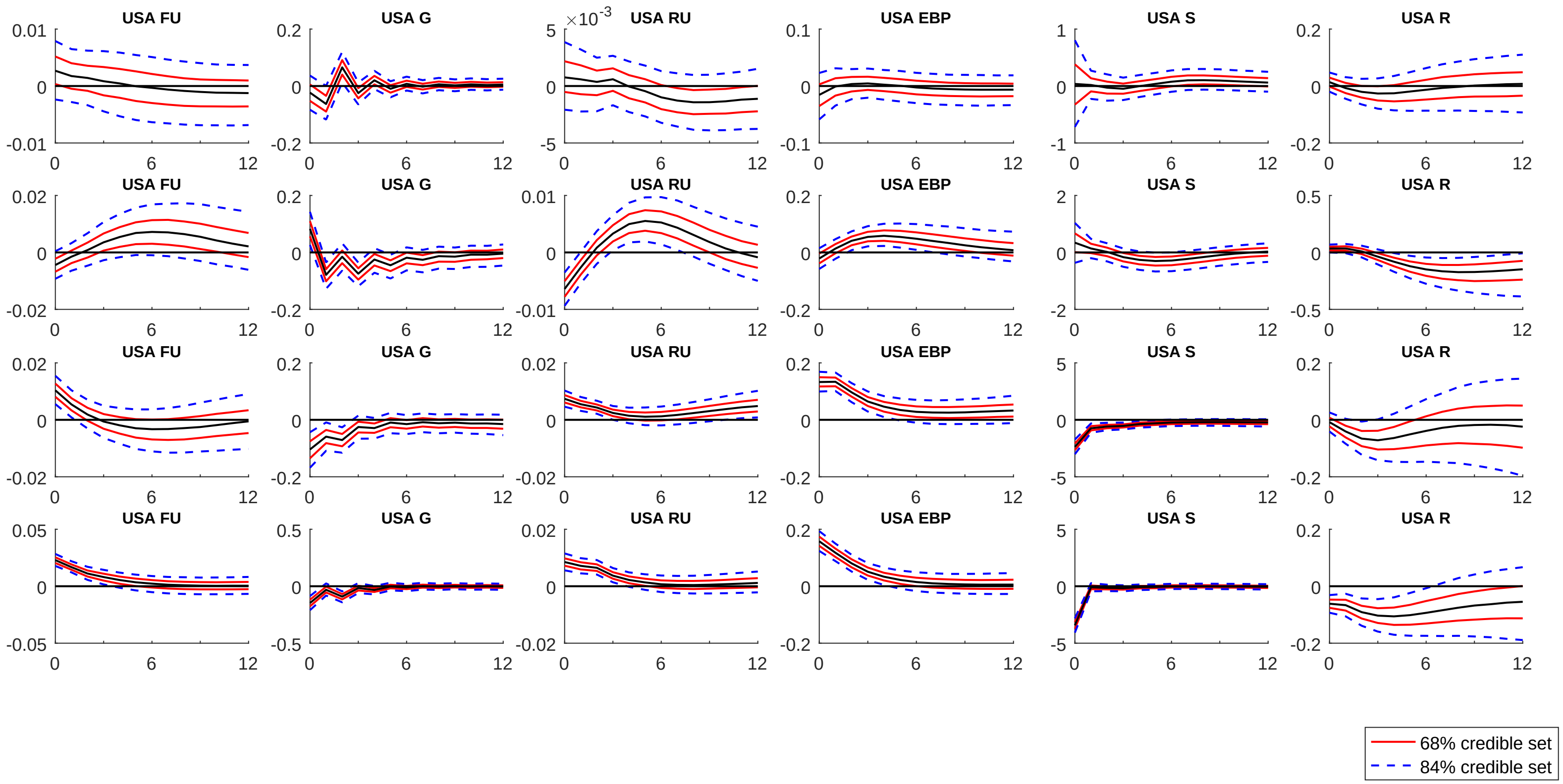
Note: From top to bottom, US impulse response functions to a deterioration in economic conditions, a monetary contraction, an increase in international competitiveness and a deterioration in financial markets.

Figure A.62: Impulse Response Functions to a One Standard Deviation Shock in each Singaporean Variable



Note: From top to bottom, US impulse response functions to a deterioration in economic conditions, a monetary contraction, an increase in international competitiveness and a deterioration in financial markets.

Figure A.63: Impulse Response Functions to a One Standard Deviation Shock in each New Zealand Variable



Note: From top to bottom, US impulse response functions to a deterioration in economic conditions, a monetary contraction, an increase in international competitiveness and a deterioration in financial markets.

Appendix B

Chapter 3 Appendix

B.1 Data Appendix

Data was carefully selected from 10 different sources as described in Table 6. Here, we point out some important features. First, Argentina's official inflation data was discredited in January 2007. In December 2015, the National Institute of Statistics and Censuses of Argentina (INDEC) stopped producing a CPI index. Only in July 2017 did INDEC resume releasing a recognised country wide CPI index. To overcome these issues we use Cavallo and Bertolotto's (2016) chained index which is based on official Argentine data till 2007 and chained to an online price index thereafter.

Second, we sought to obtain accurate short-term interest rate and exchange rate data. For Argentina, the interbank rate was used. For Brazil, the CDI, the interbank rate, was favoured over the SELIC, the base rate, due to longer time series. Finally, for Mexico the 28 day CETES treasury bill rate was used. To capture exchange rate movements we used Darvas' (2012) narrow index of the real effective exchange rate based on 41 trading partners.

Finally, both Argentine and Brazilian stock markets remained undersized and stagnant until the 1990s due to a variety of political and macroeconomic factors. Mexico's stock market also suffered following the 1982 debt crisis. We, therefore, use OECD stock price data which has the longest time series (in terms of non-zero entries) for Brazil. Since the index is recorded to be zero from January to September 1988, we record the log first difference to be zero from February to October 1988. We also use OECD stock price data for Mexico and the US to aid comparability. The OECD does not provide stock price data on Argentina. Instead, data on the MERVAL stock price index was extracted from Bloomberg.

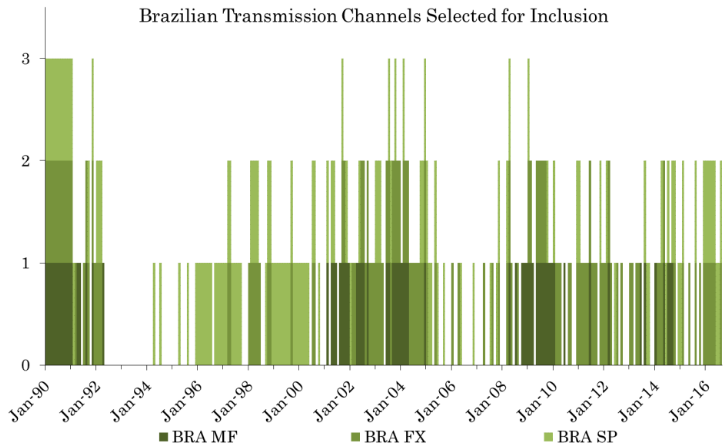
Table B.1: Data Sources

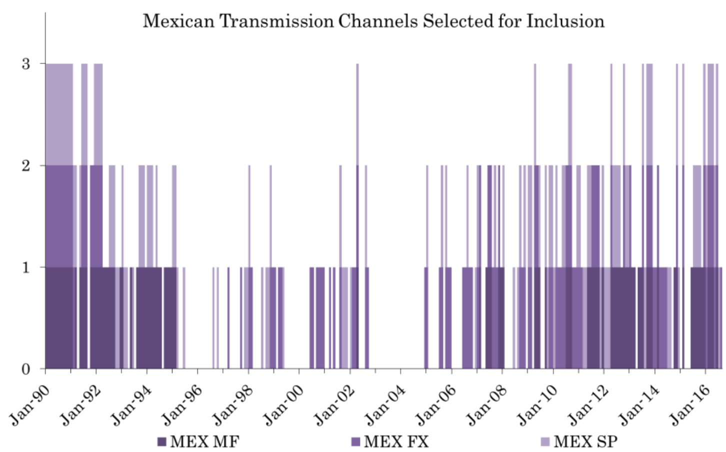
Country	Description	Source
ARG	Real industrial production index	Datastream
	Inflation (% MOM)	Cavallo and Bertolotto (2016)
	Short-term interest rate	Datastream
	Real effective exchange rate	Darvas (2012)
	Stock price index	Bloomberg
BRA	Real industrial production index	Datastream
	Inflation (% MOM)	Datastream
	Short-term interest rate	Datastream
	Real effective exchange rate	Darvas (2012)
	Stock price index	OECD Data
MEX	Real industrial production index	IMF IFS
	Inflation (% MOM)	Datastream
	Short-term interest rate	Datastream
	Real effective exchange rate	Darvas (2012)
	Stock price index	OECD Data
US	Real industrial production index	Datastream
	Inflation (% MOM)	Datastream
	Wu-Xia shadow rate during ZLB/	Wu and Xia (2016)/
	federal funds rate otherwise	FRED
	Stock price index	OECD Data
	Excess bond premium	Gilchrist and Zakrajšek (2012)
	Macroeconomic uncertainty	Ludvigson et al. (2019)
	Financial uncertainty	Ludvigson et al. (2019)
WORLD	Non-fuel commodity price index	IMF IFS
	Oil price	IMF IFS

IMF IFS = IMF international financial statistics database, FRED = St. Louis Federal Reserve Economic Data, ZLB = zero lower bound.

B.2 Figures

Figure B.1: Argentina: Transmission Channels Selected for Inclusion by Country





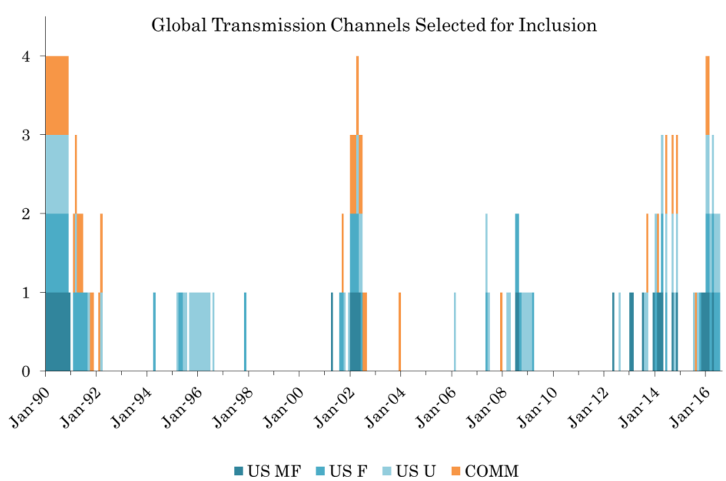
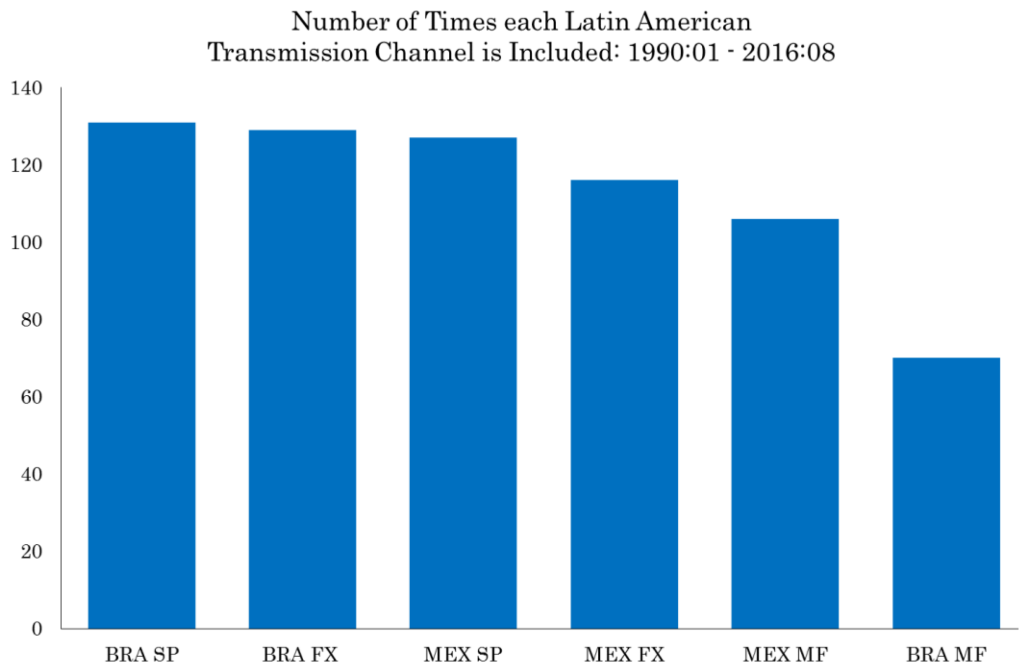


