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# Essays on the Business Cycle

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*To my dear grandma Inge*



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# List of Abbreviations

<b>AD</b>	Aggregate demand
<b>AIC</b>	Akaike information criterion
<b>AS</b>	Aggregate supply
<b>BBD</b>	Bloom, Baker, and Davis (2016)
<b>CPI</b>	Consumer price index
<b>DS</b>	Datastream
<b>EBP</b>	Excess bond premium
<b>FAVAR</b>	Factor-augmented vector autoregressive (model)
<b>FFR</b>	Federal funds rate
<b>(F)GLS</b>	(Feasible) generalized least squares
<b>FSVAR</b>	Factor structural vector autoregressive (model)
<b>HQ</b>	Hannan Quinn (criterion)
<b>IRF</b>	Impulse response function
<b>JLN</b>	Jurado, Ludvigson, and Ng (2015)
<b>LR</b>	Likelihood ratio
<b>ML</b>	Maximum likelihood
<b>NBER</b>	National Bureau of Economic Research
<b>OIC</b>	Other industrialized countries
<b>OLS</b>	Ordinary least squares
<b>PFA</b>	Penalty function approach
<b>PPI</b>	Producer price index
<b>SIC</b>	Schwarz information criterion
<b>VAR</b>	Vector autoregressive (model)



# Introduction

Business cycle analysis has a long tradition in macroeconomics. A variety of models and methods have been used traditionally for investigating the sources and effects of economic fluctuations.

The research agenda has undergone a continuous change over time. To give an example, the unprecedented disruptions of the Great Recession have cast doubt on whether traditional tools for explaining business cycle fluctuations like RBC models suffice in times of turmoil. Hence, the literature has increasingly focused on alternative sources, such as economic uncertainty. According to theory, higher uncertainty has implications for real activity since entrepreneurs defer capital investments and risk premia on external finance rise (Bloom, 2009; Christiano et al., 2014). The empirical relevance of these mechanisms has been examined extensively. Stock and Watson (2012) and Caldara et al. (2016), for example, show that the shocks that produced the Great Recession primarily were associated with heightened uncertainty and financial disruptions.

As globalization proceeds, the international connectedness of national economies has also come to the fore of economic research. Kose et al. (2012), for instance, found evidence for the proposition that trade and financial market integration has enhanced the business cycle synchronization among industrial countries and emerging economies. Besides, newly industrialized countries like China play a steadily growing role in global business cycle and inflation dynamics. Aastveit et al. (2015) show that the demand from emerging economies has become twice as important as the demand from developed countries in accounting for the fluctuations in oil prices, and these fluctuations also spill over to national price indicators in the advanced economies (Eickmeier and Kühnlenz, 2016).

In my dissertation, I empirically address questions related to these research fields. I contribute to understanding business cycle fluctuations and inflation dynamics within the advanced economies and international linkages between these. Moreover, I provide new and policy-relevant evidence on two notable economic events of the last two decades, namely the Great Recession and the downturn in global inflation rates hereafter. The empirical frameworks I use are based on medium to large-dimensional multivariate time series analysis with a focus on factor analysis. In addition, I partially allow for nonlinearity by distinguishing between discrete model regimes. The estimation methodologies rest upon state-of-the-art Bayesian and frequentist techniques.

**The dissertation consists of three essays.** The first essay is coauthored with my supervisor Kai Carstensen and has been published in a peer-reviewed journal. The two following essays are both single-authored and published as working papers. In 2018 the second essay was awarded by the Research Prize of the INFER network. I plan to publish

both my single-authored essays in high-ranked journals.

Chapter one comprises the first essay “**The G7 Business Cycle in a Globalized World**”, which is joint work with Kai Carstensen. My coauthor and I herein address the empirical relevance of business cycle shocks originating in the newly industrialized non-G7 countries for the G7 business cycle. We fit a factor structural VAR (FSVAR) model to quarterly GDP growth of 14 countries out of the G20 group and identify three common international factors, one of which represents the commonalities orthogonal to the G7. Besides, we model network effects of idiosyncratic changes in national GDP growth rates by allowing for 14 country-specific shocks that can affect other countries after one quarter.

We document that the non-G7 factor and the idiosyncratic non-G7 shocks, thus output innovations originating outside the G7, jointly account for shares of 10 to almost 25 percent in the forecast error variance of G7 GDP growth rates. Moreover, we find that these innovations are relevant, relative to G7 output innovations, in the fluctuations of other key national G7 indicators such as employment, the current account balance, inflation, and inflation volatility, and in global macroeconomic variables like the oil price, world stock market returns and exchange rate volatility. We published this essay in 2017 in the *Journal of International Money and Finance*.

Chapter two comprises my first single-authored essay “**China’s Economic Slowdown and International Inflation Dynamics**”, which addresses the impact of the downturn in the Chinese business cycle during the last decade on inflation rates outside of China. The essay is motivated by empirical results indicating a significant Chinese influence on international commodity prices (e.g., Eickmeier and Kühnlenz, 2016) and a co-movement between the cyclical trend in China and global inflation rates after the Great Recession. My empirical framework is a large-dimensional factor-augmented VAR (FAVAR) model that includes 749 international macro series plus the Chinese GDP growth rate and the Chinese inflation rate as observable variables. To identify aggregate demand and supply shocks in China, I impose sign restrictions on the impulse response profile of the two Chinese variables.

The results show that these shocks have international implications. Demand innovations in China significantly increase national inflation rates in the advanced economies, particularly transmitted by global oil and commodity prices. The impacts are most pronounced in the United States and are reflected more in terms of producer prices than consumer prices. Moreover, historical decompositions indicate that the cyclical downturn in China can be attributed to a combination of adverse domestic supply and demand innovations, and that these innovations lowered national producer prices outside of China by up to six percent between 2014 and 2017. Finally, the Chinese shocks are also reflected in foreign interest rates, as implied by the Fisher effect and monetary policy rules.

Chapter three comprises my second single-authored essay “**The Macroeconomic Impact of Uncertainty and Financial Shocks in Recessions and Booms**”. The essay is motivated by the difficulty of isolating uncertainty and financial shocks from each other, resulting in a disagreement in the literature on their macroeconomic impact. To obtain a more complete picture, I compute identification bounds instead of point estimates of



the effect of both shocks in a state-dependent FAVAR model for the United States. The bounds are constructed by employing a version of the penalty function approach proposed by Uhlig (2005) and Caldara et al. (2016).

The results show that adverse uncertainty shocks are of limited relevance for business cycle indicators in booms but have contractionary effects in recessions. By contrast, adverse financial shocks reduce real activity and asset prices in both regimes. The role of identifying assumptions also differs between both shocks. Financial disturbances exhibit relatively tight identification bounds considering the impact on stock and house prices, which confirms them as driving forces of asset price fluctuations. By contrast, the spectrum of possible effects from uncertainty shocks is relatively broad, ranging between significant and negligible in terms of asset prices. If we look at real economic activity, the effects of both shocks are hard to pin down since they considerably vary across identification schemes.

**How do the essays relate to each other?** Each essay of this dissertation asks specific research questions and uses tailored econometric methods. However, the essays also share several features, both methodologically and content-related.

Overall, all three of them address sources and transmission mechanisms of business cycle fluctuations in the globalization era. The essays in Chapters I and II both address the international connectedness of the global economy and set a focus on the role of the newly industrialized countries. Chapter I does so by looking at the reaction of the G7 business cycle to shocks originating outside the G7 group and the transmission of these shocks. Chapter II zooms into the prominent role of the Chinese economy within the non-G7 group and focuses on two significant events of the last decade, namely the slowdown in China's economic performance and the worldwide decline in inflation and interest rates. Chapter III differs from chapters I and II in that it focuses on the domestic business cycle.

All three essays build on multivariate time series methods and, in particular, factor analysis. Whereas the essay in chapter I employs the factor structural VAR model, the essays in chapters II and III apply the factor-augmented VAR approach. Both model frameworks assume that a panel of macroeconomic time series can be decomposed into a common and an idiosyncratic, i.e., series-specific part. In the FAVAR, a typically large number of time series is reduced to a handful of common factors, which are then added to an otherwise standard VAR. As a result, the FAVAR allows the dynamic analysis of large panels even if the number of time observations is limited. In addition, if the cross-section  $n$  is large relative to the time dimension  $T$ , the estimation uncertainty related to the factors becomes negligible (Bai, Ng, et al., 2006). Hence, the curse of dimensionality in multivariate analysis turns into a blessing in this case. In the FSVAR, by contrast, the factor structure is imposed on the reduced-form VAR residuals and not on the time series themselves. On the one hand, this setup implies the need of keeping  $n$  moderate. On the other hand, it allows for dynamic spillovers from idiosyncratic shocks to other series. In a multi-country VAR, for instance, national indicators can react to a common international shock and an idiosyncratic domestic shock, but also to idiosyncratic foreign shocks.

**How do the essays contribute to the literature?** Each of the three essays contributes to the business cycle literature by providing new empirical evidence on specific research questions. In brief, the contributions are in terms of the data foundation, the empirical methodology, and the identification setup. Concerning the data, I use large cross-sections of countries and economic indicators and time windows that include major economic events like the Great Recession. Methodologically, I examine the empirical relevance of network effects in the international business cycle and the state dependence of macroeconomic shocks. In terms of identification, my findings indicate to which degree macroeconomic shocks can be empirically isolated. The contributions are outlined in more detail in the following.

Chapter I adds to the literature on the newly industrialized economies and their role for the business cycles of the advanced economies, a topic on which the empirical evidence is generally scant. My coauthor and I depart from the narrative that regional and group-specific factors appear to drive the business cycle fluctuations of national economies (Crespo-Cuaresma and Fernández-Amador, 2013; Helbling and Bayoumi, 2003; Kose et al., 2012; Stock and Watson, 2005). This narrative is in part model and not data-based since it rests upon modeling commonalities among country groups and neglects effects between countries of different groups. The framework we use is more flexible in this regard since it allows for common factors but additionally accounts for spillovers between individual countries. Hence, it is informative for typical multicountry DSGE models featuring country-specific structural shocks that propagate through both national and foreign economies.

Our results indicate that regional and group-specific clustering cannot explain all aspects of business cycle fluctuations in the industrialized countries. Idiosyncratic shocks from non-G7 countries play a non-negligible role for important G7 indicators and should therefore be considered in macroeconomic modeling and forecasting. We moreover find that the indicators affected most by shocks from non-G7 countries are employment, inflation, interest rates, the current account balance, exchange rates, and world market prices for oil and manufacturing goods.

Chapter II contributes to understanding the worldwide downturn in inflation rates that took place during the last decade by examining the role of the Chinese business cycle. The existing evidence on this issue is either restricted to China's neighboring countries in Asia (Dizioli et al., 2016) or based on theoretical slowdown scenarios instead of economic data (Metelli and Natoli, 2017). I use a large-scale FAVAR model that allows analyzing the Chinese influence on different world regions while controlling for international business cycle movements. The finding that adverse Chinese shocks significantly reduced global oil prices and national prices outside of China between 2014 and 2017 emphasizes foreign business cycle shocks relative to domestic and oil market shocks (Ciccarelli et al., 2017; Bobeica et al., 2017; Baumeister and Kilian, 2016) as driving forces of inflation rates. In particular, it shows that business cycle spillovers from China have become important for price dynamics, both at the national and global level. The spillover effects on interest rates show that Chinese shocks are also relevant for financial indicators worldwide and hence

should be considered in the current debate on low yields. As a result, shocks originating in China should be taken into account in modeling inflation and interest rates in the advanced economies, also and foremost from a monetary policy maker's perspective.

The main contributions of Chapter III relate to the identification bounds and the state-dependence of uncertainty and financial shocks. First, financial shocks tend to exhibit tighter bounds than uncertainty shocks, hence their macroeconomic impact can be determined more precisely. By contrast, it is generally difficult to pin down the impact of uncertainty shocks since identifying assumptions on the shocks are crucial. These findings strengthen the view that uncertainty shocks are potentially less relevant if financial shocks are simultaneously accounted for. Second, the identification bounds unite views stressing the role of uncertainty as source of business cycle fluctuations (Bloom, 2009; Bachmann et al., 2013; Alessandri and Mumtaz, 2018; Christiano et al., 2014) with conservative views (Ludvigson et al., 2015; Popescu and Smets, 2010) in one framework. They accordingly also represent different implicit transmission mechanisms: while uncertainty shocks have real effects through a worsening in credit conditions, the contractionary impact of financial shocks is explained by a rise in uncertainty. Third, the distinction between a recession and a boom regime accounts for the special role of financial and uncertainty shocks during the Great Recession (Stock and Watson, 2012; Caldara et al., 2016). My results show that the macroeconomic impact of both shocks is more pronounced in recessions, albeit with a greater importance of identifying assumptions.

The remainder of this dissertation is structured as follows. Chapters 1 to 3 include the three essays described above. At the end of chapter 1, the contribution of my co-author to our joint essay is outlined. Appendices A to C present additional tables and figures and explanations on the methodological approaches the individual essays refer to. The document ends with a list of bibliographic references and a declaration to confirm that the dissertation has been developed independently.



## Chapter 1

# The G7 Business Cycle in a Globalized World

This chapter of the dissertation has been published as Carstensen, K. and Salzmann, L. (2017), The G7 Business Cycle in a Globalized World, *Journal of International Money and Finance* (73), 134-161.

**Abstract**

Using a factor structural VAR for 14 countries out of the G20 group, we document that output innovations originating outside the G7 account for shares of 10 to almost 25 percent in the business cycle fluctuations of G7 GDP growth. Using auxiliary regressions, we additionally find that these innovations contribute noticeably, relative to G7 output innovations, to short-term fluctuations in important other national G7 variables such as employment, the current account balance, inflation, and inflation volatility, and in global macroeconomic indicators like the oil price, world stock market returns and exchange rate volatility. The results indicate that in a globalized world spillovers from emerging markets and industrial countries other than the G7 play a relevant role for major aspects of the G7 and world business cycle.

*Keywords:* G7, international business cycle transmission, factor structural VAR.

*JEL classification:* E32, F44, F62

## 1.1 Introduction

In this paper, we assess the relevance of output innovations originating outside the G7 for the world and the national G7 business cycles, a question that has become more and more important as globalization proceeds. We fit a factor structural VAR (FSVAR) model to quarterly GDP growth of all 14 countries out of the G20 group for which long time series are available. We identify three common international factors, one of which represents the commonalities orthogonal to the G7, and 14 country-specific shocks which reflect the idiosyncratic changes in national GDP growth rates but are allowed to spill over to other countries with a lag of one quarter. With the help of forecast error variance decompositions we document that the non-G7 factor and the idiosyncratic non-G7 shocks, hence output innovations originating outside the G7, jointly account for shares of 10 to almost 25 percent in the business cycle fluctuations of G7 GDP growth rates.

Subsequently, we regress indicators for the world business cycle and the national G7 business cycles on the international factors and country-specific shocks extracted by the FSVAR model. We break the R-squared of these regressions down into a part that is due to the G7 and a part that is due to the remaining countries. Since the factors and shocks are mutually uncorrelated, this procedure can be interpreted as a forecast error variance decomposition without the need to estimate and invert additional VAR models.

We document that the relative importance of output innovations originating outside the G7 for global fluctuations pertains mostly to inflation and exchange rate volatility and to nominal variables like global stock market returns and world market prices for oil and manufacturing goods, whereas indicators of real activity like GDP of the OECD, world industrial production and world trade are affected moderately. On the national G7 level, non-G7 output innovations contribute substantially, relative to G7 innovations, to the fluctuations in relevant business cycle indicators such as employment and unemployment, the current account balance and the effective exchange rate, inflation, interest rates and stock market returns, and in inflation, stock market and exchange rate volatility. Taken together, our findings indicate that business cycle fluctuations spill over from non-G7 to G7 countries in a quantitatively significant way and that this spillover is associated particularly with world market returns and prices, and their volatilities.