Figure B.2: Argentina: Transmission Channels Selected for Inclusion by Frequency



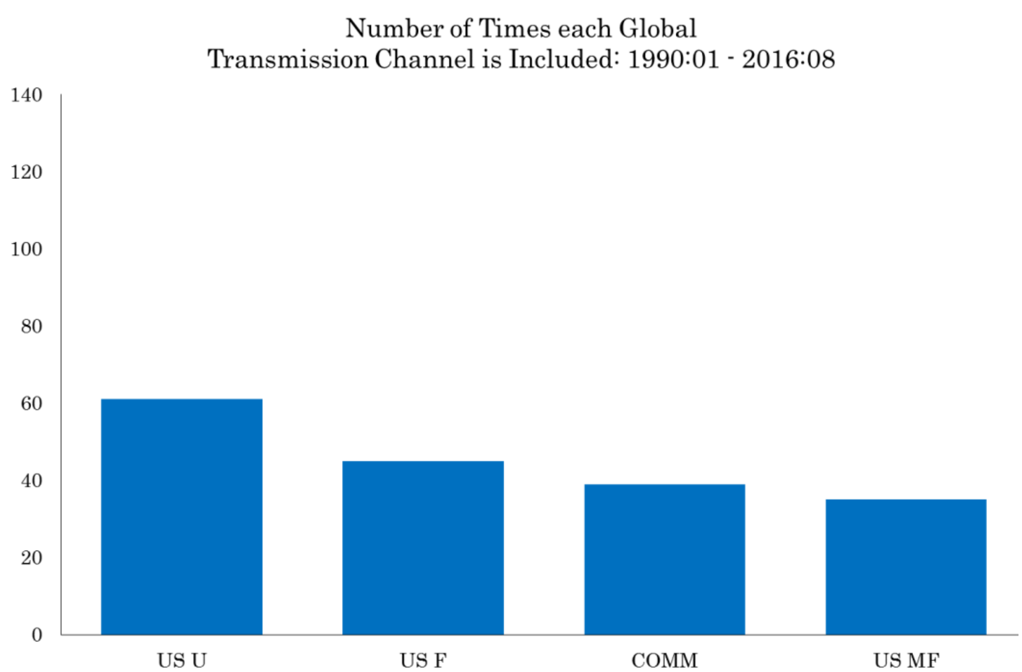
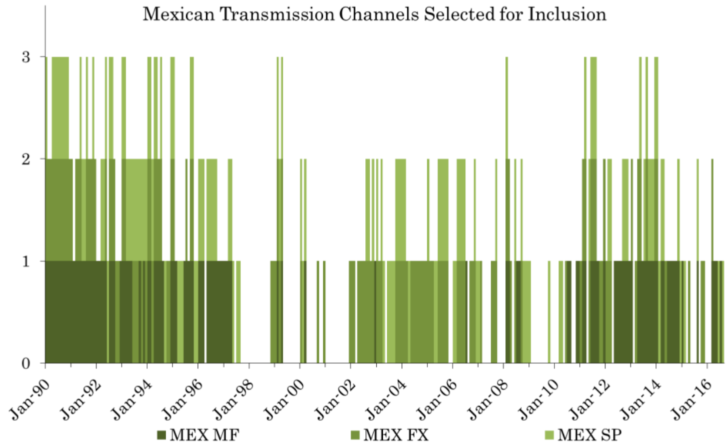
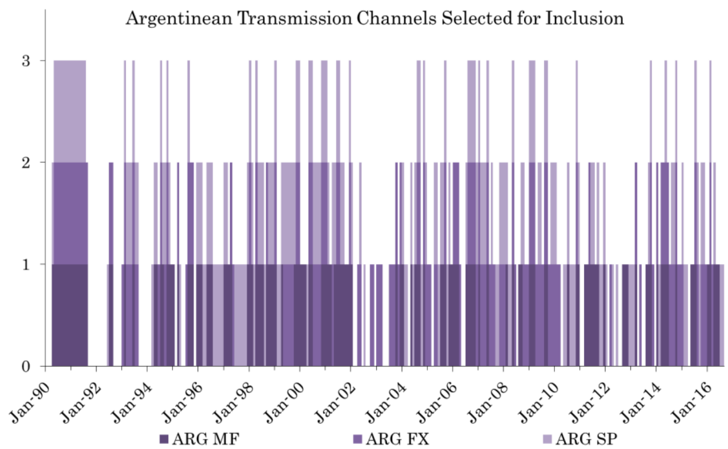


Figure B.3: Brazil: Transmission Channels Selected for Inclusion by Country





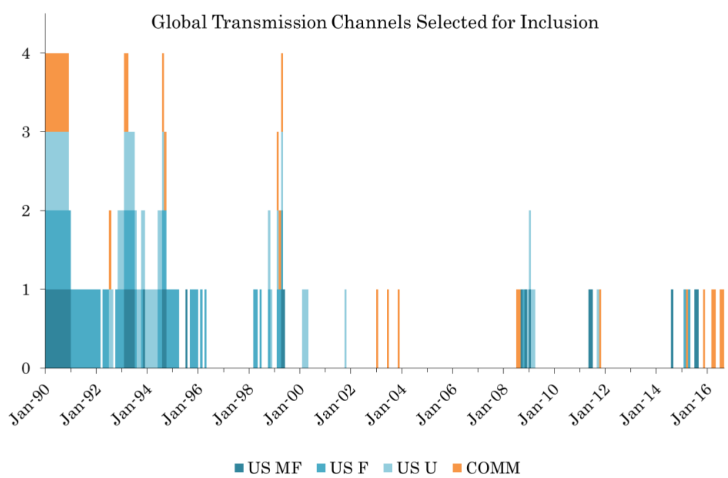
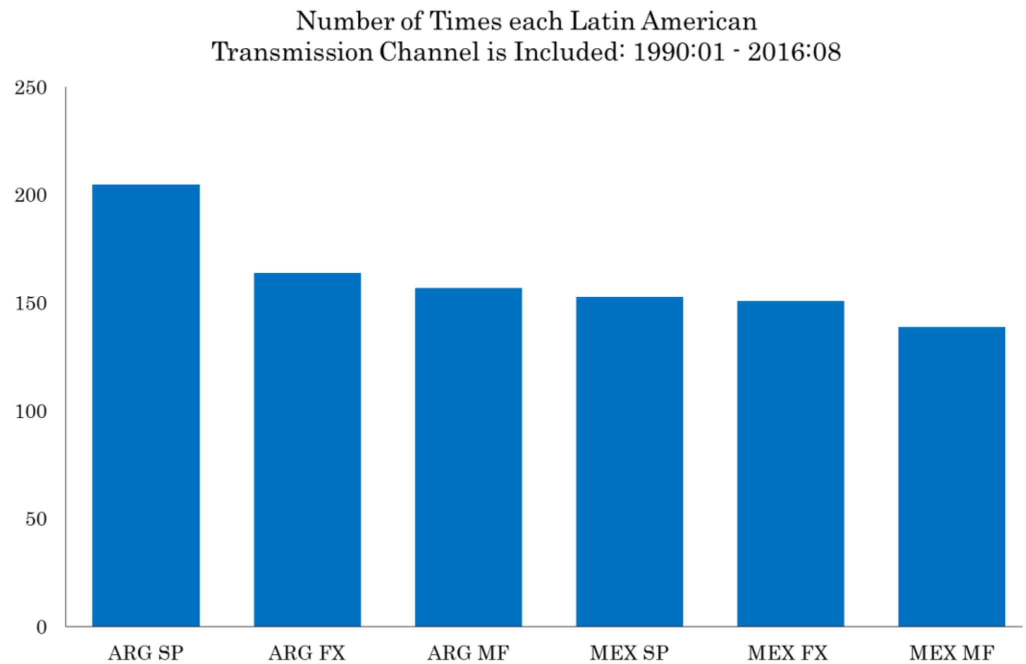


Figure B.4: Brazil: Transmission Channels Selected for Inclusion by Frequency



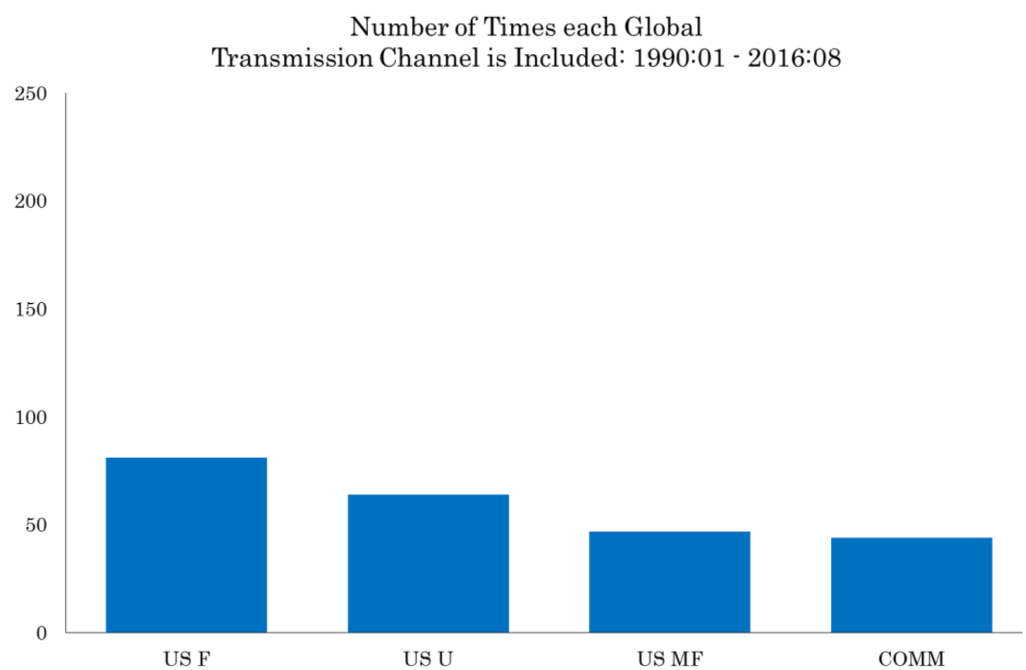


Figure B.5: Mexico: Transmission Channels Selected for Inclusion by Country

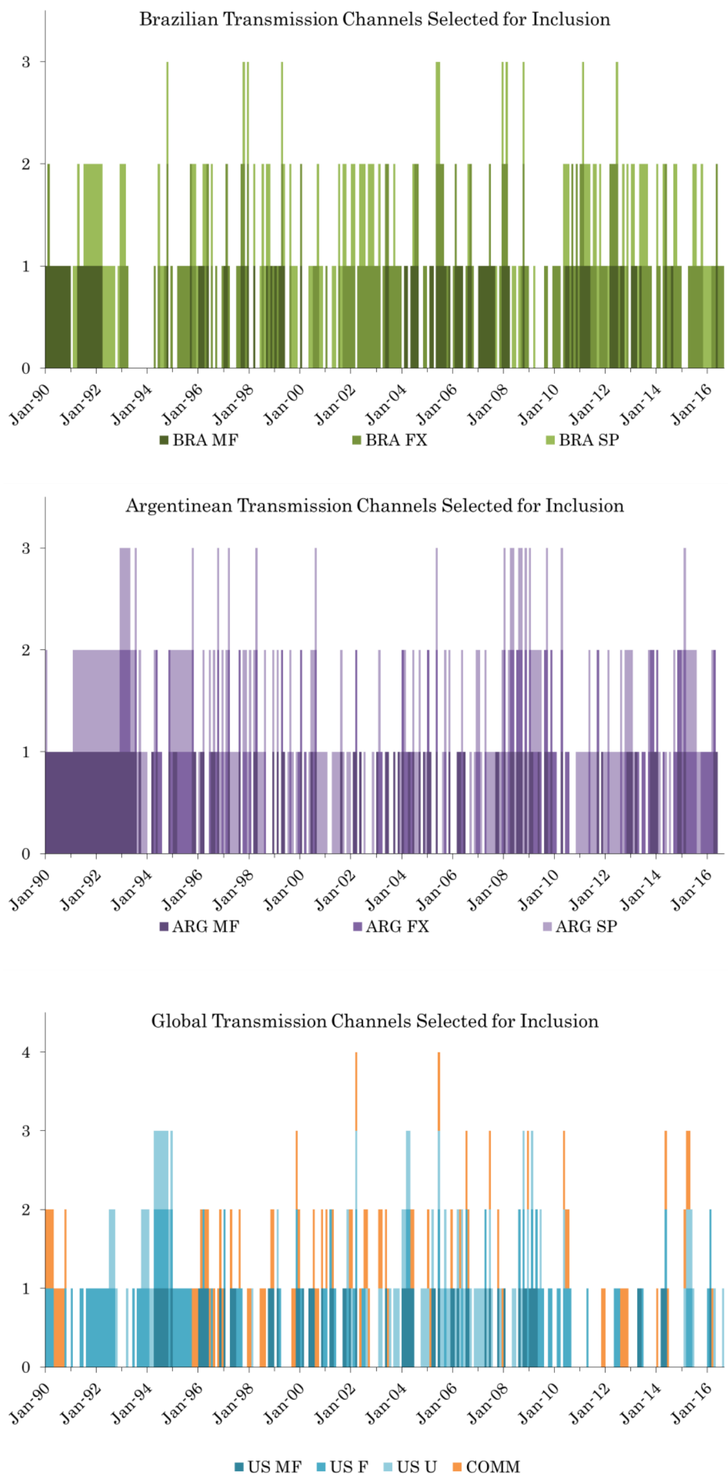
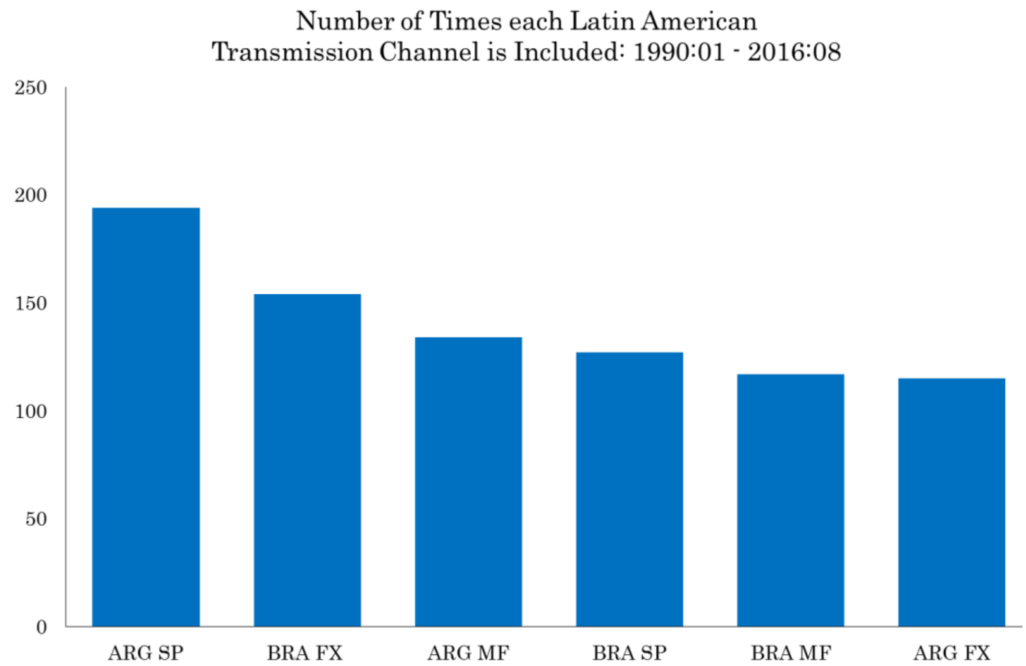