This paper is most closely related to Stock and Watson (2005) who use the same FSVAR setup to analyze the business cycle synchronization of the G7 in the Great Moderation period 1984-2002 as opposed to the more volatile period 1960-1983. We consider the time period 1991-2014 which allows us to augment the country set with Australia, Brazil, China, Mexico, South Africa, South Korea and Turkey and examine how these countries affect the G7 business cycle. Still, our results show that many of their findings for the Great Moderation period remain remarkably intact. In particular, we also find that G7 output growth is driven by two G7-factors of which one factor mainly affects euro area countries and the other one is rather associated with English-speaking countries. The third factor we identify is orthogonal to the G7 and may thus be labeled a non-G7 factor.

The latter result replicates an empirical pattern often found in the literature on international macroeconomic fluctuations during the globalization era: regional and group-specific factors rather than a single dominating world factor appear to drive the business cycle fluctuations of individual countries. Artis and Zhang (1997), Artis and Zhang (1999), Del Negro and Otrok (2003), Luginbuhl and Koopman (2004), and Crespo-Cuaresma and Fernández-Amador (2013) report a continental-European cluster consisting of Germany, France and Italy, while Helbling and Bayoumi (2003) and Stock and Watson (2005) provide evidence for an English-speaking cluster consisting of the US, UK and Canada. For a larger country group Mumtaz et al. (2011) and Hirata et al. (2013) find that the influence of a global common component has decreased during the post-WWII era while the contribution of geographic influences has increased. Similarly, Kose et al. (2012) report that the global factor has become less important for macroeconomic fluctuations relative to factors that are specific to industrial countries and emerging markets, respectively.

However, unlike most of the recent literature, we find that business cycle clustering is not the complete story: spillovers play a non-negligible role and should be taken into account both in macroeconomic modeling and in forecasting. We are able to obtain this results because we depart methodologically from related work by Kose et al. (2012), Mumtaz et al. (2011), Eickmeier (2007), Kose et al. (2003) and Crucini et al. (2011) who apply (dynamic) factor models to study international business cycle transmission. These models focus on the dynamics of the common components and shut down spillovers from one country to another which allows them to include huge numbers of variables. While this is certainly an advantage, Diebold and Yilmaz (2013) report that spillover effects of idiosyncratic shocks to foreign countries are important. For example, we may expect that a US monetary policy shock affects, at least with a lag, business conditions in other countries. In a dynamic factor model this shock would presumably be classified partly as global shock and partly as an idiosyncratic shock without international effects. In contrast, the FSVAR model allows to simultaneously identify common international factors and country-specific shocks by assuming that the latter spill over to internationally with a lag of one period. Nevertheless, it remains estimable for a sample of 14 countries.

We favor the FSVAR over the dynamic factor model also for another reason. Empirical research intends to isolate stylized empirical facts that are widely accepted and guide theorists in setting up and calibrating structural models. Typical multi-country DSGE models feature country-specific structural shocks that propagate through both national and foreign economies. To be informative for these models, we prefer to use an empirical model like the FSVAR that allows for such international transmission.

This paper is organized as follows. Section 1.2 presents the data and outlines the detrending procedure. Section 1.3 introduces the FSVAR and describes how we identify the common international factors. Section 1.4 presents the results of the FSVAR. In section 1.5, we report the results of supplementary regressions of world and G7 business cycle indicators on the factors and shocks extracted by the FSVAR. In section 1.6, we check the robustness of our main findings to specification change. Section 1.7 concludes.



## 1.2 Data and detrending

We use seasonally adjusted quarterly per capita GDP covering the period 1991Q1-2014Q4. We include all countries out of the G20 group for which data are available: The G7 and seven further industrialized countries, namely Australia, Brazil, China, Mexico, South Africa, South Korea, and Turkey. In the following we refer to the non-G7 group of countries as “Other industrialized countries” (OIC) and to the entire country set as G14.

We consider GDP rather than industrial production – another often-used indicator – as it may be better suited to reflect the overall business cycle situation of countries that generate large and increasing fractions of their value added in the service sector. In fact, the average share of industrial production in GDP over the last decade ranged only between 27% (Brazil) and 46% (China) in the OIC countries, and between 20% (France) and 30% (Germany) in the G7 countries, and was generally decreasing<sup>1</sup>.

We choose a quarterly frequency because it is widely accepted as the usual business cycle frequency. Moreover, imposing zero restrictions on the VAR impact matrix to identify structural shocks – a strategy we use below – is much less controversial when using quarterly rather than annual data. Specifically, we will identify a national business cycle shock by restricting its within-quarter effect on all other countries to zero. It would be much more difficult to argue that, e.g., a national US shock does not spill over to, say, Mexico, China, or Europe within one year.

We exclude those countries of the G20 for which no quarterly data over the whole period exist. Cutting down the sample size to 1996Q2 to include all G20 countries would not only mechanically reduce the number of observations, it would also mean to neglect some important business cycle movements like the euro area trough of 1993. We show in the robustness analysis in section 1.6 that our conclusions remain almost unchanged if we include all G20 countries (except for the EU) and start our estimation in 1996Q2.

To obtain a clean measure of the business cycle, we first adjust GDP by the population number, thereby taking out any population trend. The resulting GDP per capita is then turned into annualized growth rates. In three instances, we observe extremely large absolute growth rates. To prevent our results from being driven by these outliers, we trim any growth rate that is further than five times the interquartile range away from its median to the respective threshold. We show in the robustness analysis in section 1.6 that this adjustment scheme does not drive our results.

To account for the possibility that GDP per capita growth does not fluctuate around a constant mean but, e.g., exhibits a secular productivity trend, we apply the local-level model suggested by Stock and Watson (2005):

$$y_t = \mu_t + u_t \quad (1.1)$$

$$\mu_t = \mu_{t-1} + \tau \eta_t \quad (1.2)$$

$$u_t = \sum_{i=1}^4 \alpha_i u_{t-i} + w_t \quad (1.3)$$

---

<sup>1</sup>These shares are based on the World Development Indicators published by the World Bank.

where  $\eta_t$  and  $w_t$  are serially and mutually uncorrelated mean-zero disturbances. The measurement equation (1.1) decomposes GDP growth,  $y_t$ , into a slowly evolving mean,  $\mu_t$ , and a stationary cycle,  $u_t$ . According to (1.2)  $\mu_t$  follows a random walk, while (1.3) models  $u_t$  as an AR(4) process. The relative importance of the trend innovations,  $\eta_t$ , compared to the cyclical shocks,  $w_t$ , is reflected by the scaling factor  $\tau$ .

We estimate the local level model using an asymptotically median unbiased estimator of  $\tau$  as proposed by Stock and Watson (1998). It is based on inversion of a point-optimal invariant test of the null hypothesis  $\tau = 0$  against the local alternative  $\tau = 7/T$ . Specifically, after extracting the AR(4) component from each GDP growth series, we compute the median unbiased estimator of  $\tau$ . Then we use the Kalman smoother to remove  $\mu_t$ . This yields detrended GDP growth as shown in Figures 1.1 and 1.2. Anticipating the subsequent results, the figures include the common component extracted from a three-factor G14 structural VAR. It demonstrates that there is a strong degree of international business cycle synchronization.

FIGURE 1.1: Detrended annualized quarterly GDP growth of the G7 and the common component implied by the G14-FSVAR

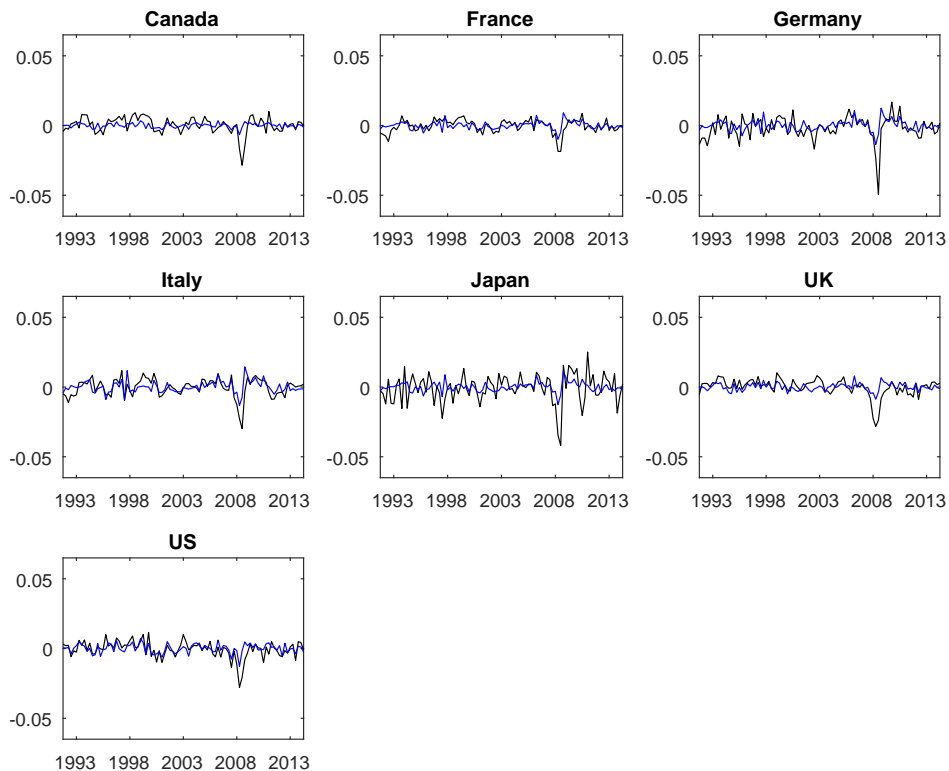
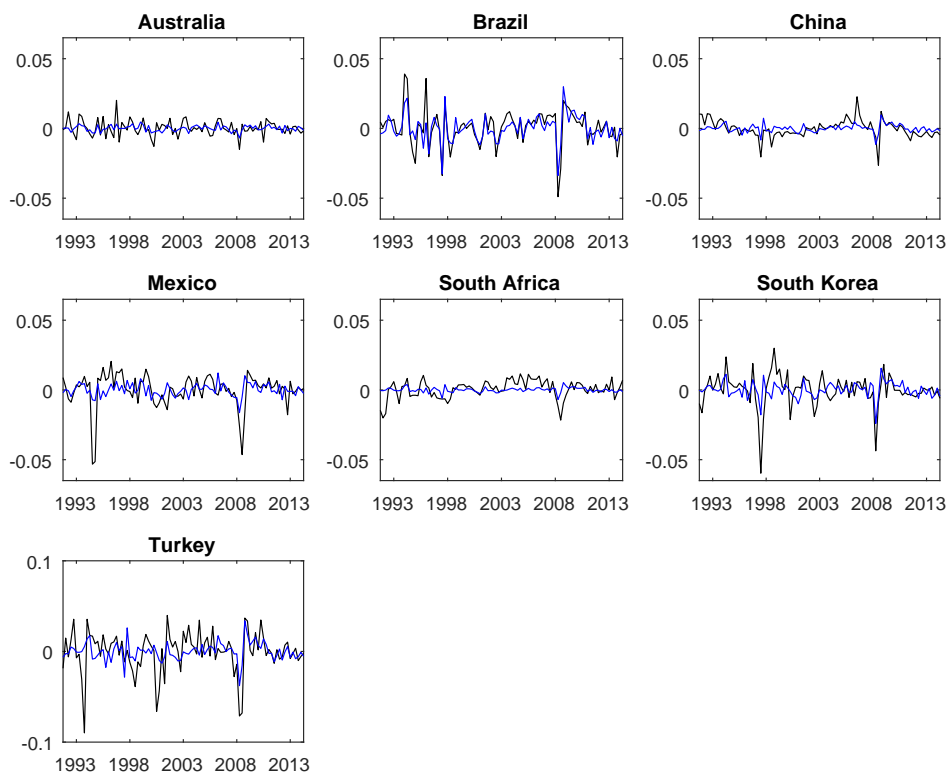


FIGURE 1.2: Detrended annualized quarterly GDP growth of the OIC and the common component implied by the G14-FSVAR



### 1.3 The factor structural VAR

To examine international business cycle synchronization, we use a structural VAR model with a factor structure in the disturbances. This allows us to separate common international factors from idiosyncratic national shocks. In this section, we describe the specification of the model and the assumptions imposed to identify the shocks.

#### 1.3.1 Choice of the lag order

We start from the unrestricted VAR model

$$Y_t = \sum_{i=1}^p A_i Y_{t-i} + v_t, \quad E(v_t v_t') = \Sigma, \quad (1.4)$$

where  $Y_t$  is a  $n$ -dimensional vector of detrended GDP growth rates,  $v_t$  is a vector of reduced-form shocks and  $A_i$  denotes a coefficient matrix. A major drawback of this model is the curse of dimensionality: the number of coefficients to be estimated increases quadratically with the number of variables. Including  $n = 14$  countries and  $p = 4$  lags – a natural choice for quarterly data – would almost exhaust the available degrees of freedom. Therefore, we impose zero restrictions on the coefficient matrices. Specifically, while we allow a lag order of  $p = 4$ , we restrict the off-diagonal elements of  $A_2$  to  $A_4$  to zero. This implies that distributed lag effects beyond one quarter work through retarded reactions of GDP to its own past only. Stock and Watson (2005) find this dynamics to be rich enough to characterize business cycle transmission among the G7<sup>2</sup>.

To account for the coefficient restrictions we estimate the parameter matrices  $A_i$  by feasible generalized least squares (FGLS). In the first step, we estimate the model equationwise by OLS and calculate the covariance matrix of the residuals. In the second step, we estimate the VAR as a system, plugging the estimated covariance matrix into the FGLS estimator.

#### 1.3.2 The factor structure

To isolate an “international cycle” from remaining idiosyncratic, i.e., country-specific, components, we follow Stock and Watson (2005) and impose an (exact) factor structure on the reduced-form shocks  $v_t$ . Thereby we decompose each of them into  $k$  common factors  $f_t$  and one idiosyncratic component:

$$v_t = \Gamma f_t + \xi_t, \quad (1.5)$$

where  $\xi_t$  denotes the  $n$ -dimensional vector of country-specific shocks,  $f_t$  denotes the  $k$ -dimensional vector of factors, and  $\Gamma$  is a  $(n \times k)$  matrix of factor loadings. We assume that both  $f_t$  and  $\xi_t$  are uncorrelated with each other and over time, with diagonal covariance

<sup>2</sup>In a robustness analysis in section 1.6 below, we demonstrate that our benchmark results are robust to different lag order specifications. We specified both a lag order of  $p = 1$  as selected by information criteria and an unrestricted FSVAR with  $p = 4$  which we estimate by Bayesian methods and a Minnesota-style prior. Both specification choices do not significantly alter our results.

matrices  $\Sigma_f = I$  and  $\Sigma_\xi$ . Hence, the variance structure is

$$\Sigma = \Gamma \Sigma_f \Gamma' + \Sigma_\xi. \quad (1.6)$$

We estimate the decomposition of the reduced form covariance matrix  $\Sigma$  into the factor structure (1.6) by means of Gaussian maximum likelihood.

The covariance structure implies that any cross-correlation of the reduced form disturbance is due to the common factors and thus identifies the factor space. Correspondingly, a factor affects GDP of all countries jointly and instantaneously, while a country-specific shock spills over to other countries only after at least one quarter. Hence, all we require is that idiosyncratic GDP shocks hitting one country need more than 3 months to transmit to another country's GDP. In our view, this assumption is not overly restrictive as even within a country, it typically takes longer than 3 months that a structural shock affects GDP significantly, see, e.g., Bernanke and Mihov (1998) for monetary policy shocks, and Romer and Romer (2010) for fiscal policy shocks.