Figure B.6: Mexico: Transmission Channels Selected for Inclusion by Frequency



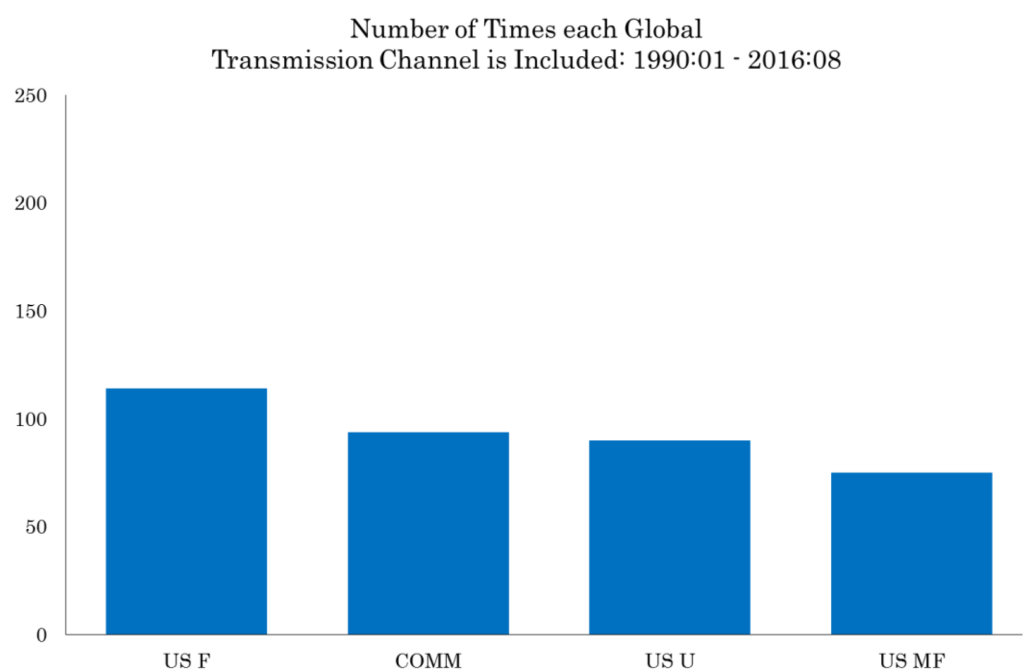
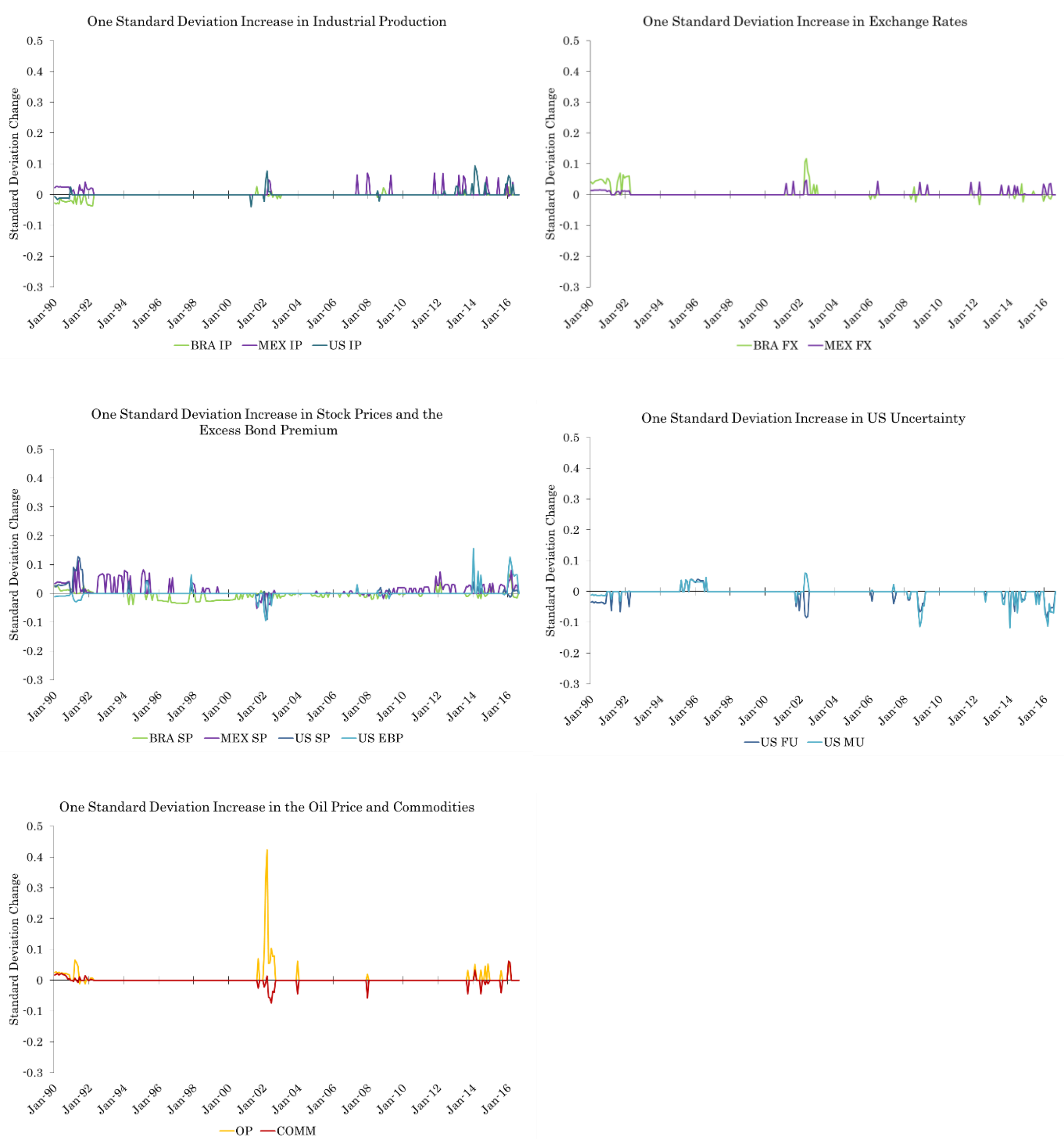


Figure B.7: Dynamic Interdependencies: Response of Argentine Industrial Production to a One Standard Deviation Increase in a Predictor

Note: IP = Industrial Production, FX = Exchange Rate, SP = Stock Price, EBP = Excess Bond Premium, FU = Financial Uncertainty, MU = Macroeconomic Uncertainty, OP = Oil Price, COMM = Non-fuel Commodity Price Index.

Figure B.8: Dynamic Interdependencies: Response of Argentine Stock Markets to a One Standard Deviation Increase in a Predictor

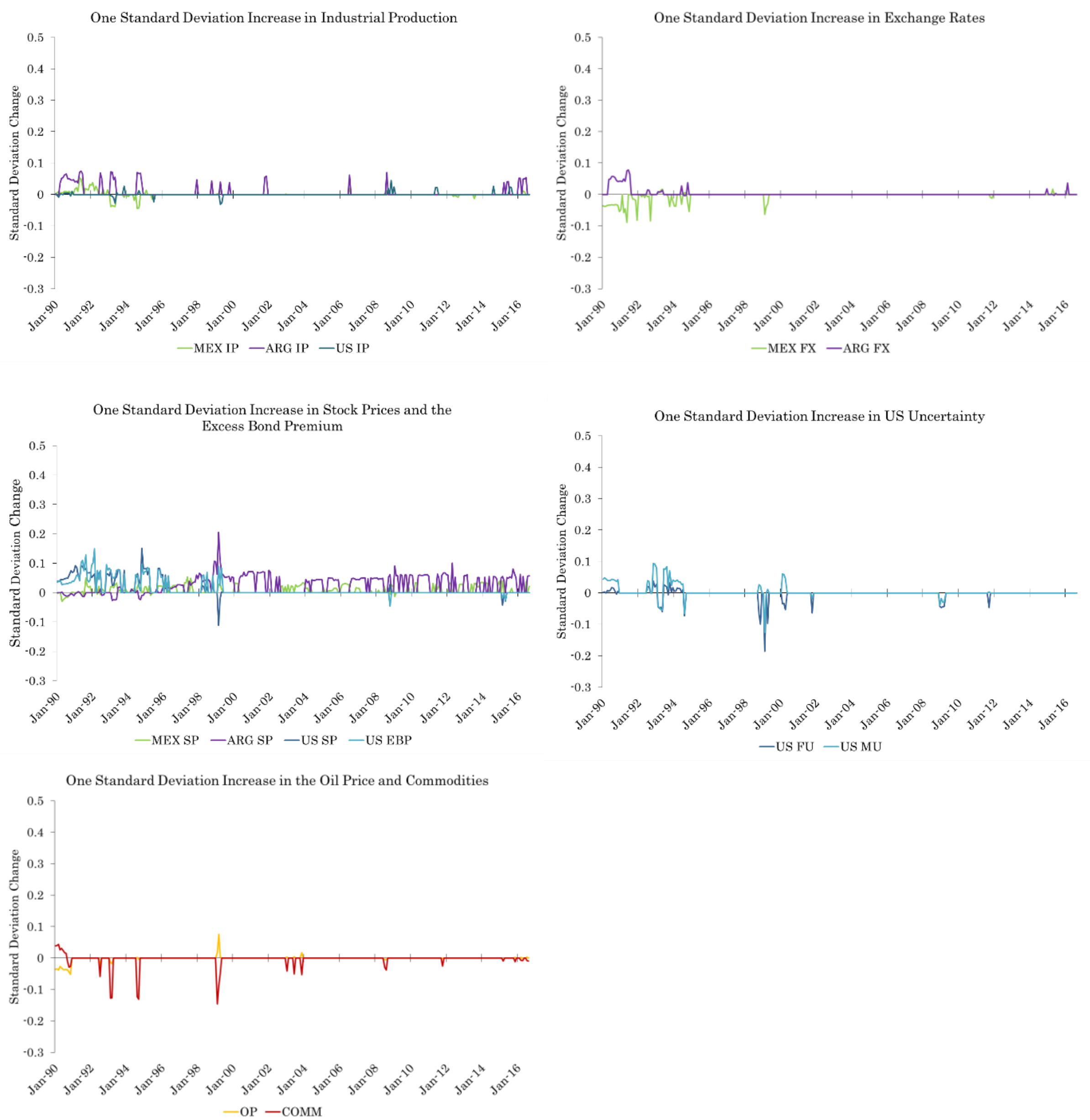


Note: IP = Industrial Production, FX = Exchange Rate, SP = Stock Price, EBP = Excess Bond Premium, FU = Financial Uncertainty, MU = Macroeconomic Uncertainty, OP = Oil Price, COMM = Non-fuel Commodity Price Index.

Figure B.9: Dynamic Interdependencies: Response of Brazilian Industrial Production to a One Standard Deviation Increase in a Predictor

Note: IP = Industrial Production, FX = Exchange Rate, SP = Stock Price, EBP = Excess Bond Premium, FU = Financial Uncertainty, MU = Macroeconomic Uncertainty, OP = Oil Price, COMM = Non-fuel Commodity Price Index.

Figure B.10: Dynamic Interdependencies: Response of Brazilian Stock Markets to a One Standard Deviation Increase in a Predictor

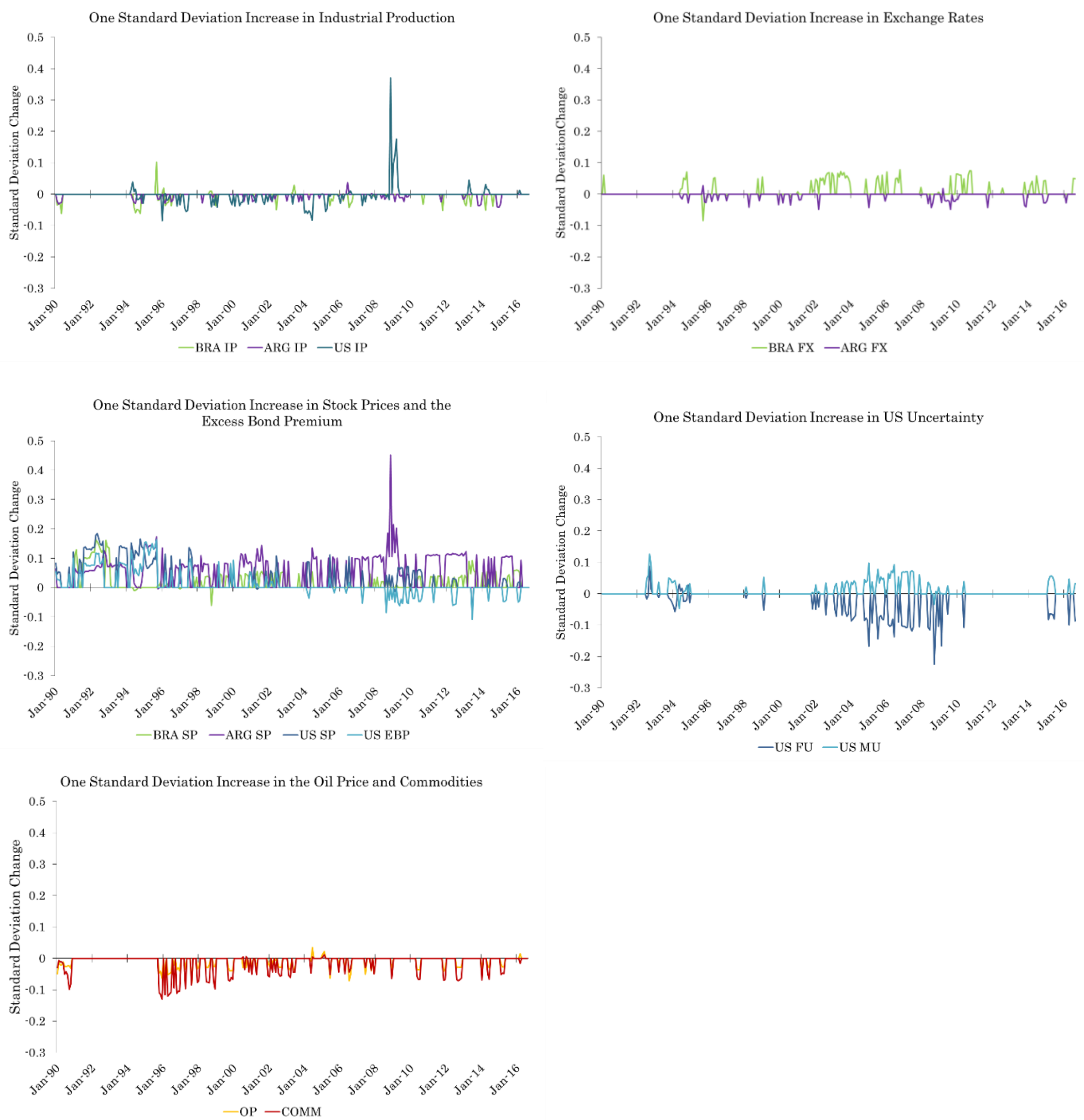


Note: IP = Industrial Production, FX = Exchange Rate, SP = Stock Price, EBP = Excess Bond Premium, FU = Financial Uncertainty, MU = Macroeconomic Uncertainty, OP = Oil Price, COMM = Non-fuel Commodity Price Index.

Figure B.11: Dynamic Interdependencies: Response of Mexican Industrial Production to a One Standard Deviation Increase in a Predictor

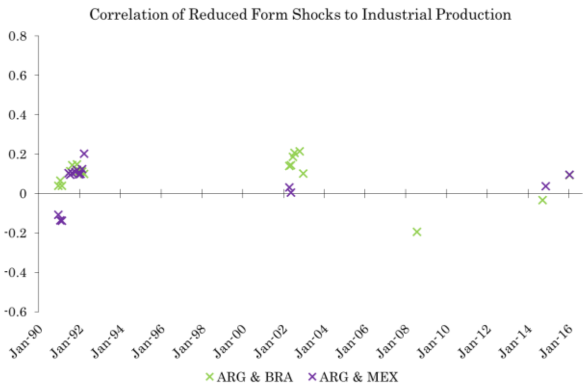
Note: IP = Industrial Production, FX = Exchange Rate, SP = Stock Price, EBP = Excess Bond Premium, FU = Financial Uncertainty, MU = Macroeconomic Uncertainty, OP = Oil Price, COMM = Non-fuel Commodity Price Index.

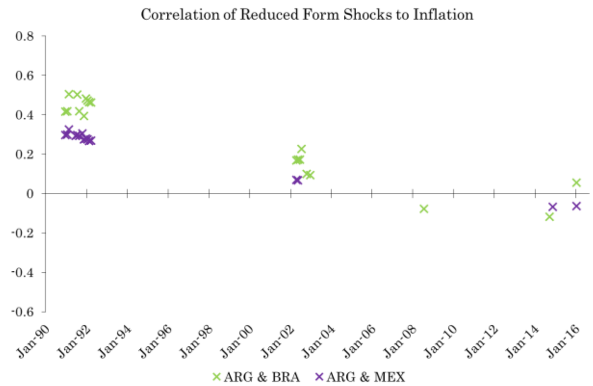
Figure B.12: Dynamic Interdependencies: Response of Mexican Stock Markets to a One Standard Deviation Increase in a Predictor

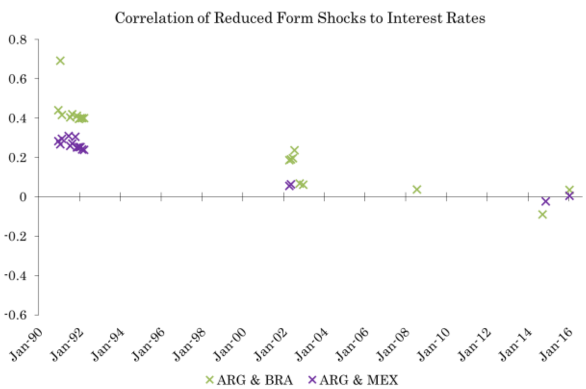


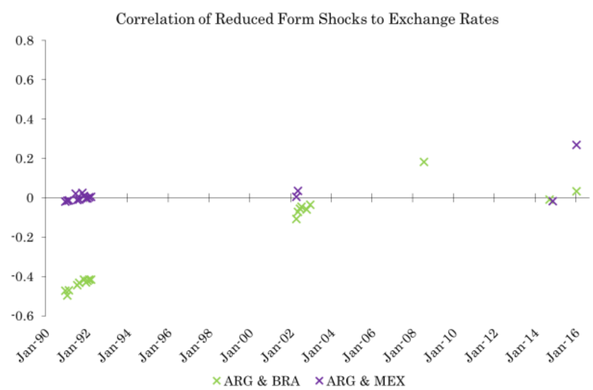
Note: IP = Industrial Production, FX = Exchange Rate, SP = Stock Price, EBP = Excess Bond Premium, FU = Financial Uncertainty, MU = Macroeconomic Uncertainty, OP = Oil Price, COMM = Non-fuel Commodity Price Index.

Figure B.13: Static Interdependencies: Correlation of Reduced Form Shocks between Argentine Variables and other Latin American Variables









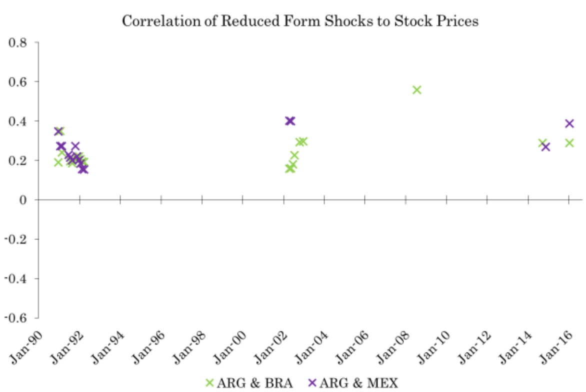


Figure B.14: Static Interdependencies: Correlation Reduced Form Shocks between Brazilian Variables and other Latin American Variables

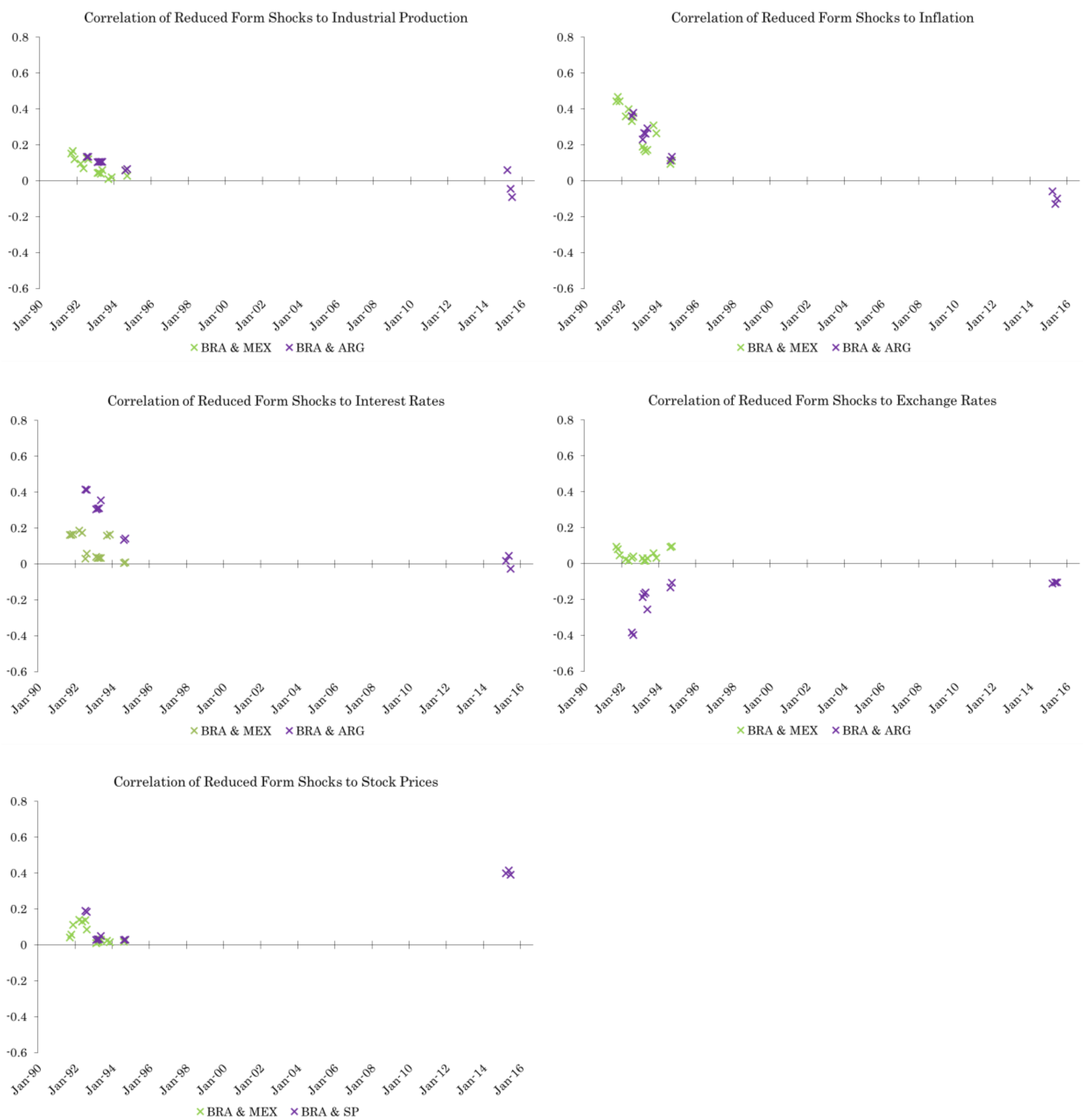


Figure B.15: Static Interdependencies: Correlation of Reduced Form Shocks between Mexican Variables and other Latin American Variables

Appendix C

Chapter 4 Appendix

C.1 Data Appendix

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.

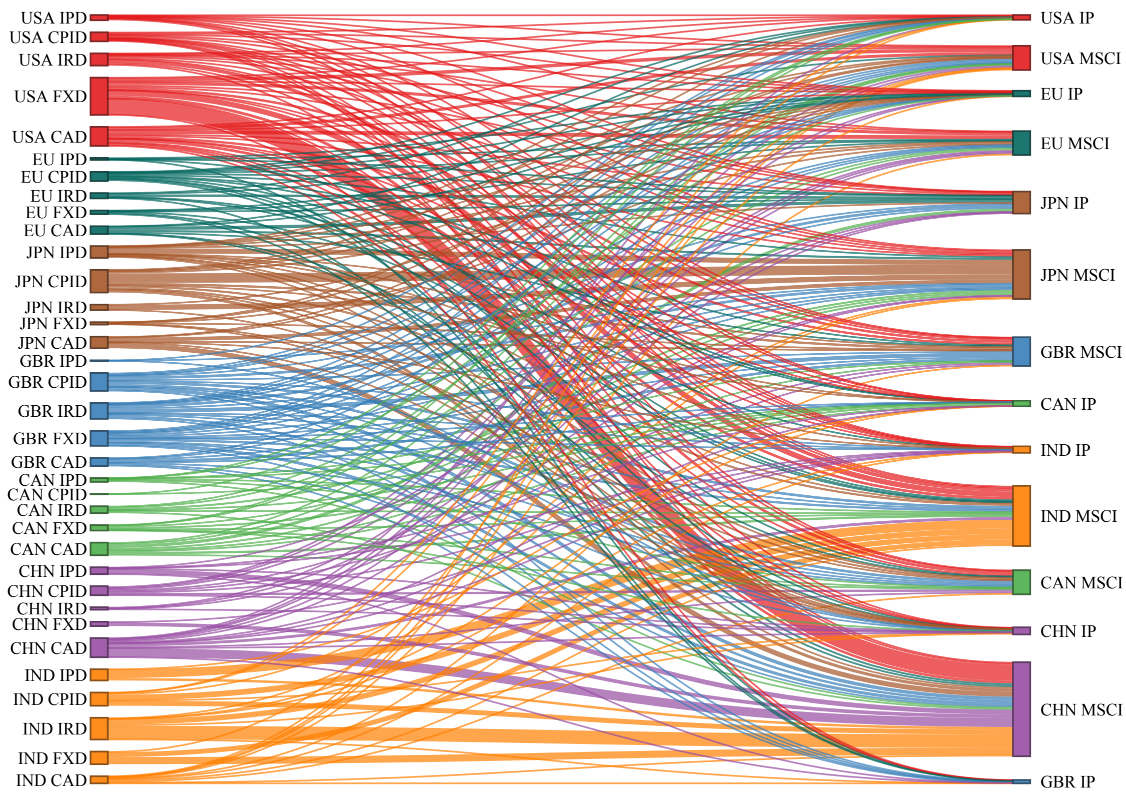
Since all exchange rate forecasts are relative to the dollar, we use options-based foreign exchange rate volatility for the G7, collected from Datastream, to proxy US idiosyncratic, common and aggregate exchange rate uncertainty. For the remaining exchange rates, it is not always possible to calculate 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).