A similar factor structure is used by Altonji and Ham (1990), Norrbin and Schlagenhau (1996), and Stock and Watson (2005). Its main advantage is that it allows all shocks to affect all variables. This turns out to be important empirically because, as we will document below, lagged international spillovers of country-specific shocks explain relevant fractions of the business cycle fluctuations in other countries' GDP. In contrast, (dynamic) factor models of the type studied by Eickmeier (2007), Kose et al. (2003), and Crucini et al. (2011) model only the dynamics of the common component. While this allows them to include huge numbers of variables – Eickmeier (2007) considers 264 –, they shut down spillovers from one country to another and thereby neglect an important channel of international business cycle transmission.

The number of factors,  $k$ , is determined by a likelihood ratio test (see Table 1.1). We first consider a VAR model that includes the G7 countries only. The null hypothesis of one factor is clearly rejected against the alternative of an unrestricted VAR, while the null of two factors cannot be rejected at the 10 percent level. Hence, we allow for two factors in the G7 model, a result that is in line with the findings of Stock and Watson (2005) and Helbling and Bayoumi (2003)<sup>3</sup>. Next we include all G14 countries into the VAR model. At the 5 percent level, the test indicates the presence of three factors. Thus, adding the OIC countries to the G7 countries requires to increase the factor space by one dimension. This already suggests that the G14 sample may give new insights compared to the G7 sample often analyzed in the literature.

### 1.3.3 Factor identification

Based on our finding of two factors for the G7 sample and three factors for the G14 sample, we pursue the following identification scheme. In the first stage, we fit the FSVAR model to the G7 sample (“G7-FSVAR”) allowing for two factors which we denote by  $f_t^{G7}$ . We identify these two factors by means of a restriction imposed on the loading matrix  $\Gamma$ .

<sup>3</sup>Stock and Watson (2005) and Helbling and Bayoumi (2003) use G7 output data for the time periods 1960-2002 and 1973-2001, respectively.

TABLE 1.1: Tests of  $k$ -factor FSVAR vs. unrestricted VAR

Number of factors $k$	G7-FSVAR			G14-FSVAR		
	d.f.	LR statistic	$p$ -value	d.f.	LR statistic	$p$ -value
1	14	29.29	0.01	77	131.68	0.00
2	8	12.41	0.13	64	89.71	0.02
3	3	1.23	0.74	52	69.29	0.05

Notes: The likelihood ratio (LR) test statistic and the  $p$ -values are with respect to the null hypothesis that the VAR error covariance matrix has a  $k$  factor structure against the alternative that it is unrestricted.

Specifically, we restrict the loading coefficient of the second factor on US GDP to zero as proposed by Stock and Watson (2005). Similar to their findings, it turns out that the first factor represents a cluster of the three English-speaking countries Canada, UK, and US with particular relevance for the US (“US factor”), while the second factor reflects the commonalities of the euro area countries France, Germany, and Italy (“euro factor”).

In the second stage, we estimate the FSVAR model for the G14 sample (“G14-FSVAR”) allowing for three factors which we denote by  $f_t^{G14}$ . Our aim is to interpret the first two factors as comparable US and euro factors and the third one as an “OIC factor”, i.e., as a factor that reflects the additional commonalities of the OIC countries. To this end, we apply a factor rotation that maximizes the correlation of the first G14 factor,  $f_{1t}^{G14}$ , with the first G7 factor,  $f_{1t}^{G7}$ , and the correlation of the second G14 factor,  $f_{2t}^{G14}$ , with the second G7 factor,  $f_{2t}^{G7}$ . A description of the rotation scheme is provided in section A.1. This rotation also identifies the third factor because it is assumed to be orthogonal to the first two. Effectively, the third factor is merely uncorrelated to the two factors extracted from the G7 sample which suggest to interpret it as OIC factor.

To identify the three factors as US, euro, and OIC factors, we could also use zero restrictions on the loading matrix. We show in the robustness analysis in section 1.6 that such an approach yields very similar results.

## 1.4 Results of the FSVAR models

In this section we present forecast error variance decompositions and historical decompositions for the FSVAR models of the G7 and G14 samples estimated over the period 1991Q1-2014Q4. The aim is to assess the quantitative importance of the common factors and idiosyncratic shocks for the national business cycles. We place particular emphasis on the question whether shocks originating in the OIC affect the G7 to any relevant extent. In order to fully appreciate the G14 results, we also show the impulse responses to each of the factors.

### 1.4.1 Variance decompositions for the G7 sample

In the first stage of our estimation procedure, we estimate the two-factor G7-FSVAR which is exclusively based on the G7 sample. Thereby, the results are directly comparable to the literature that focuses on the G7.

Table 1.2 reports for GDP growth of each country  $i$  the forecast error variance shares accounted for by each of the common factors, by the idiosyncratic shock  $i$  of this country (“own shock”), and by the sum of all other idiosyncratic shocks which spill over from other countries (“spillovers”). As a general result, we find that short-term fluctuations ( $h = 1$  and  $h = 2$ ) are strongly driven by own shocks while spillovers are more relevant at business cycle frequencies ( $h = 4$  and  $h = 8$ ). A notable exception is the UK for which own shocks consistently account for more than 70 percent of the variance while spillovers are negligible at all horizons.

The two factors are relevant at all horizons, but particularly so at business cycle frequencies. The first factor affects all G7 countries. It accounts for more than 60 percent of the variance in US GDP growth at all horizons, which is why we label it a US factor. At horizons 4 and 8 it is also very important for Canada. For the UK it is less relevant but still explains the largest variance share that is not accounted for by the own shock of the UK. This suggests that the US factor represents a kind of business cycle cluster of the English-speaking countries which is in line with Helbling and Bayoumi (2003) and Stock and Watson (2005) who also report that one of the two factors that describe the G7 business cycle is particularly related to the US, Canada, and the UK.

The second factor is barely relevant for the US and Canada, and it explains only moderate fractions of the variance in GDP growth of Japan and the UK. Instead, it is highly important for fluctuations in GDP growth of the three euro area countries France, Germany, and Italy, both in the short-term and at business cycle frequencies. This pattern suggests that a euro area business cycle has emerged. Therefore, we label the second factor a euro factor. Again these findings are in line with the literature. Stock and Watson (2005) provide evidence of a euro zone factor from the mid-eighties on. In addition, there is a bulk of empirical papers documenting cyclical characteristics which are specific to the euro area as compared to global comovements, e.g., Artis and Zhang (1997), Artis and Zhang (1999), Del Negro and Otrok (2003), Luginbuhl and Koopman (2004), Crespo-Cuaresma and Fernández-Amador (2013).

### 1.4.2 Variance decompositions for the G14 sample

In the second stage of our estimation procedure, we estimate the three-factor G14-FSVAR. It is based on the full G14 sample with the first two factors being rotated such that they are as strongly correlated as possible with the two factors extracted from the G7 sample. As we are particularly interested in the role of the OIC for the G7 business cycle, we now separately report total spillovers from the G7 and total spillovers from the OIC.

Table 1.3 shows the variance decompositions for the G7. We find that the first factor is again the most important factor for the US, Canada, and the UK, whereas the second factor is quantitatively relevant mainly for France, Germany, and Italy. Hence, finding a cluster

TABLE 1.2: Forecast error variance decomposition based on the G7-FSVAR:  
Common shocks, spillovers, and own-country shocks

Country	$h$	Forecast error s.d.	Factor 1	Factor 2	Spillovers	Own shock
Canada	1	1.49	0.13	0.01	0.00	0.86
	2	1.38	0.28	0.06	0.04	0.62
	4	1.29	0.40	0.12	0.16	0.33
	8	1.10	0.40	0.11	0.31	0.18
France	1	1.39	0.11	0.51	0.00	0.39
	2	1.26	0.19	0.49	0.03	0.29
	4	1.17	0.27	0.46	0.07	0.20
	8	1.01	0.31	0.40	0.15	0.14
Germany	1	2.54	0.03	0.36	0.00	0.61
	2	2.15	0.10	0.52	0.06	0.32
	4	1.87	0.18	0.56	0.11	0.16
	8	1.58	0.24	0.52	0.16	0.08
Italy	1	2.01	0.02	0.62	0.00	0.36
	2	1.85	0.06	0.64	0.01	0.29
	4	1.64	0.11	0.61	0.05	0.23
	8	1.31	0.15	0.53	0.13	0.18
Japan	1	3.55	0.01	0.16	0.00	0.82
	2	2.89	0.08	0.19	0.06	0.67
	4	2.22	0.11	0.20	0.11	0.58
	8	1.49	0.14	0.20	0.14	0.52
UK	1	1.65	0.11	0.14	0.00	0.74
	2	1.61	0.15	0.13	0.02	0.70
	4	1.62	0.16	0.11	0.03	0.70
	8	1.47	0.16	0.08	0.04	0.73
US	1	1.85	0.94	0.00	0.00	0.06
	2	1.55	0.86	0.01	0.09	0.04
	4	1.45	0.73	0.02	0.22	0.03
	8	1.27	0.62	0.02	0.33	0.02

Notes: The table shows the square root of the forecast error variance of detrended GDP growth and its decomposition into factors, spillovers, and own shocks. The results are based on the two-factor G7-FSVAR. The standard deviations are in percentage points at an annual level, i.e.  $400/h$  times the forecast error where  $h$  is the forecast horizon.



of English-speaking countries and a cluster of euro area countries is robust to the inclusion of more countries into the sample. However, increasing the set of countries produces also a notable difference: The first factor loses some of its relevance for the US business cycle (mainly due to the inclusion of Mexico). Using the G14 sample it is estimated to account for 59 percent of the short-term fluctuations in US GDP, while using the G7 sample it was found to account for 94 percent which is not very plausible. Including more countries appears to help distinguishing between international factors and country-specific shocks.

The third factor has a small share in the forecast error variance of the G7. This is in line with the LR test which indicated that two factors are sufficient to describe the commonalities of the G7. However, it does not mean that business cycle fluctuations originating in the OIC are irrelevant for the G7. In fact, at business cycle frequencies of  $h = 4$  and  $h = 8$ , spillovers from the OIC are approximately as important as spillovers from other G7 countries and affect particularly Germany, Italy, and Japan which are countries that export relatively large shares of their GDP to the OIC. For these countries a portion of up to 17, 22, and 19 percent is attributed to idiosyncratic shocks in the OIC, respectively. The total effect of the OIC on the G7 countries defined as the sum of the variance shares explained by the third factor and the spillovers from the OIC, is even higher. It ranges between 10 and 23 percent at the horizon of eight quarters.

Own shocks are mainly responsible for fluctuations in the short-term and much less at business cycle frequencies. For Italy and France, they are even of moderate relevance at the one quarter horizon. This finding is in line with the result of Crucini et al. (2011) that France and Italy are the most integrated countries out of the G7 group.

Table 1.4 shows the variance decompositions for the OIC. Similar to Kose et al. (2012), we find that the share of idiosyncratic shocks is larger in the OIC than in the G7. With the exception of Brazil and Mexico own shocks account for more than 50 percent of the error variance, even at business cycle frequencies. This finding may partly be a consequence of national crises (“Efecto tequila”, Asian crisis) that took place during the 1990s. Nevertheless, international factors and spillovers turn out to be relevant. Not surprisingly, the US factor affects mainly Mexico and, to some extent, the Asian countries. The euro factor appears to have some explanatory power for Turkey and China, and particularly Brazil. (The latter is somewhat unexpected because Brazil trades more with the US than with the euro area. We come back to this issue when we discuss the historical decomposition below.) The OIC factor accounts for non-negligible fractions in the variance of Brazilian and Asian GDP growth but is of minor importance for Mexico, South Africa, and Turkey.

Let us summarize the two main findings of the forecast error variance decomposition. First, we document that shocks originating in the OIC explain G7 GDP growth to a notable extent at business cycle frequencies. Hence, neglecting non-G7 countries may lead to an incomplete assessment of the sources and commonalities of G7 business cycle fluctuations. Second, our findings are consistent with the narrative in the literature that group- and regional-specific factors have emerged during the globalization era, as we identify two business cycle clusters of English-speaking countries and euro area countries. The OIC are much more heterogenous which is why no clear OIC factor emerged (even though we label

TABLE 1.3: Forecast error variance decomposition based on the G14-FSVAR: Common shocks, spillovers, and own-country shocks for the G7

Country	$h$	Forecast error s.d.	Factor 1	Factor 2	Factor 3	Spillovers from G7	Spillovers from OIC	Own shock
Canada	1	1.34	0.24	0.00	0.00	0.00	0.00	0.76
	2	1.32	0.41	0.04	0.00	0.03	0.04	0.48
	4	1.23	0.49	0.07	0.00	0.14	0.04	0.24
	8	1.07	0.42	0.06	0.02	0.28	0.08	0.13
France	1	1.33	0.15	0.41	0.00	0.00	0.00	0.45
	2	1.16	0.22	0.39	0.00	0.03	0.02	0.35
	4	1.09	0.27	0.34	0.00	0.09	0.08	0.23
	8	0.96	0.26	0.25	0.01	0.19	0.15	0.14
Germany	1	2.42	0.10	0.23	0.00	0.00	0.00	0.67
	2	2.01	0.18	0.37	0.01	0.06	0.02	0.36
	4	1.78	0.23	0.36	0.01	0.13	0.10	0.18
	8	1.59	0.24	0.29	0.00	0.22	0.17	0.09
Italy	1	1.79	0.05	0.65	0.02	0.00	0.00	0.28
	2	1.66	0.08	0.61	0.02	0.02	0.06	0.20
	4	1.54	0.11	0.47	0.01	0.10	0.17	0.13
	8	1.32	0.12	0.33	0.01	0.22	0.22	0.10
Japan	1	3.20	0.04	0.10	0.00	0.00	0.00	0.86
	2	2.67	0.09	0.12	0.02	0.09	0.05	0.64
	4	2.06	0.09	0.11	0.01	0.15	0.13	0.51
	8	1.40	0.09	0.09	0.01	0.23	0.19	0.40
UK	1	1.61	0.21	0.13	0.06	0.00	0.00	0.60
	2	1.54	0.20	0.12	0.05	0.02	0.01	0.59
	4	1.57	0.17	0.09	0.05	0.03	0.05	0.61
	8	1.48	0.14	0.06	0.06	0.04	0.08	0.62
US	1	1.78	0.59	0.00	0.00	0.00	0.00	0.41
	2	1.50	0.58	0.01	0.02	0.07	0.02	0.30
	4	1.40	0.50	0.02	0.04	0.16	0.05	0.23
	8	1.23	0.41	0.01	0.06	0.24	0.10	0.19

Notes: The table shows the square root of the forecast error variance of detrended GDP growth and its decomposition into factors, spillovers, and own shocks. The results are based on the three factor G14-FSVAR. The standard deviations are in percentage points at an annual level, i.e.  $400/h$  times the forecast error where  $h$  is the forecast horizon.