C.2 Supplementary Figures

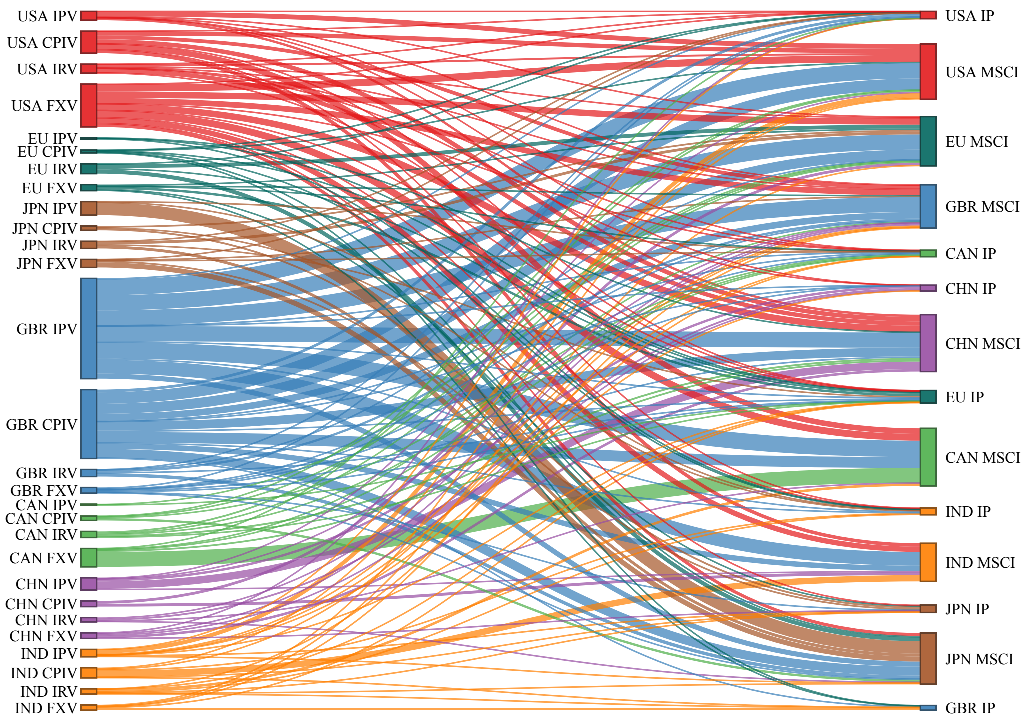
C.2.1 Summary of Impulse Responses at the 68% level

Figure C.1: Idiosyncratic Uncertainty: Summary of Impulse Responses Showing Important Declines in Real and Financial Growth Following a Shock to a Component of Uncertainty



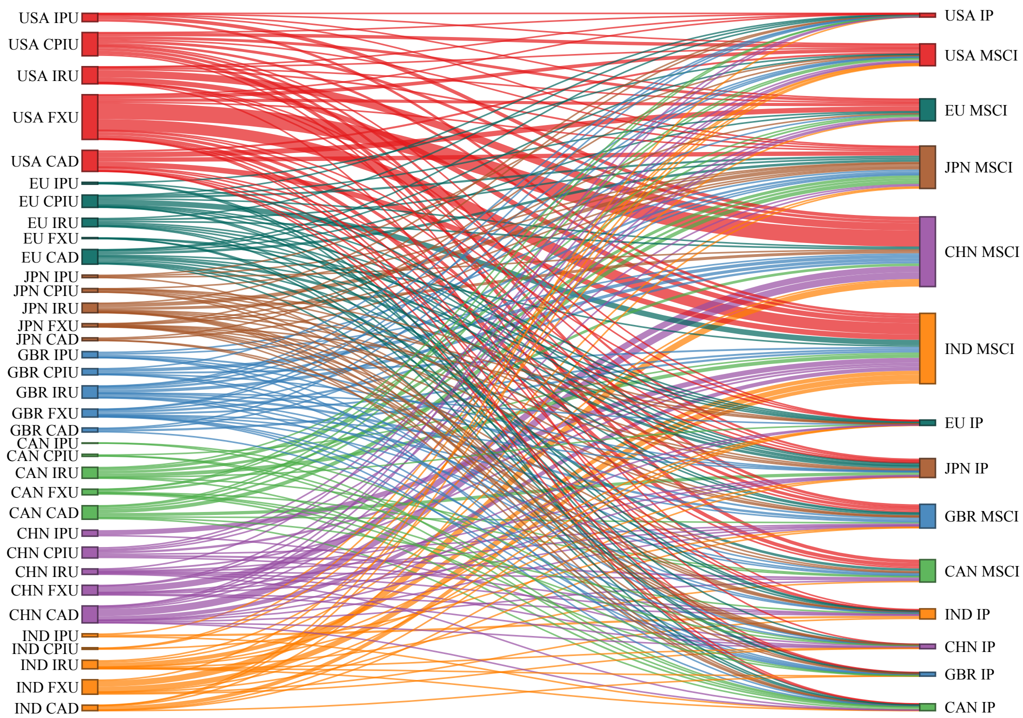
Note: We report impulse response functions for industrial production growth (IP) and stock market growth (MSCI) where the uncertainty shock has a negative effect which is non-zero according to the 68 percent credible interval. The width of each line corresponds to the depth of the median impulse response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

Figure C.2: Common Uncertainty: Summary of Impulse Responses Showing Important Declines in Real and Financial Growth Following a Shock to a Component of Uncertainty



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

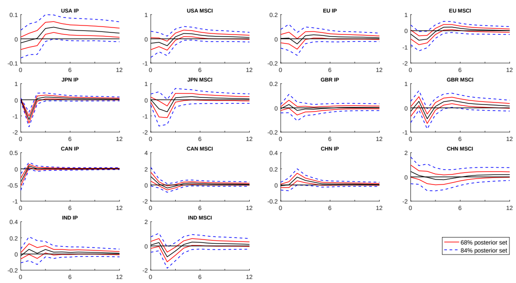
Figure C.3: Aggregate Uncertainty: Summary of Impulse Responses Showing Important Declines in Real and Financial Growth Following a Shock to a Component of Uncertainty



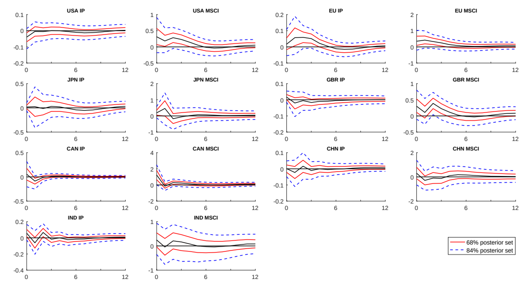
Note: We report impulse response functions for industrial production growth (IP) and stock market growth (MSCI) where the uncertainty shock has a negative effect which is non-zero according to the 68 percent credible interval. The width of each line corresponds to the depth of the median impulse response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

C.2.2 Responses to Disagreement Shocks

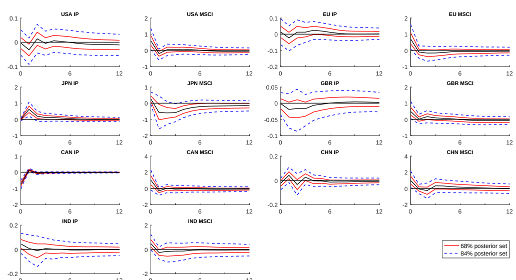
Figure C.4: Responses to Canada Disagreement Shocks



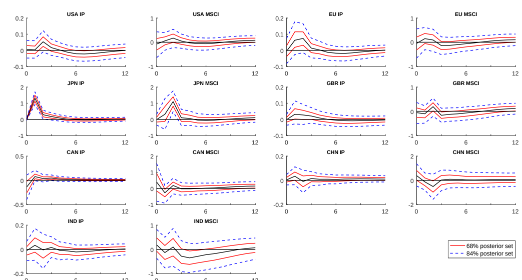
(a) CAD



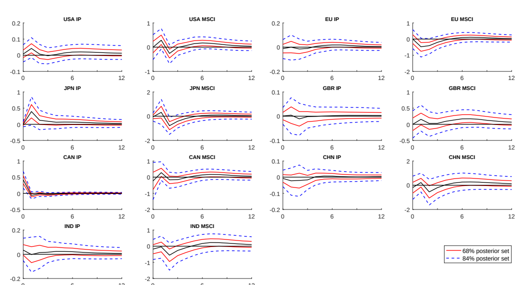
(b) CPID



(c) FXD



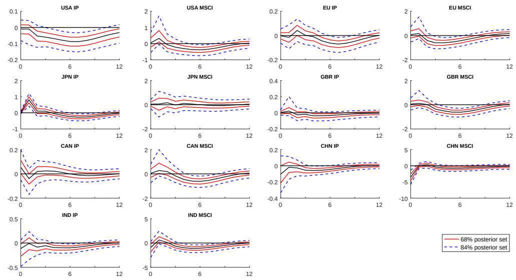
(d) IPD



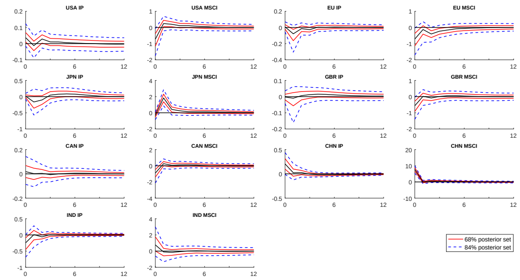
(e) IRD

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.

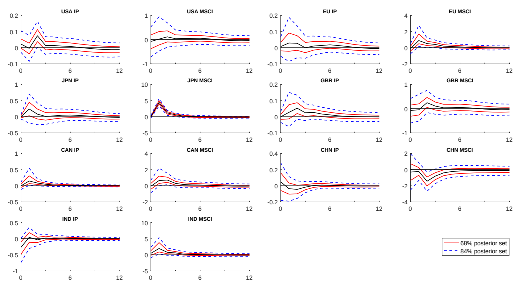
Figure C.5: Responses to China Disagreement Shocks



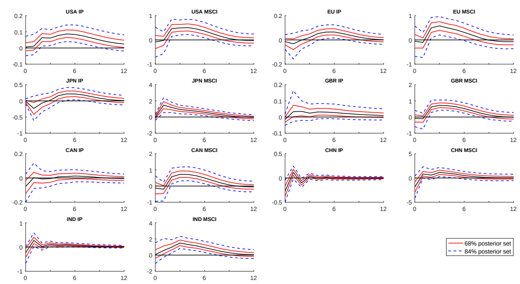
(a) CAD



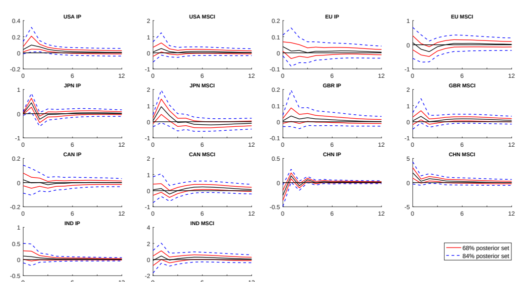
(b) CPID



(c) FXD



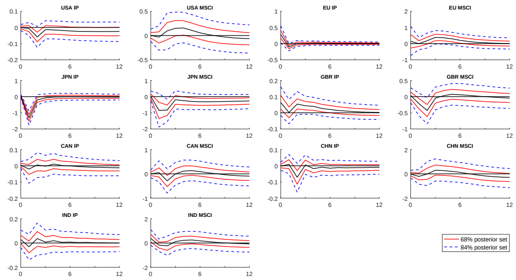
(d) IPD



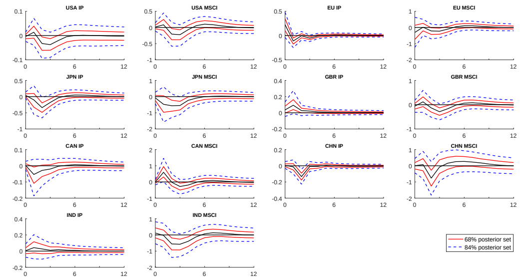
(e) IRD

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.

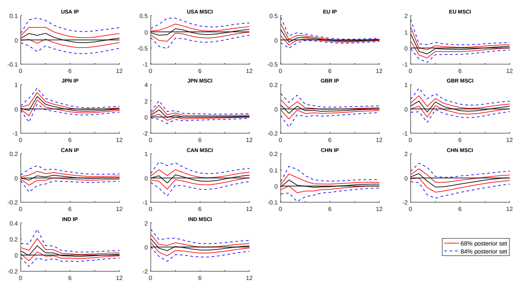
Figure C.6: Responses to Eurozone Disagreement Shocks



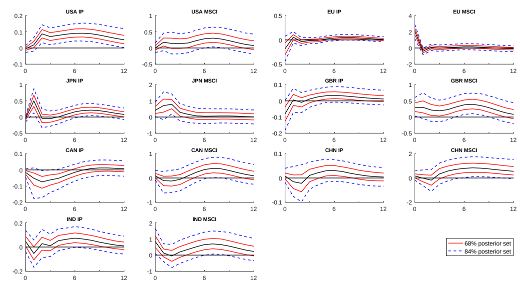
(a) CAD



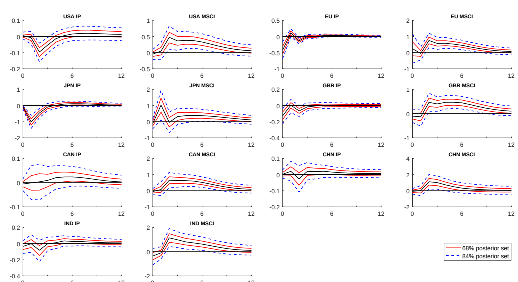
(b) CPID



(c) FXD



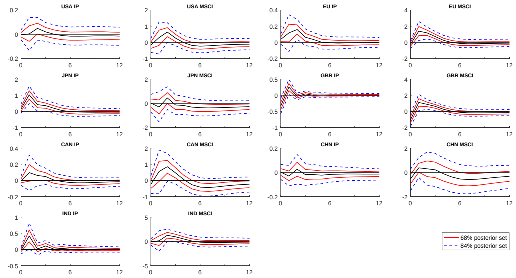
(d) IPD



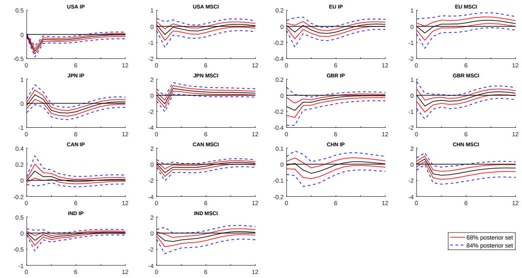
(e) IRD

Note: The 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.

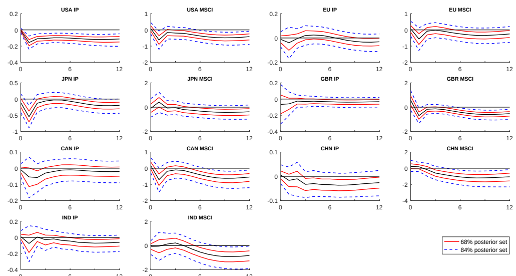
Figure C.7: Responses to UK Disagreement Shocks



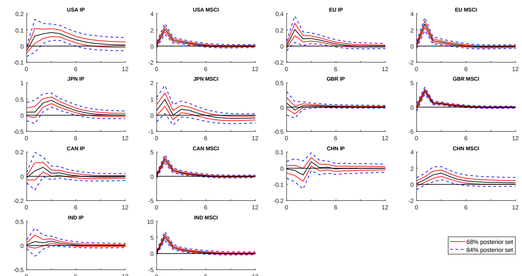
(a) CAD



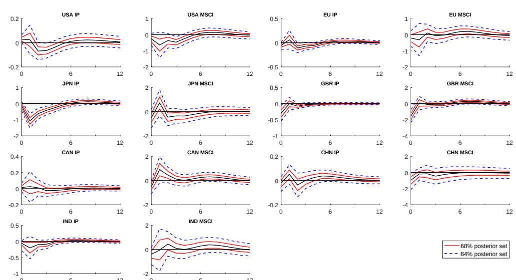
(b) CPID



(c) FXD



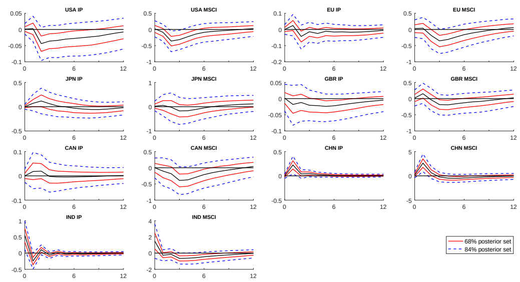
(d) IPD



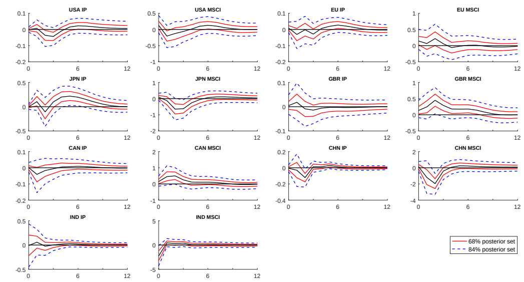
(e) IRD

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.

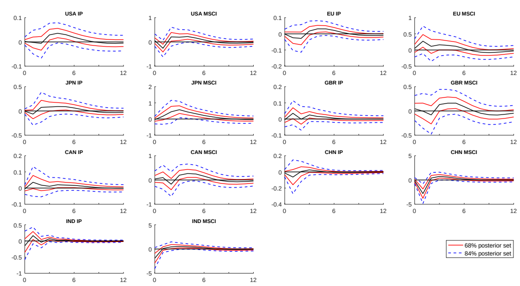
Figure C.8: Responses to India Disagreement Shocks



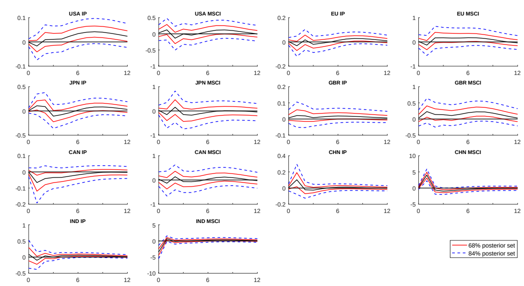
(a) CAD



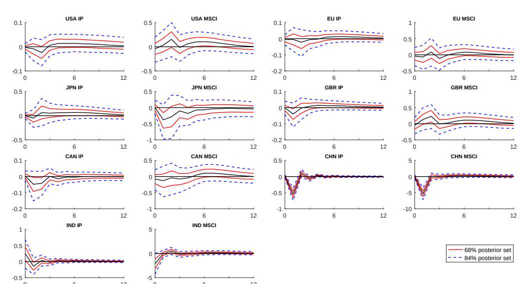
(b) CPID



(c) FXD



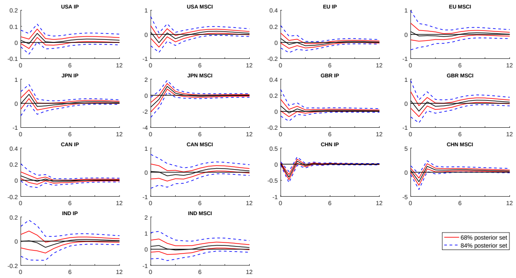
(d) IPD



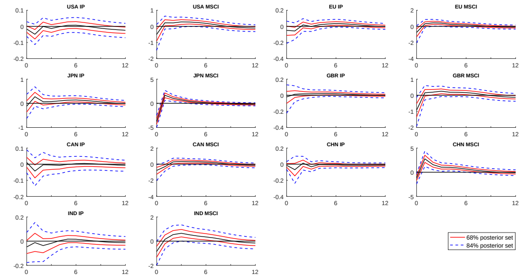
(e) IRD

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.

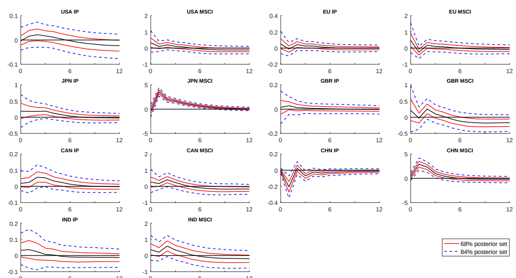
Figure C.9: Responses to Japanese Disagreement Shocks



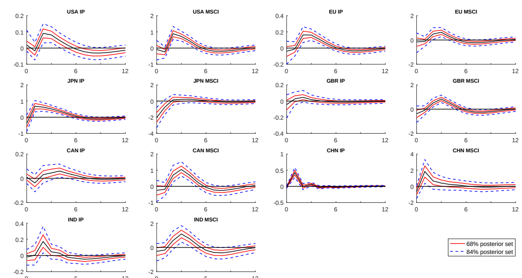
(a) CAD



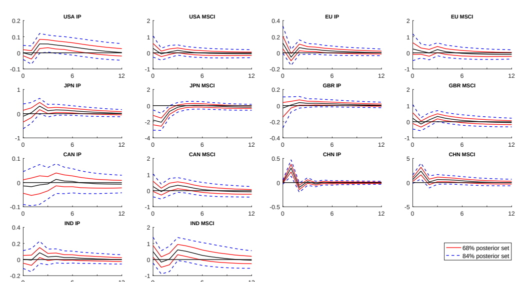
(b) CPID



(c) FXD



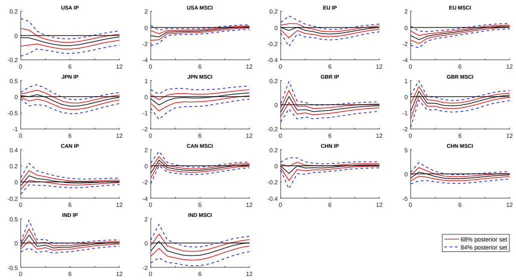
(d) IPD



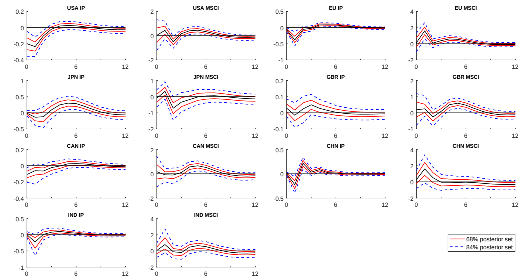
(e) IRD

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.

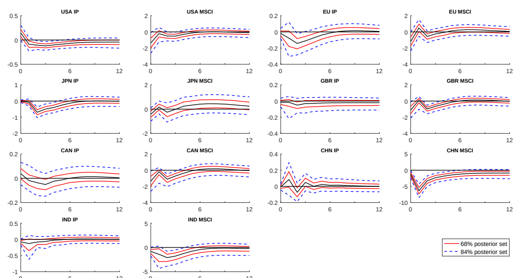
Figure C.10: Responses to US Disagreement Shocks



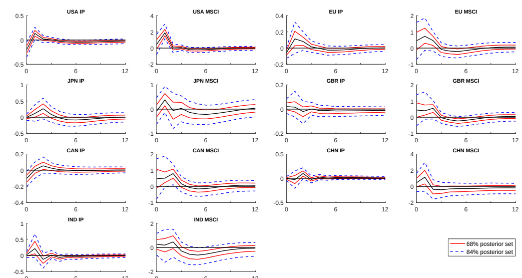
(a) CAD



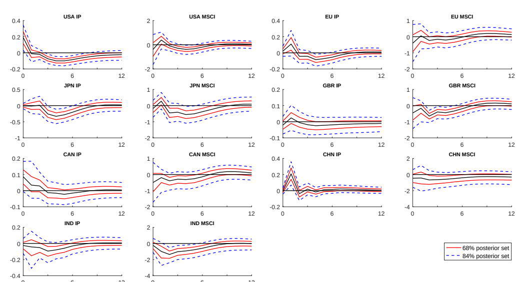
(b) CPID



(c) FXD



(d) IPD

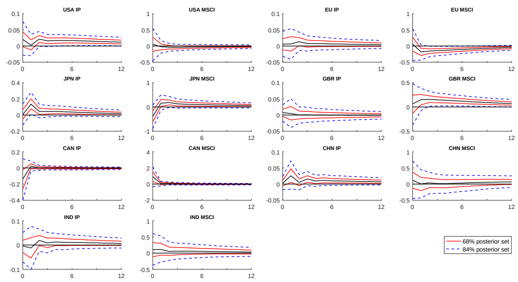


(e) IRD

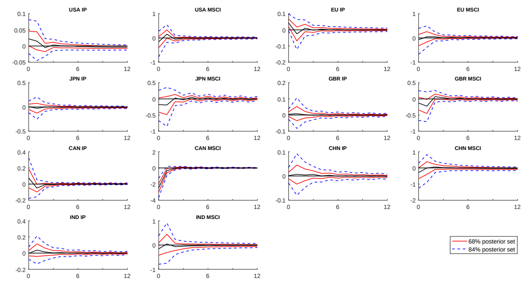
Note: The figure shows the response of each macro-financial variable to a shock in US disagreement regarding the current account (CAD), inflation (CPID), the exchange rate (FXD), industrial production (IPD) and short-term interest rate (IRD). 68 and 84 percent credible intervals are provided.

C.2.3 Responses to Forecast Error Variance Shocks

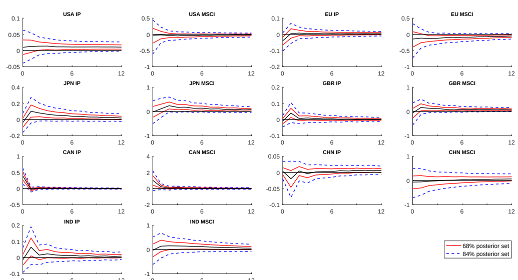
Figure C.11: Responses to Canada Forecast Error Variance Shocks



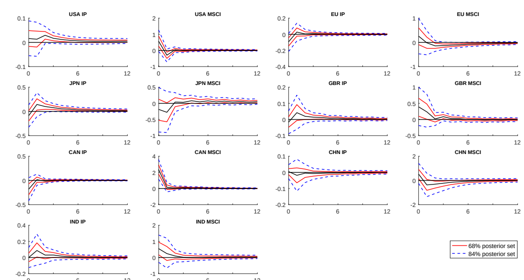
(a) CPIV



(b) FXV



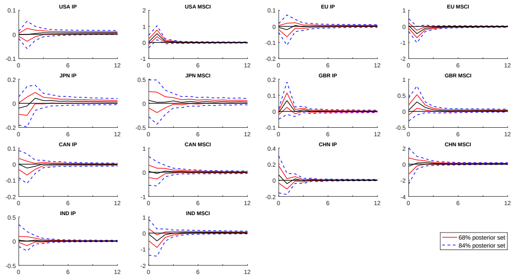
(c) IPV



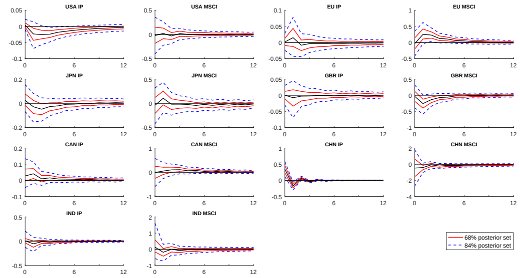
(d) IRV

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.

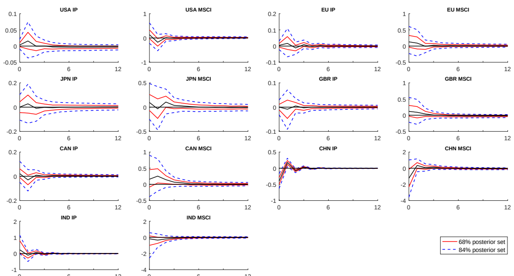
Figure C.12: Responses to China Forecast Error Variance Shocks



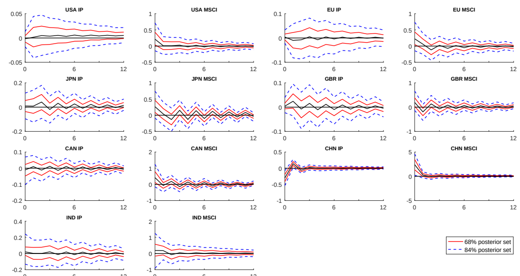
(a) CPIV



(b) FXV



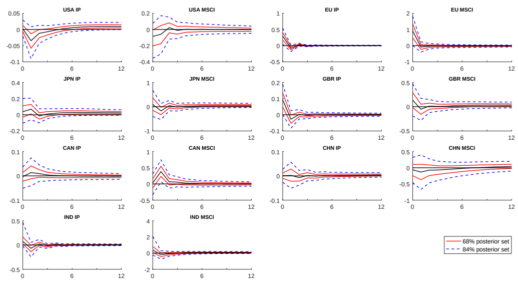
(c) IPV



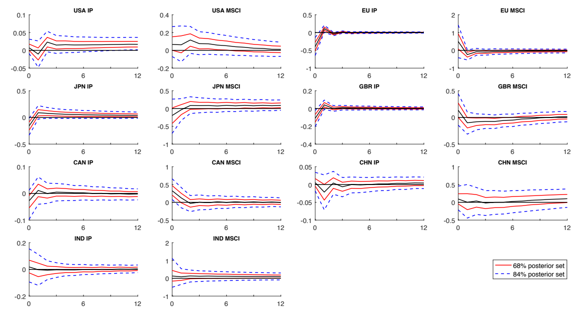
(d) IRV

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.