TABLE 1.4: Forecast error variance decomposition based on the G14-FSVAR: Common shocks, spillovers, and own-country shocks for the OIC

Country	$h$	Forecast error s.d.	Factor 1	Factor 2	Factor 3	Spillovers from G7	Spillovers from OIC	Own shock
Australia	1	1.86	0.18	0.00	0.01	0.00	0.00	0.80
	2	1.25	0.18	0.00	0.03	0.03	0.05	0.70
	4	0.84	0.16	0.00	0.07	0.07	0.07	0.62
	8	0.52	0.19	0.01	0.09	0.11	0.07	0.54
Brazil	1	4.57	0.03	0.25	0.39	0.00	0.00	0.33
	2	3.51	0.06	0.24	0.37	0.01	0.03	0.29
	4	2.47	0.08	0.24	0.32	0.03	0.07	0.25
	8	1.62	0.10	0.25	0.29	0.07	0.09	0.21
China	1	1.91	0.06	0.16	0.08	0.00	0.00	0.70
	2	1.61	0.09	0.17	0.10	0.02	0.02	0.60
	4	1.34	0.08	0.17	0.09	0.05	0.03	0.58
	8	1.24	0.07	0.15	0.08	0.05	0.03	0.61
Mexico	1	3.72	0.16	0.03	0.01	0.00	0.00	0.79
	2	3.37	0.25	0.06	0.02	0.03	0.01	0.64
	4	2.80	0.32	0.08	0.02	0.10	0.01	0.47
	8	2.00	0.34	0.08	0.04	0.14	0.01	0.39
South Africa	1	1.82	0.02	0.03	0.09	0.00	0.00	0.86
	2	1.70	0.04	0.05	0.08	0.03	0.01	0.79
	4	1.68	0.06	0.05	0.07	0.08	0.02	0.73
	8	1.49	0.06	0.04	0.04	0.17	0.04	0.66
South Korea	1	3.96	0.10	0.04	0.17	0.00	0.00	0.69
	2	3.30	0.11	0.03	0.16	0.02	0.02	0.65
	4	2.70	0.09	0.02	0.14	0.08	0.07	0.61
	8	1.88	0.08	0.01	0.11	0.14	0.08	0.57
Turkey	1	7.82	0.03	0.13	0.05	0.00	0.00	0.79
	2	6.07	0.06	0.12	0.07	0.04	0.02	0.69
	4	4.59	0.07	0.10	0.06	0.11	0.04	0.62
	8	2.95	0.07	0.08	0.04	0.19	0.04	0.57

Notes: The table shows the square root of the forecast error variance of detrended GDP growth and its decomposition into factors, spillovers, and own shocks. The results are based on the three factor G14-FSVAR. The standard deviations are in percentage points at an annual level, i.e.  $400/h$  times the forecast error where  $h$  is the forecast horizon.

it so). Based on the findings of Mumtaz et al. (2011) and Hirata et al. (2013) we conjecture that once quarterly GDP data of more countries become available for longer time periods, a comparable analysis to ours may yield more than one additional factor which then can be interpreted more straightforwardly as regional business cycle factors.

### 1.4.3 Historical decompositions for the G14 sample

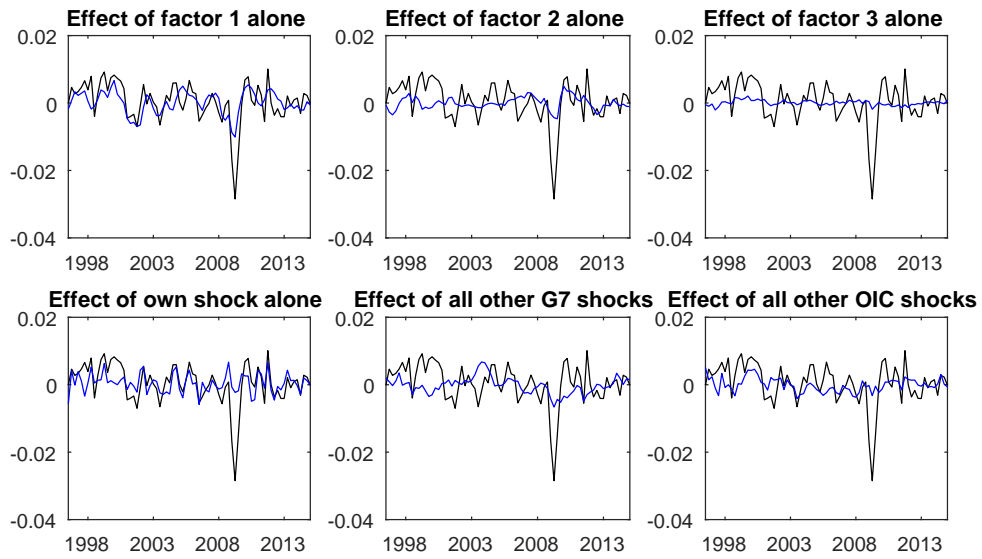
Next we use the G14-FSVAR to assess for each country how the various shocks and factors contributed to the observed fluctuations in detrended GDP growth. These historical decompositions are displayed in Figures 1.3 to 1.16. In each panel of a figure we depict realized GDP growth (black) together with a hypothetical series (blue) that results from a counterfactual analysis in which certain shocks are set to their estimates and all others are shut down. Specifically, we report the contributions of: factors one to three in the three upper panels, the own shock in the lower left panel, all idiosyncratic G7 shocks (except for the own shock if a G7 country is considered) in the lower middle panel, and all idiosyncratic OIC shocks (except for the own shock if a OIC country is considered) in the lower right panel. This allows us to assess how relevant factors, idiosyncratic shocks and spillovers are for specific historical episodes.

The most pronounced episode in the sample is the Great Recession which is visible as a large negative spike for all countries at the end of 2008 or the beginning of 2009. The decomposition indicates that both the US and the euro factor contributed strongly to the Great Recession. The idiosyncratic shocks of Germany, the UK, Brazil, China, and Mexico also account for part of the downturn in these countries and subsequently spilled over to other countries. According to these results, the Great Recession was thus the outcome of a multitude of international and country-specific shocks.

The European debt crisis that started in 2010 is clearly visible in the evolution of French, German, and Italian GDP growth and almost fully absorbed by the second factor. This observation strengthens its interpretation as a euro factor. Based on the historical decomposition, we can now also answer the question why the euro factor accounts for about a quarter of the forecast error variance of Brazilian GDP growth. The upper middle panel of Figure 1.11 shows that the euro factor contributed markedly to the Brazilian business cycle during the Great Recession but also at the end of the 1990s and during the European debt crisis.

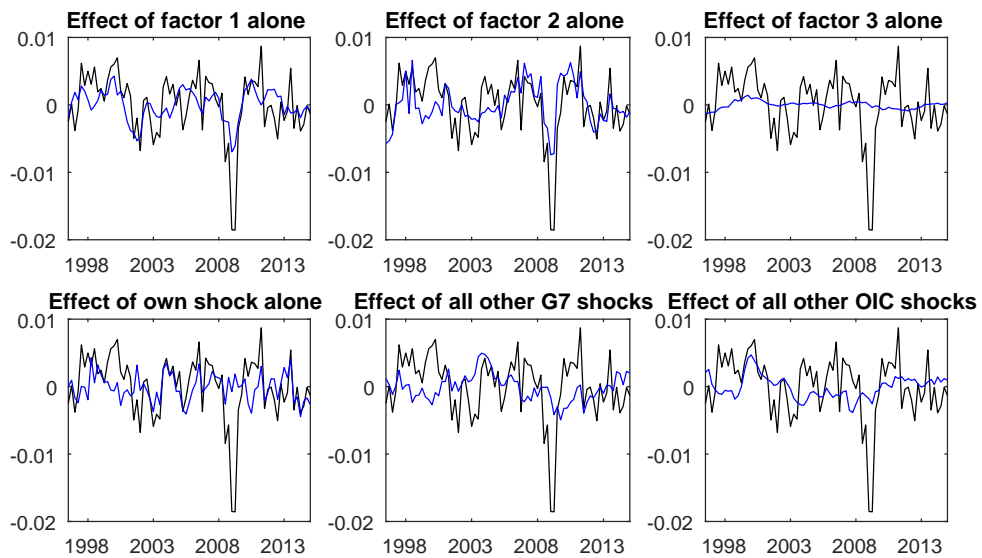
Finally, we use the historical decomposition to better understand the relevance of the OIC for the G7 business cycles. While the OIC factor has little to say about G7 GDP growth, spillovers from idiosyncratic OIC shocks make a difference (see lower right panels in Figures 1.3 to 1.9). In particular, the recovery from the Asian crisis after 1998 and the subsequent slowdown appears to have contributed to the business cycles in the euro area countries but also, to a smaller extent, in Canada and Japan.

FIGURE 1.3: Historical decompositions – Canada



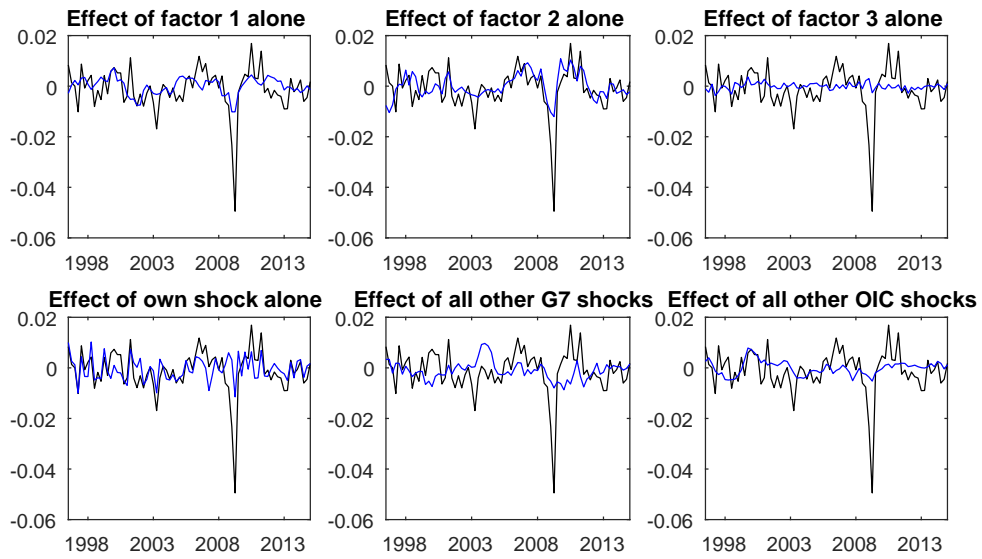
Notes: In each panel of the figure we show the realized series of detrended GDP growth (black) and a hypothetical series (blue) that is implied by the G14-FSVAR. The hypothetical series results from a counterfactual analysis in which one (set of) structural shock(s) is allowed for. Details are given in section 1.4.3.

FIGURE 1.4: Historical decompositions – France



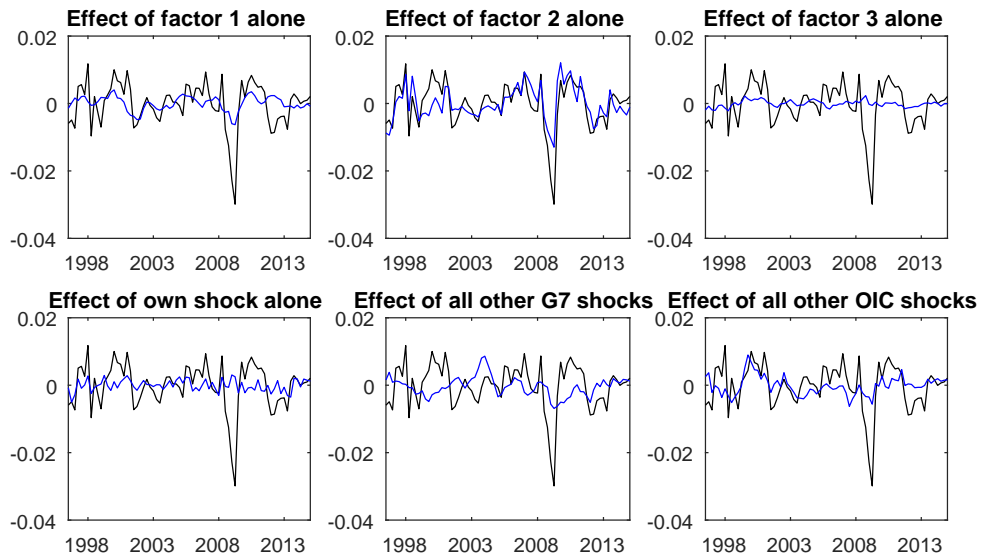
See figure 1.3 for a detailed description of the graphs.

FIGURE 1.5: Historical decompositions – Germany



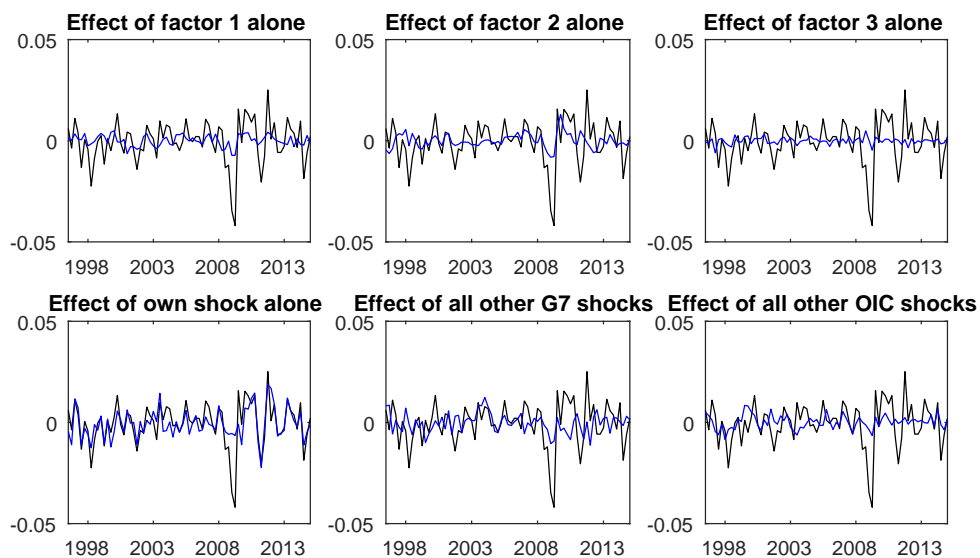
See figure 1.3 for a detailed description of the graphs.

FIGURE 1.6: Historical decompositions – Italy



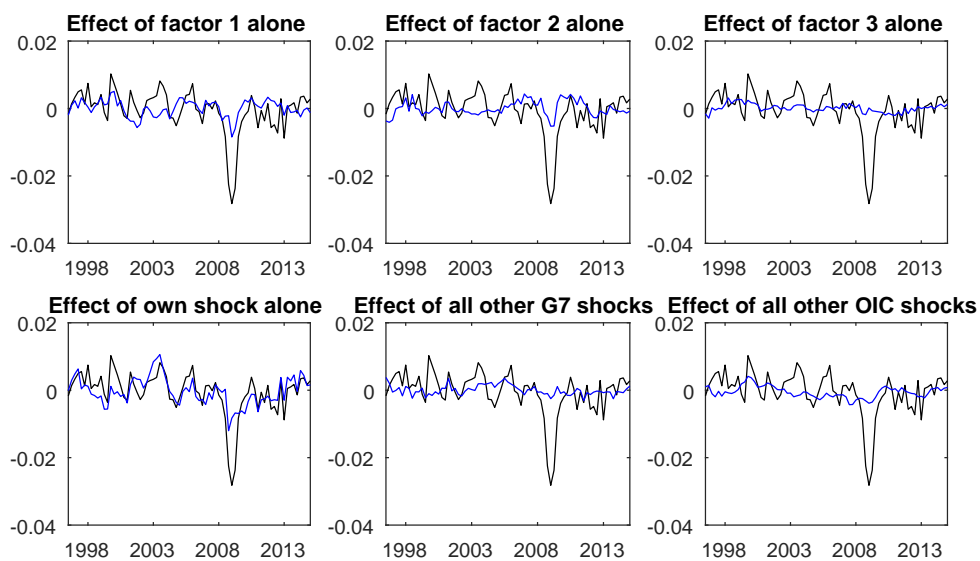
See figure 1.3 for a detailed description of the graphs.