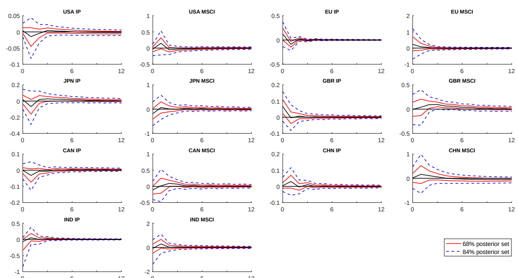
Figure C.13: Responses to Eurozone Forecast Error Variance Shocks



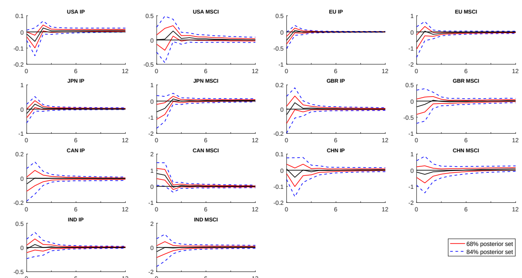
(a) CPIV



(b) FXV



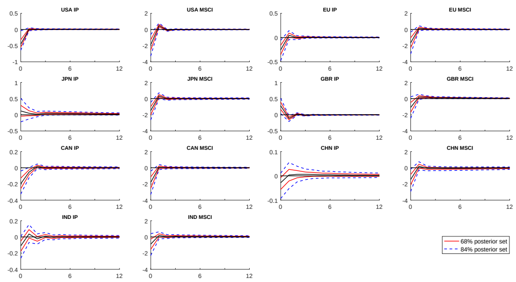
(c) IPV



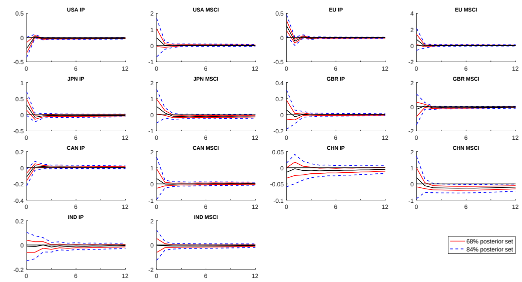
(d) IRV

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.

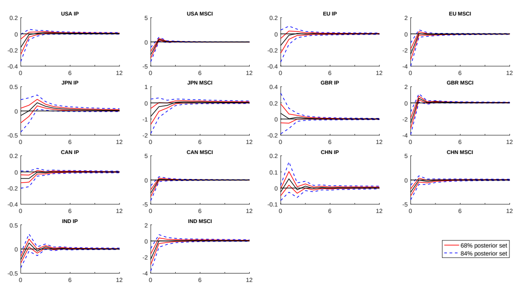
Figure C.14: Responses to UK Forecast Error Variance Shocks



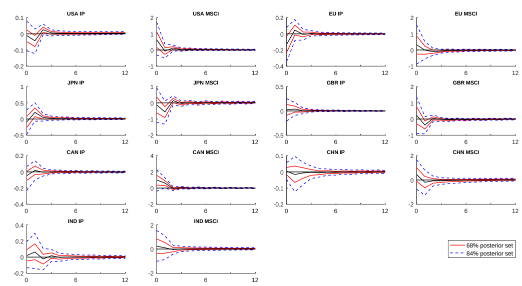
(a) CPIV



(b) FXV



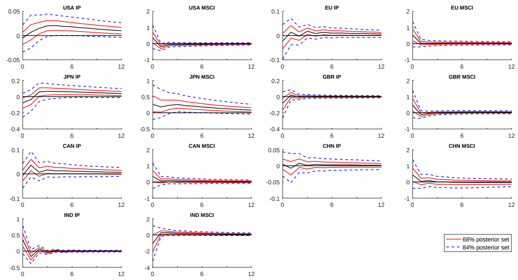
(c) IPV



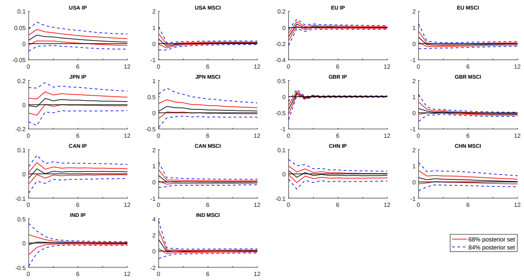
(d) IRV

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.

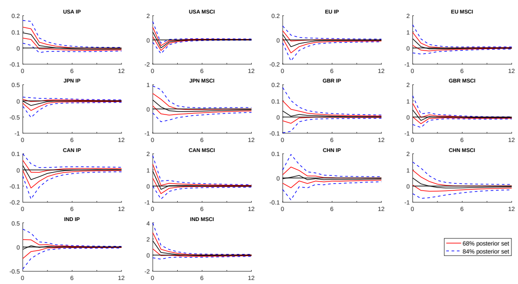
Figure C.15: Responses to India Forecast Error Variance Shocks



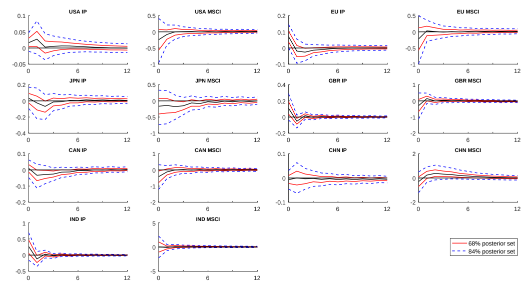
(a) CPIV



(b) FXV



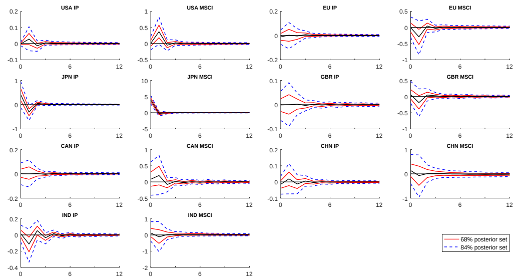
(c) IPV



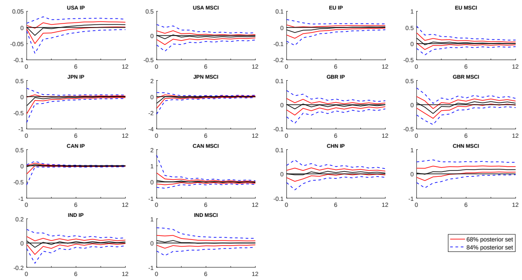
(d) IRV

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.

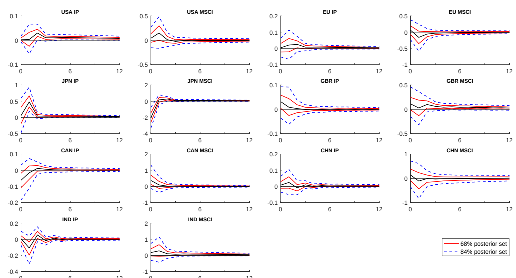
Figure C.16: Responses to Japan Forecast Error Variance Shocks



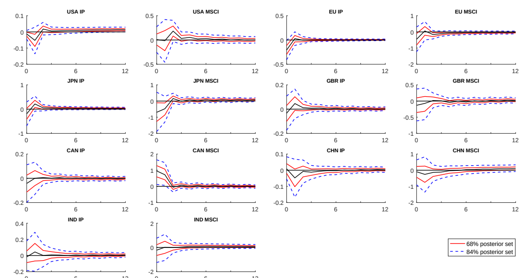
(a) CPIV



(b) FXV



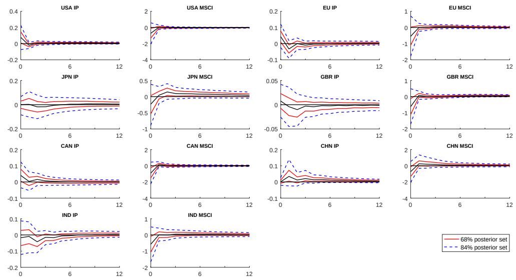
(c) IPV



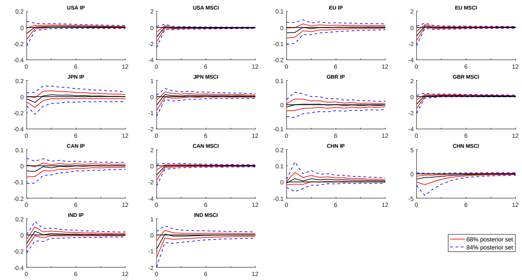
(d) IRV

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.

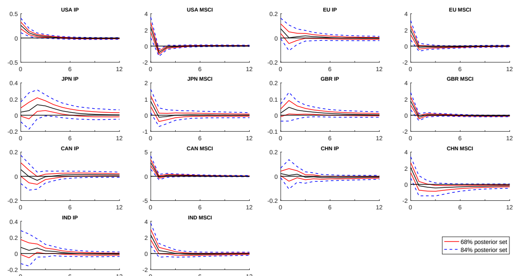
Figure C.17: Responses to US Forecast Error Variance Shocks



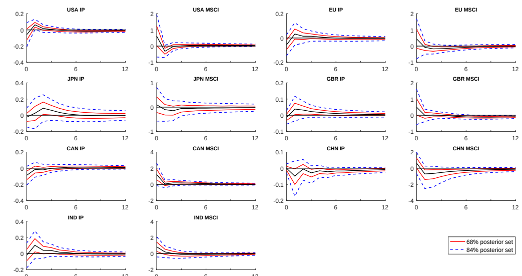
(a) CPIV



(b) FXV



(c) IPV

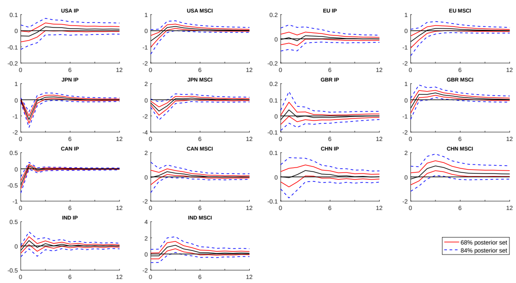


(d) IRV

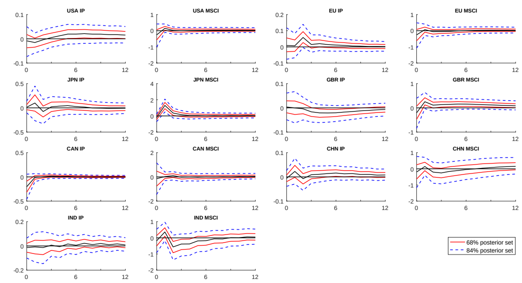
Note: The figure shows the response of each macro-financial variable to a shock in US forecast error variances regarding inflation (CPIV), the exchange rate (FXV), industrial production (IPV) and short-term interest rate (IRV). 68 and 84 percent credible intervals are provided.

C.2.4 Responses to Combined Uncertainty Shocks

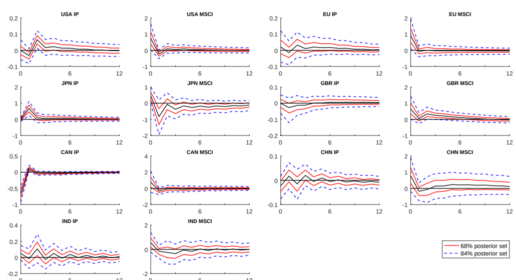
Figure C.18: Responses to Canada Combined Uncertainty Shocks



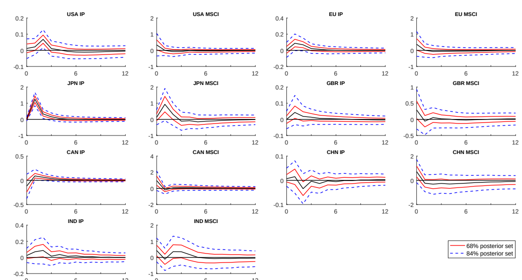
(a) CAD



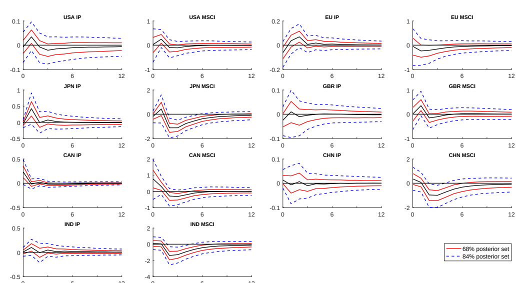
(b) CPIU



(c) FXU



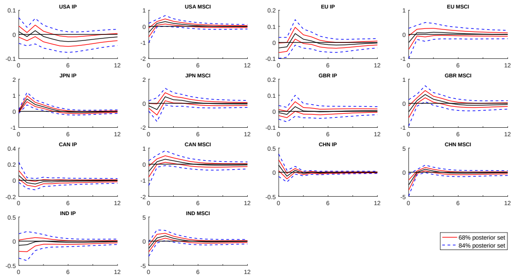
(d) IPU



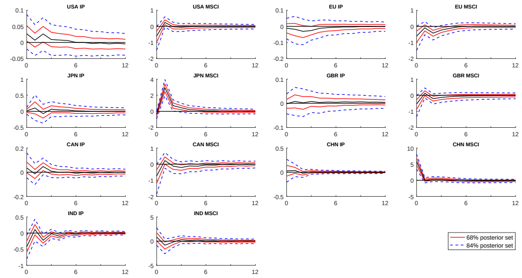
(e) IRU

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.