FIGURE 1.7: Historical decompositions – Japan



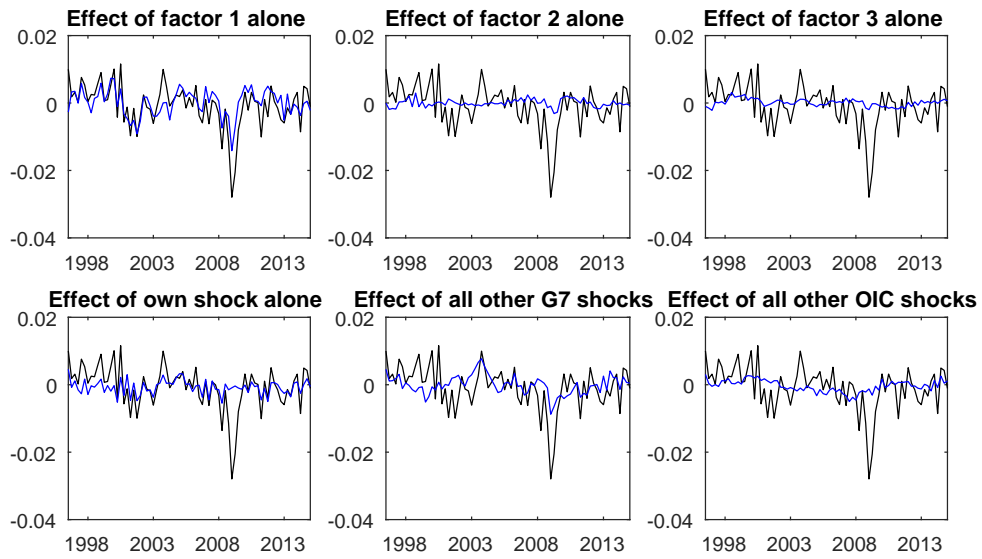
See figure 1.3 for a detailed description of the graphs.

FIGURE 1.8: Historical decompositions – UK



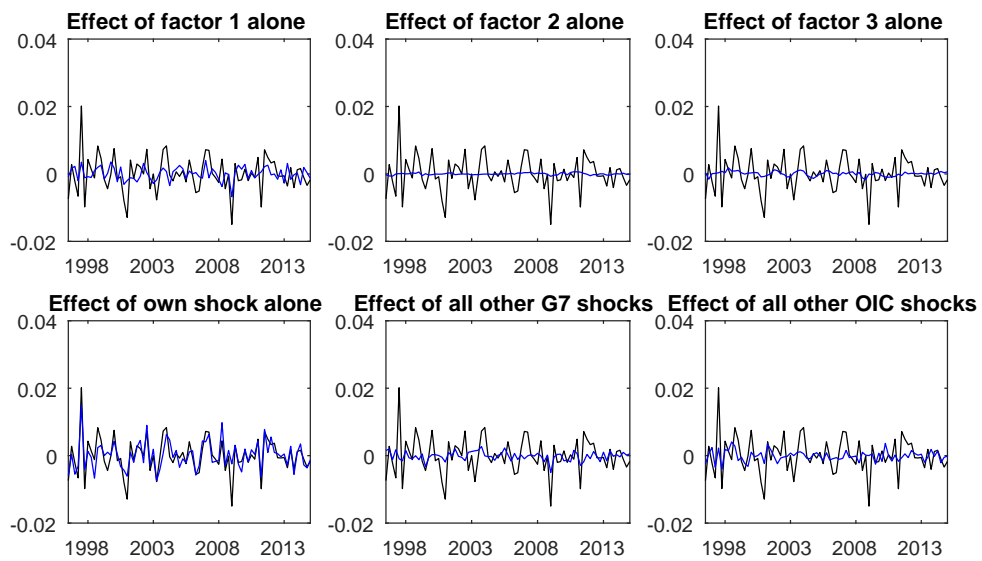
See figure 1.3 for a detailed description of the graphs.

FIGURE 1.9: Historical decompositions – US



See figure 1.3 for a detailed description of the graphs.

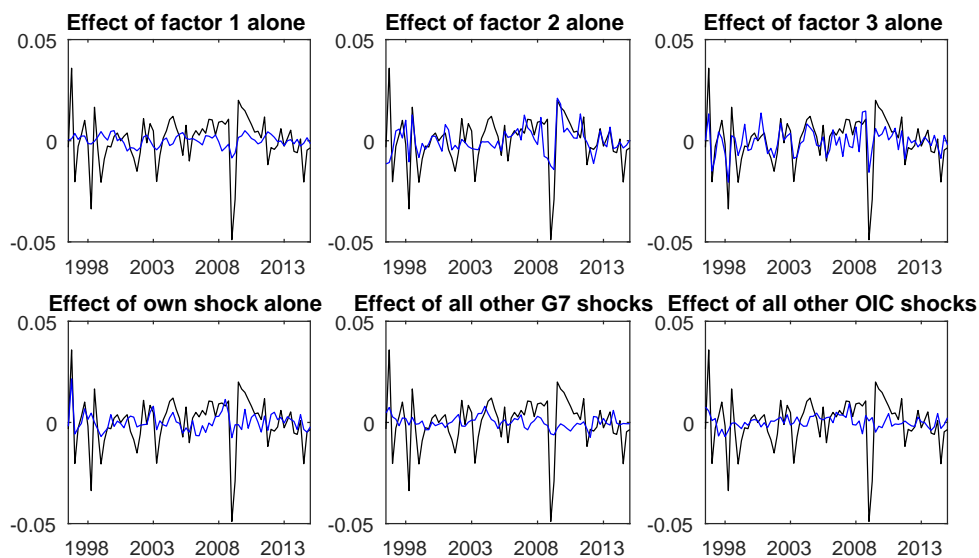
FIGURE 1.10: Historical decompositions – Australia



See figure 1.3 for a detailed description of the graphs.

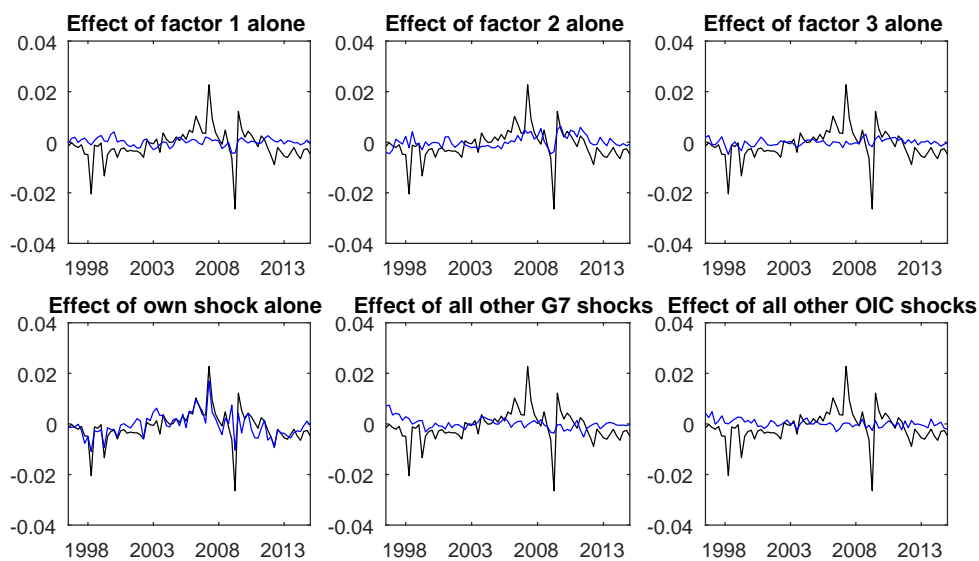


FIGURE 1.11: Historical decompositions – Brazil



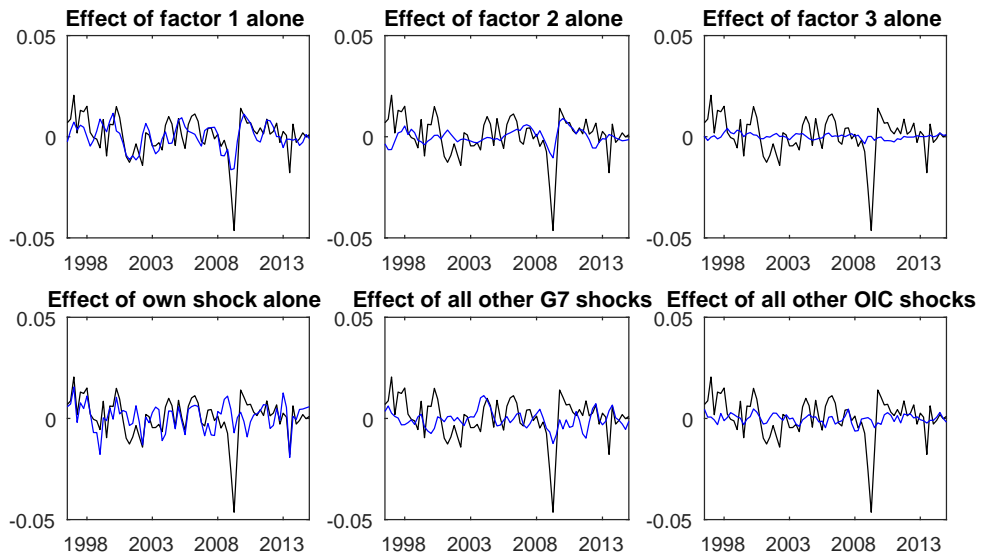
See figure 1.3 for a detailed description of the graphs.

FIGURE 1.12: Historical decompositions – China



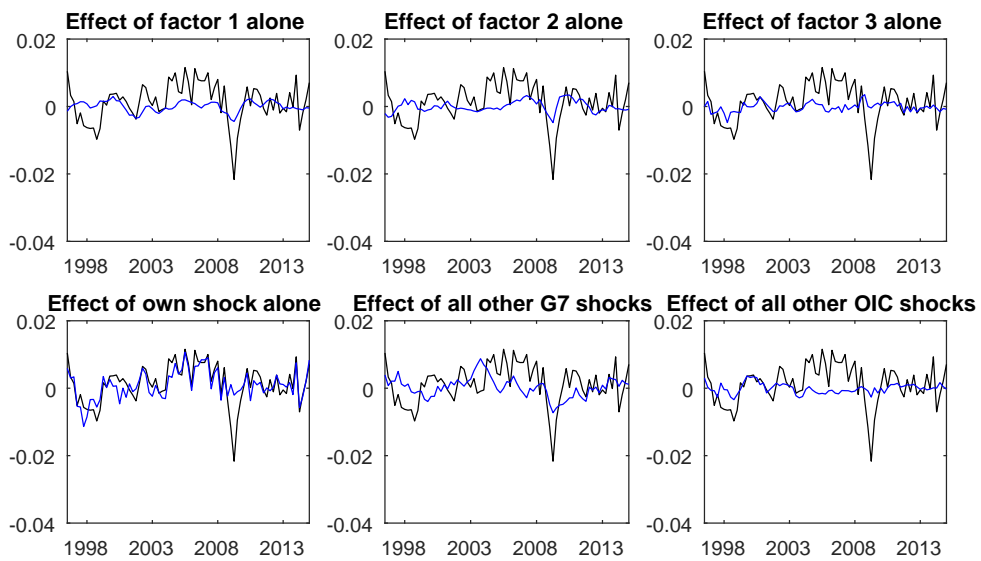
See figure 1.3 for a detailed description of the graphs.

FIGURE 1.13: Historical decompositions – Mexico



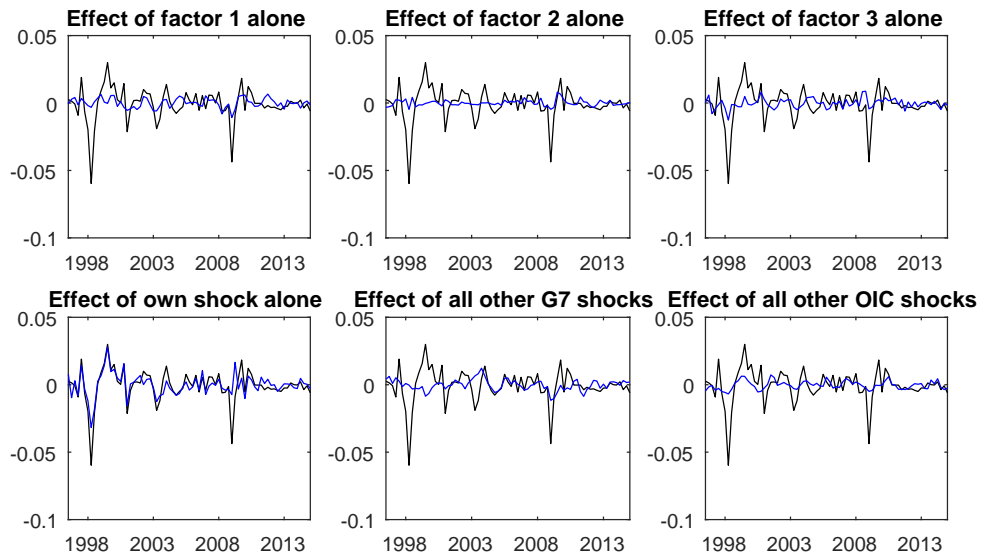
See figure 1.3 for a detailed description of the graphs.

FIGURE 1.14: Historical decompositions – South Africa



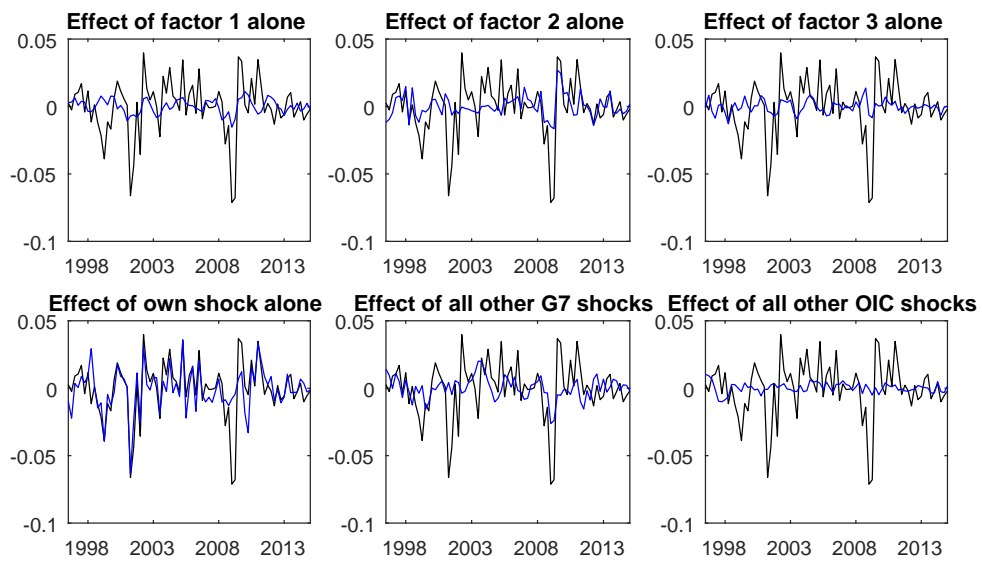
See figure 1.3 for a detailed description of the graphs.

FIGURE 1.15: Historical decompositions – South Korea



See figure 1.3 for a detailed description of the graphs.

FIGURE 1.16: Historical decompositions – Turkey



See figure 1.3 for a detailed description of the graphs.

#### 1.4.4 Impulse response functions for the G14 sample

In order to fully appreciate the results of the G14 sample, we show the impulse responses of detrended GDP growth to an increase of one standard deviation in each of the factors, see Figures 1.17 to 1.20 where we display the point estimates together with a bootstrapped 68 percent confidence interval.

The instantaneous responses to the US factor are positive in all countries and fade out after 4 to 6 quarters implying that an expansion in the US goes hand in hand with a simultaneous world upswing. The point estimates appear quantitatively relevant for most countries even if statistical significance as indicated by the confidence interval is limited to Canada, UK, US, Australia, and Mexico. Given the relatively short sample, the latter is not very surprising.

The euro factor has quantitatively relevant and statistically significant positive effects on all countries except for the US, which is by assumption, and Australia. They are particularly pronounced and statistically significant in the European countries but also in Japan, Brazil, China, and Turkey, which coincides well with the results of the forecast error variance decomposition.

The OIC factor has negligible effects on the G7 countries. Given our identifying restrictions, this is expected. However, an increase in the OIC factor strongly and significantly elevates detrended GDP growth in the Asian OIC countries (China, South Korea, Turkey), and in Brazil and South Africa. This corroborates our interpretation of it as an OIC, and not a purely regional, shock.

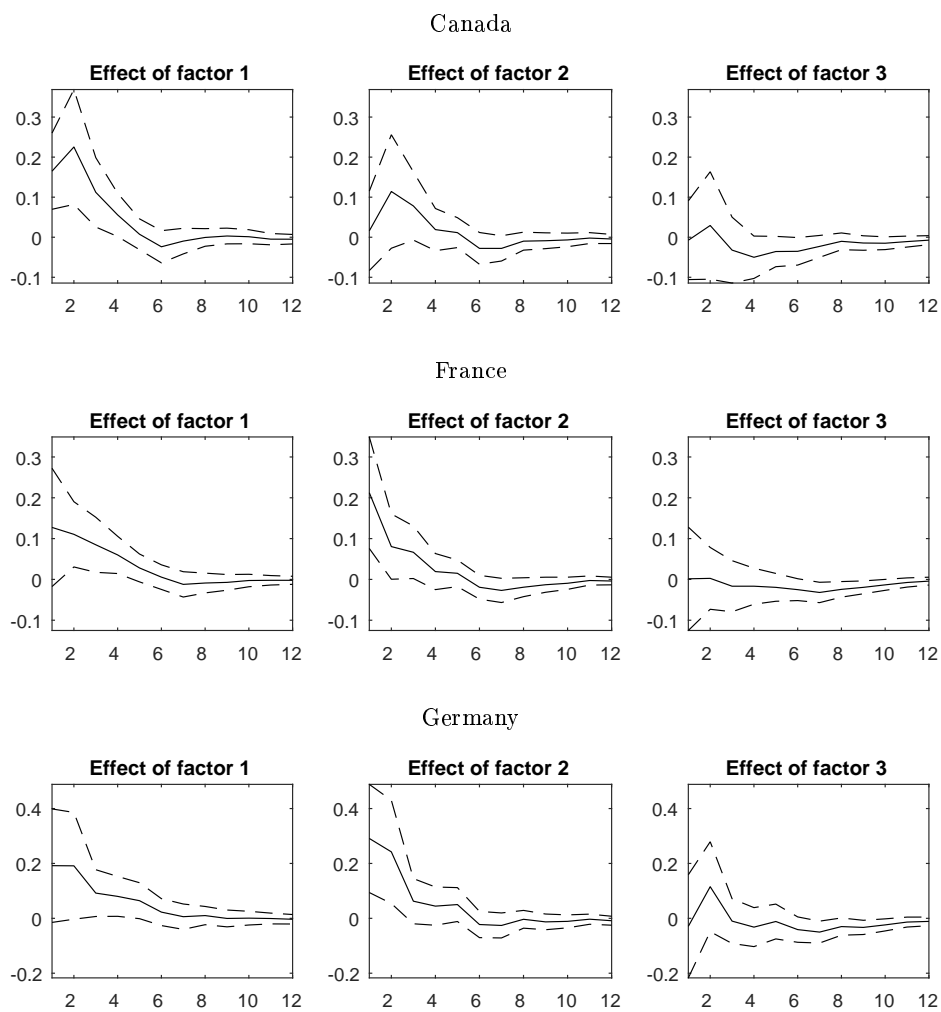
### 1.5 The relevance of OIC shocks

In this section, we further assess the relevance of fluctuations originating from outside the G7 for the global and G7 business cycles. To this end, we estimate for important global and G7 macroeconomic indicators the forecast error variance shares accounted for by the OIC factor and the idiosyncratic OIC shocks. All indicators are made stationary by taking (log) differences if necessary. In addition, we filtered out any secular trend by applying the same detrending procedure as for GDP growth (for details, see section A.4).

#### 1.5.1 Indicators of the world business cycle

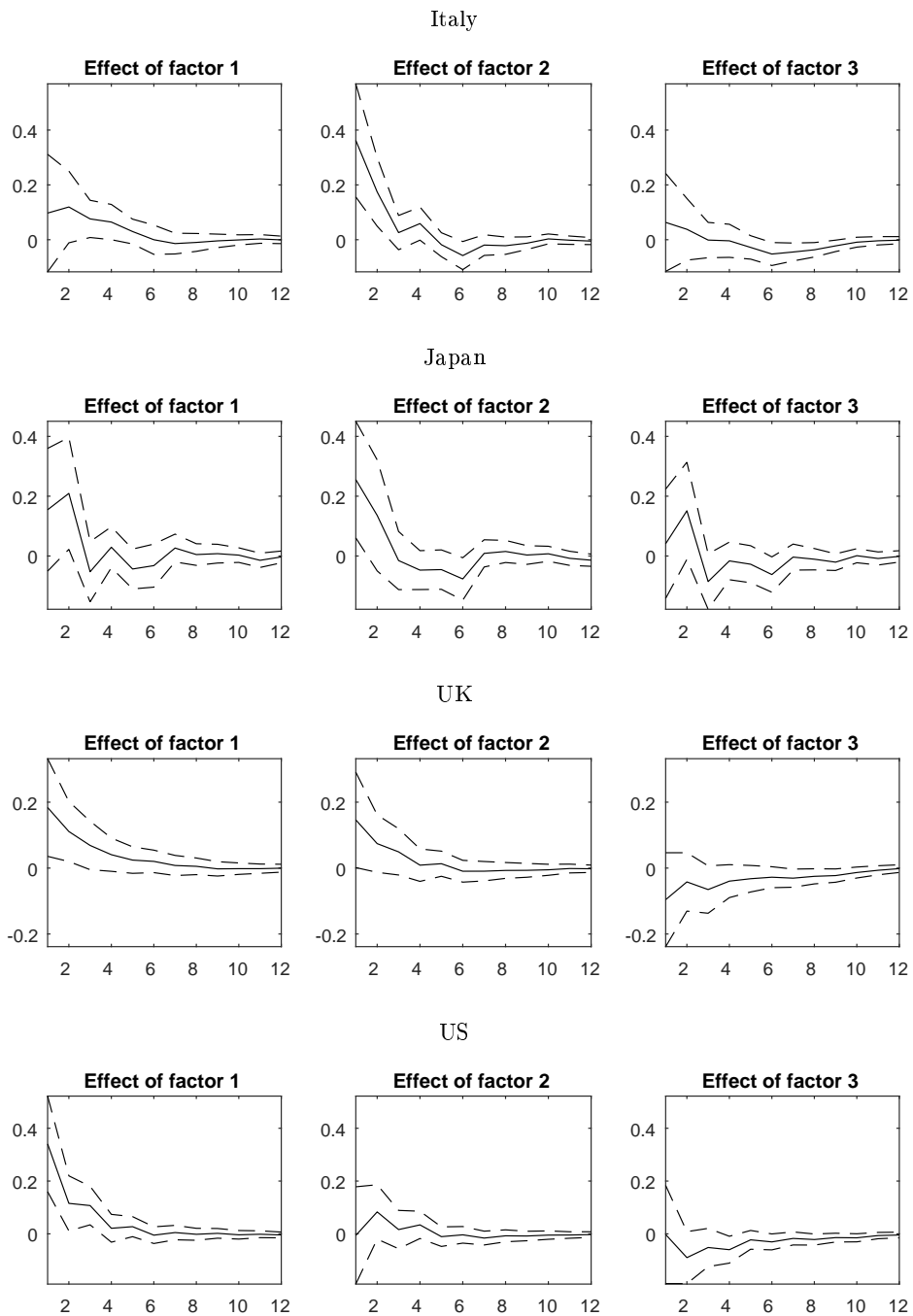
In the first step, we focus on the association between OIC shocks and global business cycle indicators  $z_{it}$ . A straightforward way to measure this association is to augment the G14-FSVAR with the indicators, re-estimate it, and invert it to compute  $h$ -step forecast error variance decompositions. However, this would entail estimating a large number of extra parameters in an already highly parameterized model or require additional zero restrictions that are potentially controversial. Therefore, we directly estimate the inverted augmented G14-FSVAR, see Kilian (2009) for a comparable approach. Specifically, consider the moving average representation of such an augmented FSVAR of which the equation for an

FIGURE 1.17: Impulse response functions



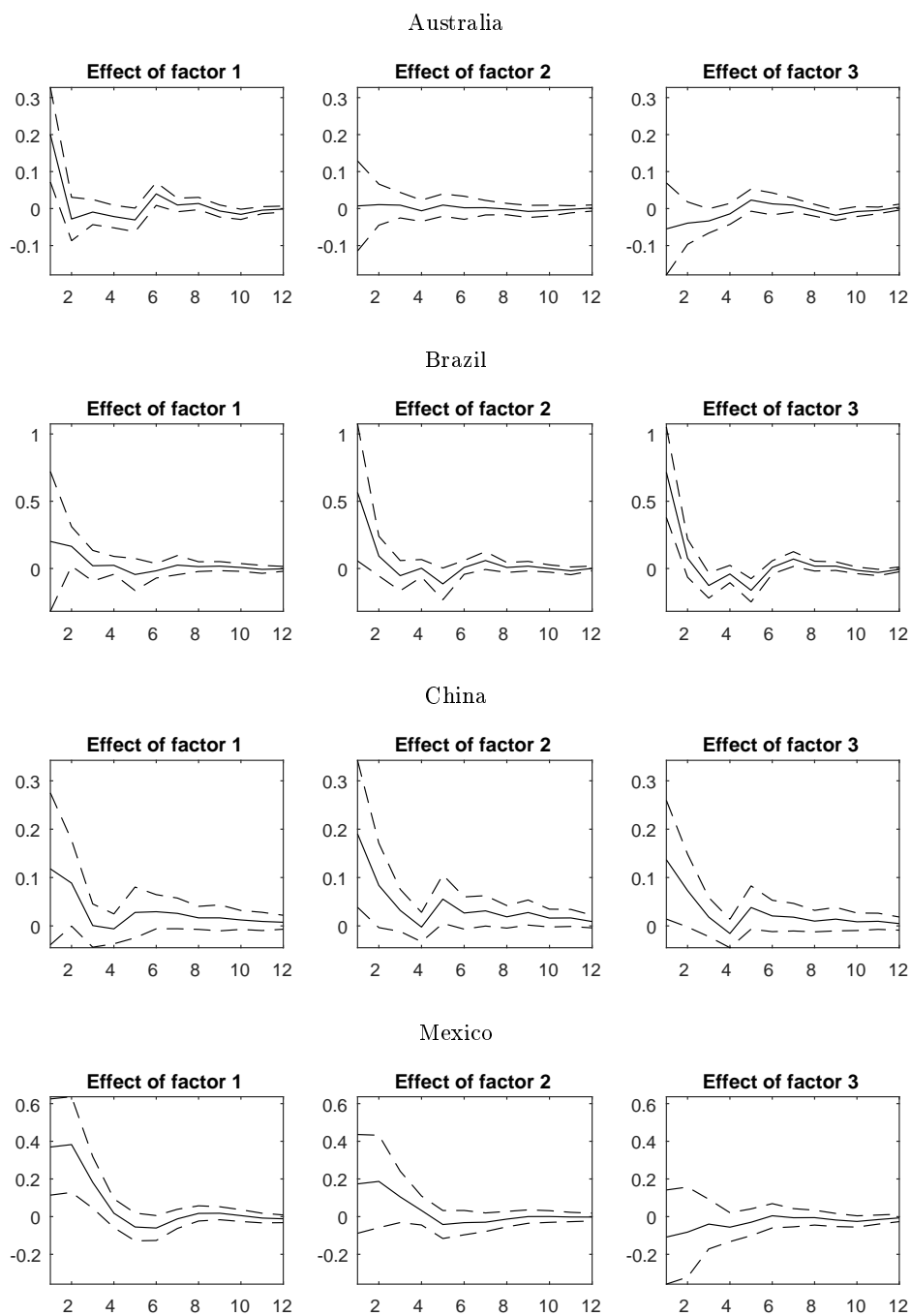
Notes: In each figure we show the impulse response functions of detrended GDP growth to a shock of one standard deviations in the factors 1-3. The black solid lines are impulse responses from the G14-FSVAR. The dashed black lines are the respective standard deviations resulting from a bootstrapping and 1000 re-estimations.

FIGURE 1.18: Impulse response functions



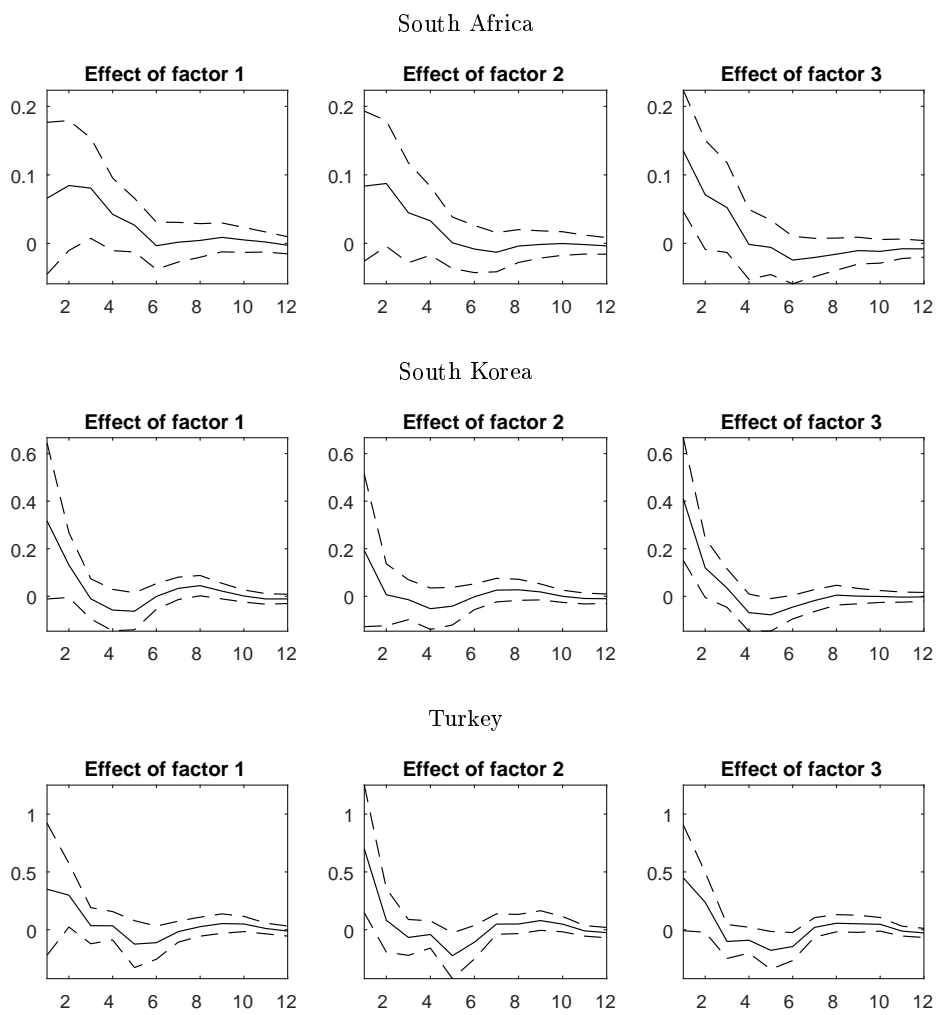
See figure 1.17 for a detailed description of the graphs.

FIGURE 1.19: Impulse response functions



See figure 1.17 for a detailed description of the graphs.