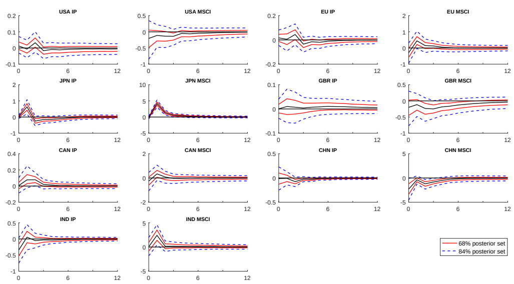
Figure C.19: Responses to China Combined Uncertainty Shocks



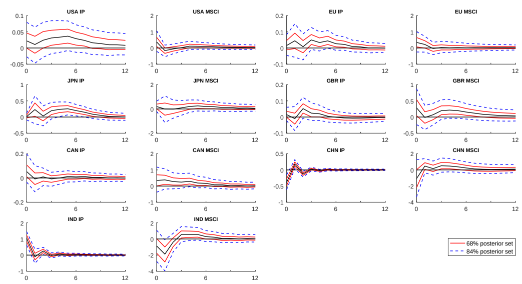
(a) CAD



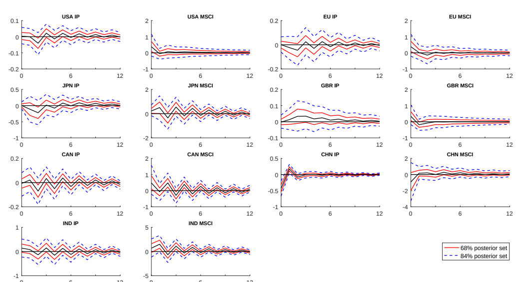
(b) CPIU



(c) FXU



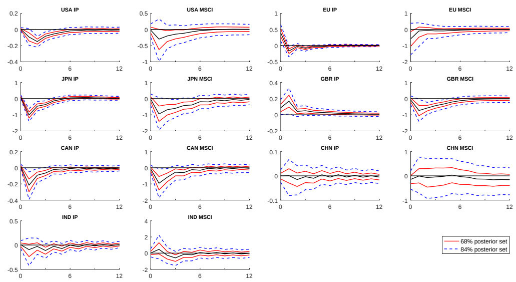
(d) IPU



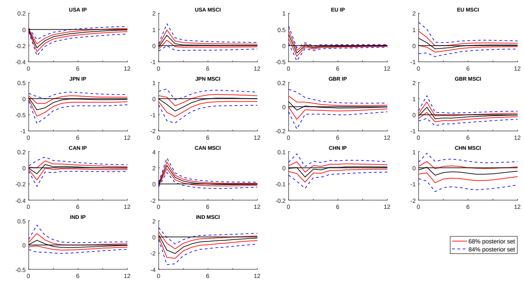
(e) IRU

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.

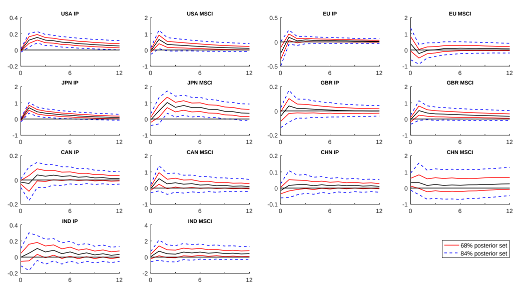
Figure C.20: Responses to Eurozone Combined Uncertainty Shocks



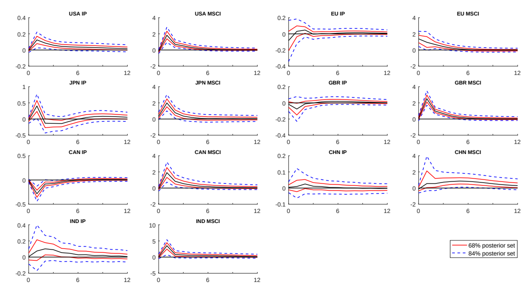
(a) CAD



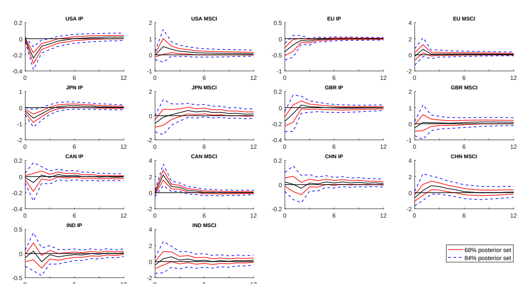
(b) CPIU



(c) FXU



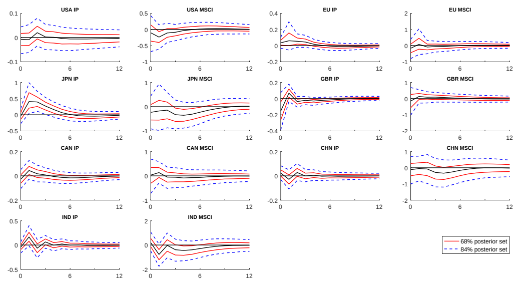
(d) IPU



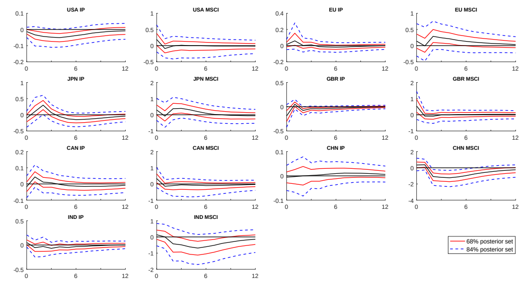
(e) IRU

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.

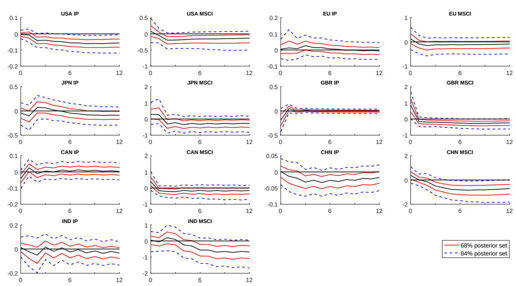
Figure C.21: Responses to UK Combined Uncertainty Shocks



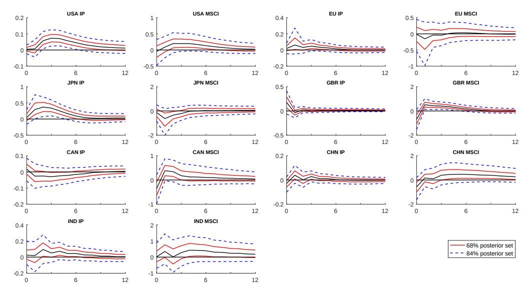
(a) CAD



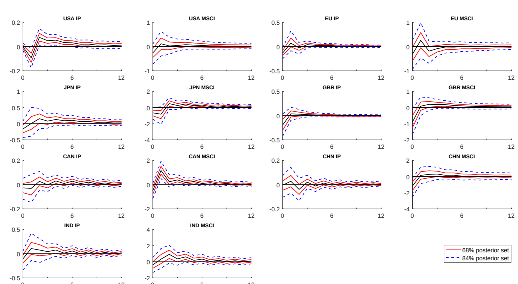
(b) CPIU



(c) FXU



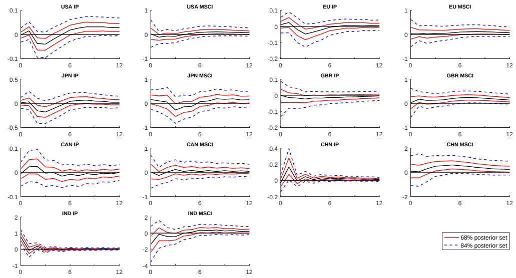
(d) IPU



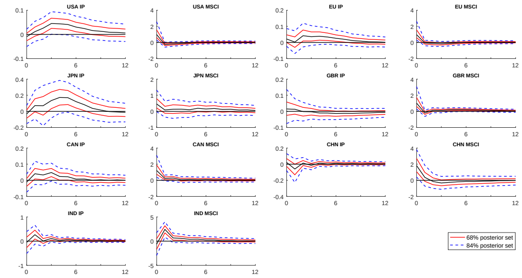
(e) IRU

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.

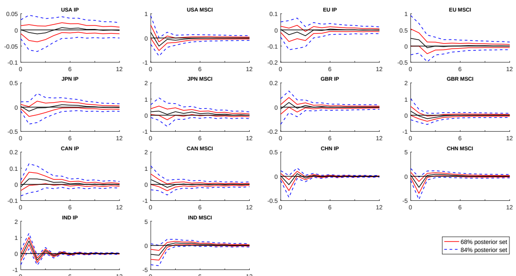
Figure C.22: Responses to India Combined Uncertainty Shocks



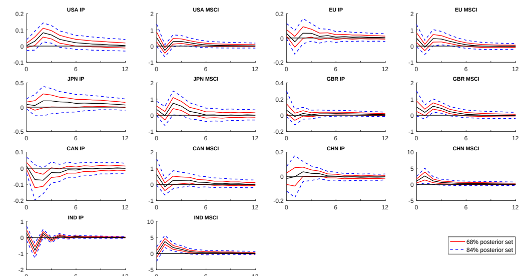
(a) CAD



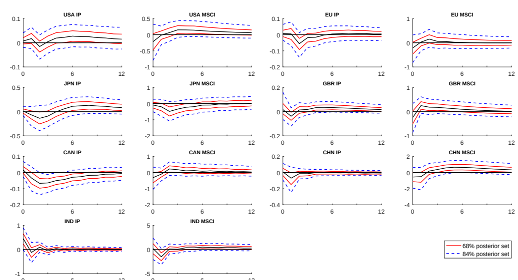
(b) CPIU



(c) FXU



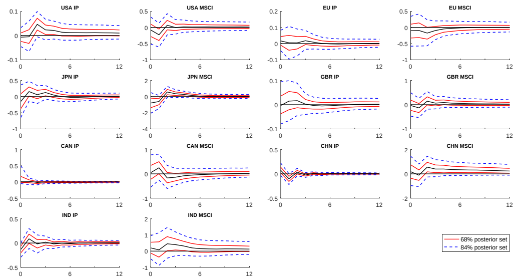
(d) IPU



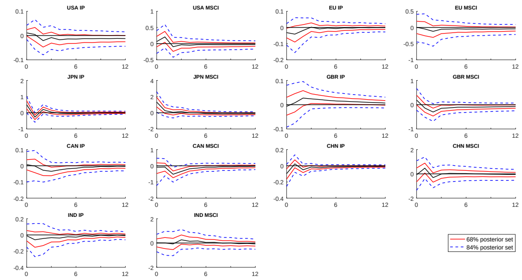
(e) IRU

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.

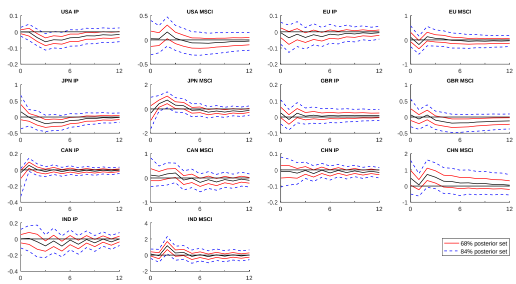
Figure C.23: Responses to Japan Combined Uncertainty Shocks



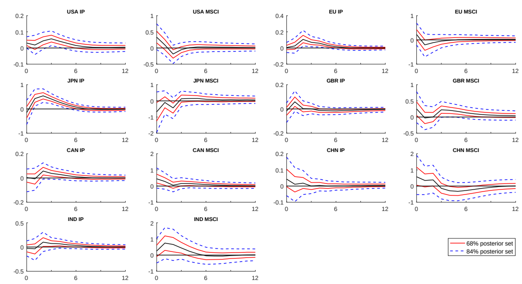
(a) CAD



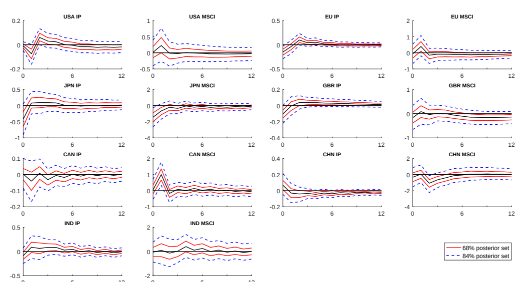
(b) CPIU



(c) FXU



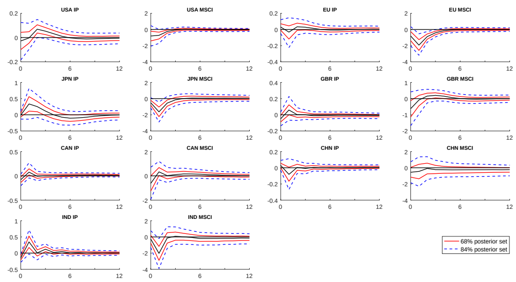
(d) IPU



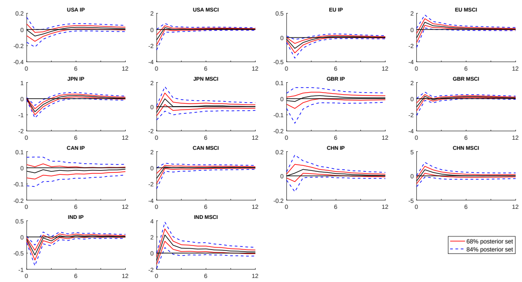
(e) IRU

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.

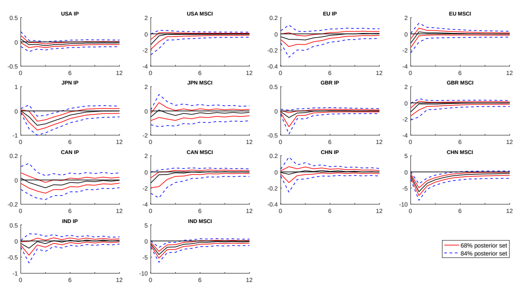
Figure C.24: Responses to US Combined Uncertainty Shocks



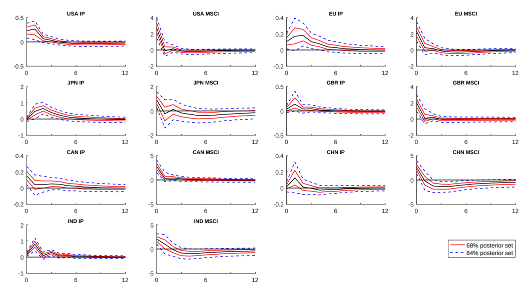
(a) CAD



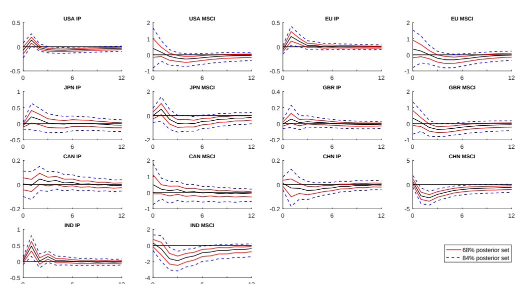
(b) CPIU



(c) FXU



(d) IPU



(e) 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.