FIGURE 1.20: Impulse response functions



See figure 1.17 for a detailed description of the graphs.



indicator  $z_{it}$  is

$$z_{it} = [\phi_0^1 \ \phi_0^2 \ \phi_0^3] \begin{pmatrix} f_t \\ \xi_t \\ \varepsilon_t \end{pmatrix} + [\phi_1^1 \ \phi_1^2 \ \phi_1^3] \begin{pmatrix} f_{t-1} \\ \xi_{t-1} \\ \varepsilon_{t-1} \end{pmatrix} + \dots,$$

where  $f_t$  denotes the  $(3 \times 1)$  dimensional vector of global factors,  $\xi_t$  denotes the  $(14 \times 1)$  dimensional vector of idiosyncratic shocks, and  $\varepsilon_t$  takes up all additional shocks. By assumption,  $f_t$ ,  $\xi_t$ , and  $\varepsilon_t$  are mutually and serially uncorrelated. Hence, to infer the 1-step forecast error variance share accounted for by OIC shocks, we simply compute the R-squared,  $R_{\text{OIC}}^2$ , of the regression

$$z_{it} = \phi_0^{1,\text{OIC}} f_t^{\text{OIC}} + \phi_0^{2,\text{OIC}} \xi_t^{\text{OIC}} + u_t,$$

where  $f_t^{\text{OIC}}$  denotes the OIC factor, and  $\xi_t^{\text{OIC}}$  denotes the  $(7 \times 1)$  dimensional vector of idiosyncratic OIC shocks. Similarly, for the G7 we compute the R-squared,  $R_{\text{G7}}^2$ , of the regression

$$z_{it} = \phi_0^{1,\text{G7}} f_t^{\text{G7}} + \phi_0^{2,\text{G7}} \xi_t^{\text{G7}} + u_t,$$

where  $f_t^{\text{G7}}$  denotes the two G7 factors, and  $\xi_t^{\text{G7}}$  denotes the  $(7 \times 1)$  dimensional vector of idiosyncratic G7 shocks.

To obtain the 2-step forecast error variance share accounted for by OIC shocks, we compute the R-squared of the regression

$$z_{it} = \phi_0^{1,\text{OIC}} f_t^{\text{OIC}} + \phi_0^{2,\text{OIC}} \xi_t^{\text{OIC}} + \phi_1^{1,\text{OIC}} f_{t-1}^{\text{OIC}} + \phi_1^{2,\text{OIC}} \xi_{t-1}^{\text{OIC}} + u_t$$

and compare it to the R-squared of an analogous regression for the G7. Due to the limited number of observations in our sample, we refrain from estimating forecast error variance shares for forecasts of higher horizon than two even though this seems fruitful given that OIC shocks are particularly relevant at business cycle frequencies.

In Table 1.5 we report the variance shares of detrended global macro indicators accounted for by all shocks extracted from the G14-FSVAR (computed as  $R_{\text{G7}}^2 + R_{\text{OIC}}^2$ ) and the relative importance of the OIC factor and shocks (computed as  $R_{\text{OIC}}^2 / (R_{\text{G7}}^2 + R_{\text{OIC}}^2)$ ). Note that the assumption of mutual and serial uncorrelatedness is not exactly satisfied in sample. While there remains only a limited amount of cross-correlation, we nevertheless orthogonalize the OIC factor and each idiosyncratic OIC shock as follows. We regress each of them on the G7 factors and idiosyncratic G7 shocks and use the residuals. This parallels a Choleski decomposition and thus implies an ordering of G7 before the OIC. Therefore, the variance shares accounted for by OIC factors and shocks should be interpreted as lower bound estimates.

We find that all G14 shocks together account for a large fraction of the forecast error variance of all included global macro indicators. This is expected because the G14 contribute 70% percent to world output. Shocks originating in the OIC play an interesting role. While they are moderately relevant for fluctuations in real quantities like OECD GDP, world industrial production, and world trade, their relative R-squared varies between 10

TABLE 1.5: Forecast error variance shares of global business cycle indicators accounted for by G7 and OIC shocks

Indicator	All shocks		OIC shocks	
	$h = 1$	$h = 2$	$h = 1$	$h = 2$
OECD GDP	0.39	0.71	0.01	0.06
World industrial production	0.33	0.69	0.03	0.10
CPB world trade	0.27	0.57	0.01	0.11
CPB manufacturing prices	0.13	0.39	0.29	0.19
Brent oil price	0.33	0.57	0.27	0.43
World fuel prices	0.38	0.63	0.29	0.44
World commodity prices	0.36	0.51	0.10	0.16
MSCI World	0.34	0.54	0.15	0.22
Inflation volatility	0.16	0.42	0.26	0.33
Stock market volatility	0.26	0.54	0.18	0.18
Exchange rate volatility	0.40	0.60	0.42	0.53

Note:  $h$  denotes the forecast horizon. The columns “All shocks” report the variance share accounted for by all factors and shocks extracted from the G14-FSVAR,  $R_{G7}^2 + R_{OIC}^2$ . The columns “OIC shocks” report the variance share of all shocks accounted for by OIC factors and shocks,  $R_{OIC}^2 / (R_{G7}^2 + R_{OIC}^2)$ . The variables are described in section A.4.

and 53 percent for world market prices and price volatilities. For example, all G14 shocks explain 33 percent of the one-quarter ahead variance and 57 percent of the two-quarter ahead variance of the Brent oil price, of which 27 percent and 43 percent, respectively, are contributed by OIC shocks. This result is in line with Aastveit et al. (2015) and Kilian and Hicks (2013) who find that demand shocks in the emerging markets have contributed markedly to the rise in oil prices during the past decade. The numbers are also relatively high for inflation and exchange rate volatility. Even 22 percent of the two-quarter ahead variance in the world MSCI that can be explained by G14 shocks are accounted for by the OIC. These results parallel the finding of Eickmeier and Kühnlenz (2016) who find that Chinese shocks affect global inflation dynamics significantly.

We thus conclude that OIC shocks are particularly important for high-frequency fluctuations in international price movements and volatilities, much more than for quantities. This indicates that, at the horizon of half a year, prices react much more elastically to OIC shocks than quantities. With the limited data set at hand it is however difficult to speculate about the reasons. One possibility is that prices overshoot while output and trade volumes are generally less affected by developments within the OIC. However, we tend to the interpretation that real quantities simply react with a delay of 4 or even 8 quarters, a regularity we uncovered above using the G14-FSVAR. We leave this question to future research because it requires the availability of longer time series which would allow us to estimate regressions for, say, horizons  $h = 4$  and  $h = 8$ .

### 1.5.2 Indicators of the national G7 business cycles

In the next step, we assess the relationship between OIC shocks and national business cycle indicators of the G7. We estimate 1-step and 2-step forecast error variance shares in the same way as above. We report the relative importance of the OIC factor and shocks, again computed as  $R_{\text{OIC}}^2 / (R_{\text{G7}}^2 + R_{\text{OIC}}^2)$ , in Table 1.6.

The results indicate that OIC shocks are relevant for important aspects of the G7 business cycles that are complementary to GDP. We replicate our previous finding that OIC shocks do not contribute appreciably to the understanding of short-run GDP fluctuations<sup>4</sup>. Similarly, at the one and two quarter horizon they generally have also limited explanatory power for GDP components such as investment, private consumption, imports, and exports. In contrast, they contribute, relative to G7 shocks, noticeably to fluctuations in variables of the labor market (employment, unemployment rate) and the external sector (current account balance in percent of GDP, real and nominal effective exchange rate). As already documented for the world indicators above, we also find that OIC shocks account for non-negligible fractions of the forecast variance in nominal variables (inflation, interest rate, stock market returns) and volatilities. Again, this picture may change once longer time series become available and typical business cycle horizons like  $h = 4$  and  $h = 8$  can be examined.

## 1.6 Robustness checks

In this section we report the results of an extensive robustness analysis. Table 1.7 displays, for each country, the forecast error variance decomposition at horizon  $h = 4$  computed from the three factor G14-FSVAR. In the first row of each country panel, we report the results of the baseline G14-FSVAR discussed above. In the subsequent rows we show the outcomes of various ceteris-paribus changes in the estimation setup. We discuss the details in the following.

### Clustered factor loadings

In the baseline G14-FSVAR, we rotated the first two factors such that their correlation with the two factors of the G7-FSVAR was maximized. By this procedure, the factor loading matrix  $\Gamma$  was implicitly defined. Alternatively, in accordance with the literature and our previous findings, we now identify a continental-European and an English-speaking business cycle cluster by directly restricting the factor loading matrix. Specifically, we restrict the first factor to load only on Canada, the UK, and US; the second factor to load only on France, Germany, and Italy; and the third factor to load only on the OIC.

The results are qualitatively robust to the baseline (see row “Clustered loadings”). The three factors identified under the baseline and alternative identification procedures exhibit large correlations with each other (96% for the first factor, 77% for the second factor, and 92% for the third factor). This result corroborates our previous interpretation of the three

<sup>4</sup>Since we use the same detrended GDP growth here as in the G14-FSVAR above, this is an expected outcome. In fact, the results are, up to approximation error, quantitatively identical.

TABLE 1.6: Forecast error variance shares of G7 business cycle indicators accounted for by OIC shocks

Indicator	$h$	CAN	FRA	GER	ITA	JAP	UK	US
GDP	1	0.00	0.00	0.00	0.01	0.01	0.03	0.00
	2	0.03	0.06	0.09	0.16	0.13	0.05	0.03
Investment	1	0.29	0.01	0.03	0.28	0.18	0.21	0.02
	2	0.20	0.07	0.17	0.26	0.36	0.14	0.07
Private consumption	1	0.24	0.10	0.24	0.17	0.06	0.44	0.21
	2	0.25	0.08	0.19	0.16	0.22	0.49	0.39
Imports	1	0.03	0.40	0.12	0.09	0.10	0.16	0.07
	2	0.06	0.32	0.12	0.10	0.35	0.30	0.10
Exports	1	0.05	0.05	0.03	0.19	0.03	0.08	0.05
	2	0.02	0.23	0.18	0.26	0.19	0.11	0.10
Employment	1	0.26	0.40	0.42	0.19	0.29	0.29	0.27
	2	0.14	0.28	0.43	0.34	0.31	0.18	0.23
Unemployment rate	1	0.23	0.21	0.38	0.42	0.45	0.41	0.33
	2	0.23	0.26	0.45	0.45	0.41	0.39	0.31
Current account balance	1	0.32	0.58	0.35	0.45	0.20	0.13	0.17
	2	0.32	0.58	0.28	0.47	0.21	0.24	0.34
Real effective exchange rate	1	0.31	0.38	0.30	0.56	0.26	0.26	0.22
	2	0.34	0.18	0.23	0.44	0.48	0.24	0.24
Nominal eff. exchange rate	1	0.29	0.38	0.39	0.57	0.27	0.31	0.14
	2	0.31	0.21	0.28	0.49	0.47	0.24	0.18
CPI inflation	1	0.25	0.23	0.23	0.70	0.13	0.19	0.13
	2	0.41	0.33	0.28	0.63	0.16	0.41	0.25
10-year government bond rate	1	0.46	0.51	0.43	0.49	0.48	0.24	0.29
	2	0.51	0.56	0.45	0.49	0.44	0.30	0.30
Stock market returns	1	0.32	0.24	0.16	0.22	0.23	0.21	0.21
	2	0.36	0.39	0.26	0.38	0.24	0.32	0.25
Inflation volatility	1	0.43	0.42	0.29	0.14	0.40	0.32	0.39
	2	0.32	0.29	0.17	0.30	0.45	0.19	0.22
Stock market volatility	1	0.23	0.25	0.29	0.26	0.27	0.21	0.15
	2	0.19	0.26	0.31	0.25	0.24	0.24	0.19
Exchange rate volatility	1	0.13	0.17	0.23	0.26	0.16	0.18	0.20
	2	0.14	0.24	0.29	0.31	0.21	0.22	0.24

Note:  $h$  denotes the forecast horizon. Reported is the variance share of all shocks accounted for by OIC factor and shocks extracted from the G14-FSVAR,  $R_{\text{OIC}}^2 / (R_{\text{G7}}^2 + R_{\text{OIC}}^2)$ . The variables are described in section A.4.

factors identified by rotation as US, euro, and OIC factors. The forecast error variance decompositions also do not differ strongly between identification procedures except that under the alternative restrictions on the factor loadings, the factors are more “targeted” to the respective country sets. In particular, the first factor accounts for a larger share of the forecast variance of the UK than before and a smaller share of non English-speaking countries. The second factor becomes more tightly associated with France and Germany but less so with all countries outside the euro area. Finally, the third factor becomes more important for the OIC while its relevance for the G7 – which we are particularly interested in – remains near zero.

We do not use this alternative identification procedure as our baseline because it imposes strong zero restrictions that are statistically rejected at the 1 percent level if tested against an unrestricted three factor FSVAR.

### Including outliers

As a further robustness check we show that the trimming procedure by which any detrended quarterly growth rate that is further than five times the interquartile range away from the median is set to the respective threshold does not drive the estimation results. This procedure identified two “lower outliers”, namely the recessions in Mexico in 1995Q1 and South Korea in 1998Q1, and one “upper outlier”, namely Turkey in 1994Q2. We trimmed these three outliers in order to prevent them from overly influencing variance estimates and variance decompositions. However, including the three outliers as they are leads to results barely distinguishable from the baseline results (see row “Incl. outliers”).

### Alternative lag order

For the baseline G14-FSVAR models we chose a lag order of  $p = 4$  but restricted the off-diagonal elements of the coefficient matrices  $A_2$  to  $A_4$  to zero. While we argued above that this should be appropriate for our analysis, here we examine how sensitive our results are to this assumption. As a first check, we use information criteria to determine the lag order. It turns out that the AIC, BIC, and HQ all prefer  $p = 1$ . Re-running the G14-FSVAR based on this specification yields only negligible changes in the results (see row “VAR(1)” of Table 1.7).

We also check whether our baseline specification is too restrictive. A concern is that business cycle dynamics may lead to spillovers lagged by more than one quarter in which case our baseline results may underestimate the true cross-country connectedness. However, estimating four unrestricted coefficient matrices  $A_1$  to  $A_4$  of dimension  $14 \times 14$  by OLS/GLS may ask too much of the data. Therefore, we replace the OLS/GLS step of our estimation procedure with a shrinkage estimator. Specifically, we apply a Bayesian approach with Normal-Wishart prior on the VAR coefficients. We follow standard practice and use the procedure developed by Litterman (1986) with modifications proposed by Kadiyala and Karlsson (1997), Sims and Zha (1998) and Bańbura et al. (2010), see section A.2 for details.

TABLE 1.7: Forecast error variance decompositions: Robustness checks

Country	Restriction	Forecast error standard deviation	Factor 1+ Factor 2+ Spillovers from G7	Factor 3	Spillovers from OIC	Own shock
Canada	<b>Baseline</b>	1.23	0.70	0.00	0.04	0.24
	Clustered loadings	1.13	0.66	0.00	0.06	0.28
	Incl. outliers	1.23	0.71	0.00	0.04	0.25
	VAR(1)	1.26	0.70	0.00	0.05	0.24
	Bayesian VAR	0.97	0.70	0.00	0.07	0.23
	Time-varying variance	1.22	0.71	0.00	0.04	0.25
	G19	1.16	0.68	0.01	0.16	0.15
	Drop Australia	1.20	0.68	0.01	0.06	0.26
	Drop Brazil	1.23	0.71	0.00	0.05	0.23
	Drop China	1.25	0.73	0.00	0.03	0.24
	Drop Mexico	1.22	0.70	0.03	0.05	0.22
	Drop South Africa	1.23	0.72	0.00	0.04	0.23
	Drop South Korea	1.22	0.71	0.01	0.03	0.25
	Drop Turkey	1.23	0.71	0.00	0.03	0.25
France	<b>Baseline</b>	1.09	0.70	0.00	0.08	0.23
	Clustered loadings	1.02	0.79	0.01	0.09	0.12
	Incl. outliers	1.09	0.73	0.00	0.06	0.20
	VAR(1)	1.11	0.67	0.00	0.08	0.24
	Bayesian VAR	0.93	0.61	0.03	0.07	0.29
	Time-varying variance	1.09	0.72	0.00	0.06	0.23
	G19	1.12	0.74	0.00	0.14	0.12
	Drop Australia	1.10	0.71	0.01	0.06	0.23
	Drop Brazil	1.09	0.72	0.01	0.08	0.19
	Drop China	1.16	0.74	0.00	0.03	0.22
	Drop Mexico	1.09	0.67	0.01	0.09	0.23
	Drop South Africa	1.10	0.69	0.00	0.08	0.22
	Drop South Korea	1.09	0.78	0.01	0.05	0.16
	Drop Turkey	1.08	0.70	0.00	0.06	0.24
Germany	<b>Baseline</b>	1.78	0.72	0.01	0.10	0.18
	Clustered loadings	1.57	0.62	0.01	0.14	0.23
	Incl. outliers	1.79	0.75	0.00	0.08	0.17
	VAR(1)	1.78	0.71	0.00	0.12	0.17
	Bayesian VAR	1.53	0.74	0.00	0.14	0.11
	Time-varying variance	1.78	0.73	0.00	0.08	0.19
	G19	2.00	0.71	0.01	0.15	0.14
	Drop Australia	1.79	0.72	0.00	0.10	0.18
	Drop Brazil	1.79	0.69	0.01	0.13	0.17
	Drop China	1.80	0.74	0.00	0.09	0.17
	Drop Mexico	1.78	0.68	0.01	0.13	0.18
	Drop South Africa	1.83	0.70	0.01	0.10	0.19
	Drop South Korea	1.80	0.74	0.01	0.08	0.17
	Drop Turkey	1.77	0.72	0.01	0.10	0.17

Table 1.7 continued

Country	Restriction	Forecast error standard deviation	Factor 1+ Factor 2+ Spillovers from G7	Factor 3	Spillovers from OIC	Own shock
Italy	<b>Baseline</b>	1.54	0.68	0.01	0.17	0.13
	Clustered loadings	1.43	0.50	0.00	0.21	0.29
	Incl. outliers	1.54	0.70	0.02	0.13	0.15
	VAR(1)	1.54	0.68	0.00	0.17	0.15
	Bayesian VAR	1.27	0.72	0.00	0.15	0.13
	Time-varying variance	1.53	0.70	0.01	0.14	0.14
	G19	1.69	0.57	0.02	0.32	0.10
	Drop Australia	1.57	0.79	0.00	0.10	0.11
	Drop Brazil	1.56	0.69	0.00	0.17	0.13
	Drop China	1.58	0.77	0.00	0.12	0.11
	Drop Mexico	1.56	0.62	0.02	0.19	0.17
	Drop South Africa	1.56	0.67	0.00	0.19	0.14
	Drop South Korea	1.55	0.71	0.02	0.08	0.20
	Drop Turkey	1.52	0.65	0.04	0.13	0.19
Japan	<b>Baseline</b>	2.06	0.35	0.01	0.13	0.51
	Clustered loadings	1.97	0.21	0.01	0.14	0.65
	Incl. outliers	2.07	0.34	0.03	0.12	0.50
	VAR(1)	2.13	0.34	0.01	0.10	0.55
	Bayesian VAR	1.73	0.39	0.10	0.14	0.38
	Time-varying variance	2.05	0.35	0.01	0.09	0.55
	G19	2.18	0.45	0.02	0.20	0.32
	Drop Australia	2.07	0.31	0.01	0.18	0.50
	Drop Brazil	2.13	0.30	0.45	0.19	0.06
	Drop China	2.09	0.34	0.00	0.15	0.50
	Drop Mexico	2.11	0.34	0.08	0.18	0.41
	Drop South Africa	2.14	0.30	0.02	0.12	0.57
	Drop South Korea	2.14	0.30	0.25	0.16	0.28
	Drop Turkey	2.06	0.29	0.02	0.17	0.52
UK	<b>Baseline</b>	1.57	0.29	0.05	0.05	0.61
	Clustered loadings	1.72	0.28	0.01	0.05	0.66
	Incl. outliers	1.57	0.28	0.01	0.04	0.67
	VAR(1)	1.60	0.27	0.04	0.04	0.64
	Bayesian VAR	1.34	0.37	0.00	0.05	0.59
	Time-varying variance	1.56	0.30	0.05	0.04	0.61
	G19	1.63	0.30	0.07	0.13	0.50
	Drop Australia	1.59	0.31	0.09	0.02	0.58
	Drop Brazil	1.59	0.26	0.04	0.05	0.65
	Drop China	1.60	0.29	0.04	0.05	0.63
	Drop Mexico	1.61	0.32	0.43	0.06	0.19
	Drop South Africa	1.60	0.26	0.05	0.04	0.65
	Drop South Korea	1.58	0.33	0.09	0.04	0.54
	Drop Turkey	1.55	0.31	0.02	0.05	0.62

Table 1.7 continued

Country	Restriction	Forecast error standard deviation	Factor 1+ Factor 2+ Spillovers from G7	Factor 3	Spillovers from OIC	Own shock
US	<b>Baseline</b>	1.40	0.68	0.04	0.05	0.23
	Clustered loadings	1.43	0.70	0.02	0.05	0.23
	Incl. outliers	1.40	0.70	0.02	0.05	0.24
	VAR(1)	1.39	0.67	0.04	0.06	0.23
	Bayesian VAR	1.07	0.65	0.01	0.06	0.28
	Time-varying variance	1.38	0.68	0.03	0.05	0.24
	G19	1.44	0.85	0.05	0.09	0.00
	Drop Australia	1.38	0.54	0.06	0.03	0.36
	Drop Brazil	1.40	0.64	0.02	0.05	0.29
	Drop China	1.42	0.67	0.03	0.04	0.26
	Drop Mexico	1.43	0.43	0.13	0.05	0.40
	Drop South Africa	1.42	0.69	0.03	0.03	0.25
	Drop South Korea	1.43	0.59	0.03	0.04	0.34
Drop Turkey	1.40	0.59	0.02	0.05	0.34	

Notes: The entries are forecast error standard deviations of detrended GDP growth and their decomposition into factors, spillovers, and own shocks at horizon  $h = 4$ . The row “Baseline” refers to results from the rotated three-factor G14-FSVAR from section 1.4. The subsequent rows report results from ceteris-paribus changes to that estimation setup.

An important difference to classical estimation is shrinkage towards a prior which we specify –in line with the literature– as a diagonal VAR model with one lag. Hence, the Bayesian estimates of the off-diagonal elements are shrunk towards zero and thus away from non-zero spillovers. Our results thus depend on the amount of shrinkage which is controlled by the parameter  $\lambda$ . For  $\lambda = 0$  the posterior equals the prior, while for  $\lambda \rightarrow \infty$  the posterior equals the ML estimator. Carriero et al. (2015a) report that a choice of  $\lambda = 0.5$  is optimal in a forecasting sense for a monthly VAR model of 18 US variables irrespective of the lag order. As we include a similar number of variables, we follow that paper. In the row “BVAR” we report the variance decomposition computed for a FSVAR that is estimated based on the posterior means of the VAR matrices  $A_1$  to  $A_4$ . We find that our conclusions remain largely unchanged.

### Time-varying volatility

There is evidence that macroeconomic variables exhibit time-varying volatility, see, e.g., Stock and Watson (2012) and Keating and Valcarcel (2012). While our G14 sample of 1991Q1 to 2014Q4 mainly covers the Great Moderation for which volatility changes might be less of a problem, it also includes the Asian crisis and the Great Recession. We therefore check whether our baseline assumption of constant volatility distorts the results.

We based most of our conclusions on variance decompositions, which are a function of both variance matrices of the structural shocks,  $\Sigma_f$  and  $\Sigma_\varepsilon$ , and the VAR coefficient matrices  $A_1$  to  $A_4$ . Giving up the assumption of constant volatility can affect the estimated variance decompositions along these two dimensions. On the one hand, shifts in the relative



variance of two structural shocks obviously changes their relative importance as borne out by a variance decomposition. On the other hand, OLS/GLS estimation of the VAR parameter matrices  $A_1$  to  $A_4$  based on the (wrong) assumption of constant volatility is inefficient compared to a GLS estimator that takes the time-varying volatility into account. In the following, we directly analyze only the second dimension. However, since we find only mild heteroscedasticity, we conclude that shifts in relative variances are not a major issue in our sample.

Since it is beyond the scope of this paper to estimate a FSVAR with stochastic volatility in the spirit of Aguilar and West (2000), we proceed as follows. In a first step, we estimate the parameters of the baseline G14-FSVAR under the assumption of constant volatility and extract the structural shocks,  $x_t = (f'_t, \xi'_t)'$ . As these shocks are assumed to be independent, we then estimate univariate stochastic volatility models for each of these shocks. Finally, we re-estimate the FSVAR parameters by feasible GLS taking the estimated time-varying volatilities into account.

We specify and estimate univariate stochastic volatility models as proposed by Justiniano and Primiceri (2008) and Chan and Hsiao (2013). Each of the structural shocks  $x_{it}$  is assumed to follow

$$x_{it} = e^{\frac{1}{2}h_{it}}\varepsilon_{it}. \quad (1.7)$$

Hence, the conditional variance of  $x_{it}$  is  $\text{Var}(x_{it}|h_{it}) = e^{h_{it}}$ . Like Justiniano and Primiceri (2008) we specify log-volatility as a random walk

$$h_{it} = h_{i,t-1} + \zeta_{it} \quad (1.8)$$

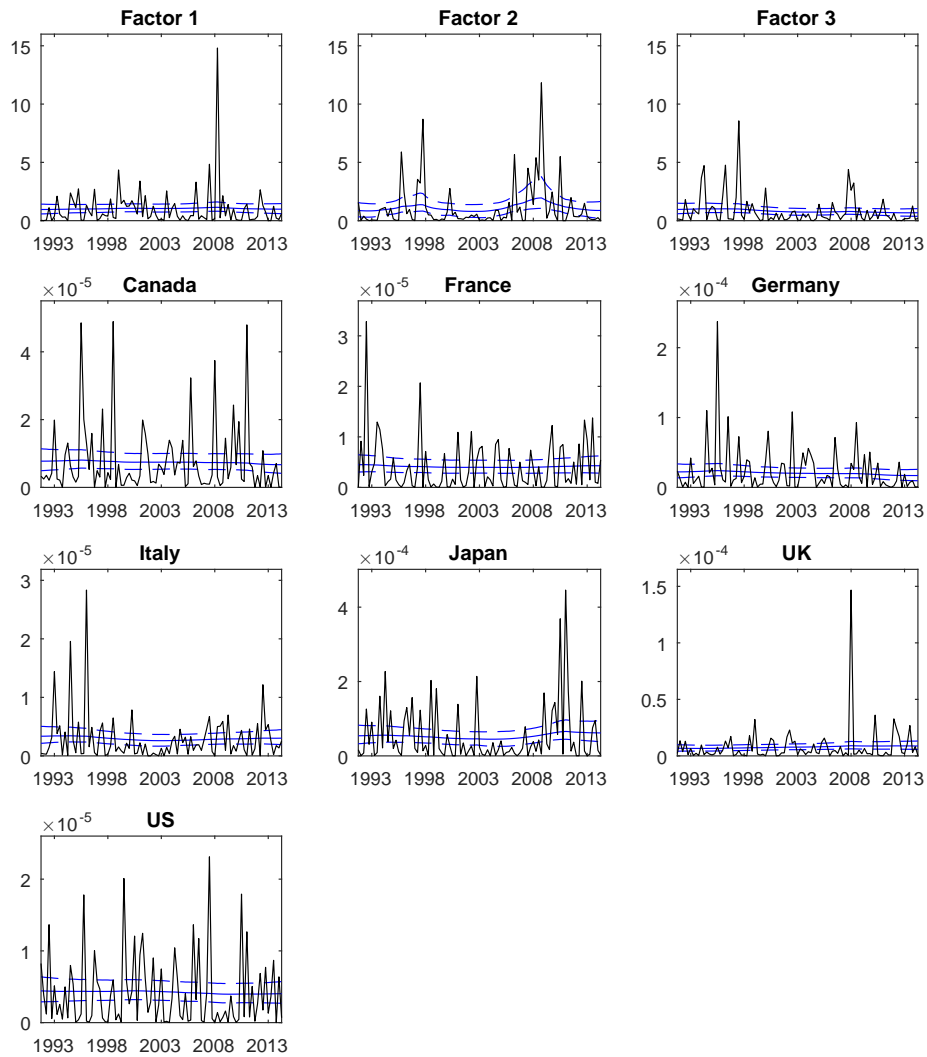
with independent shocks  $\varepsilon_{it} \sim N(0, 1)$  and  $\zeta_{it} \sim N(0, \omega_i^2)$ . We estimate the model using 20,000 draws from the Gibbs sampler. Further details regarding the priors and the estimation can be found in section A.3.

Figures 1.21 and 1.22 display the posterior means and posterior 95% intervals of the time-varying standard deviation  $\exp(h_t/2)$  of the estimated shocks. For comparison we also show the squares of the respective series. It turns out that the majority of structural shocks exhibit only a moderate degree of heteroscedasticity, especially if one takes estimation uncertainty into account<sup>5</sup>. Exceptions are due to the Great Recession and the economic crises some emerging market had to face. Given that our sample begins in 1991 and thus after the Great Moderation started, this result is not particularly surprising. Accordingly, taking the estimated time-varying volatilities into account when we estimate the FSVAR parameters by feasible GLS does not change the results to a notable extent. As shown in row “Time-varying variance” of Table 1.7 the variance decompositions remain almost identical.

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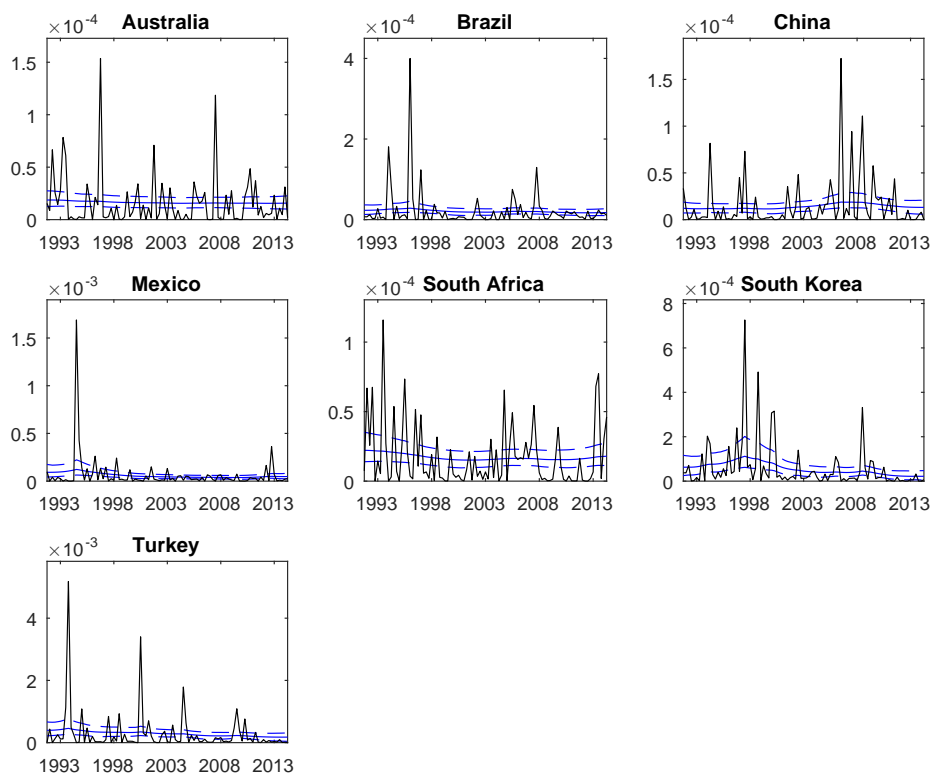
<sup>5</sup>When we allow the log-volatilities to follow stationary AR(1) processes,  $h_{it} = \mu + \phi h_{i,t-1} + \zeta_{it}$ ,  $|\phi| < 1$ , they are estimated as even less volatile. As a robustness check, we also fitted stationary GARCH models to each  $x_{it}$  and obtained the same result that variances are only moderately time-varying if at all.

FIGURE 1.21: Time-varying variances of GDP growth



Notes: In each panel of the figure we show the series of squared detrended GDP growth (black) and the time-varying variance of detrended GDP growth (solid blue) implied by the stochastic volatility model. In addition, 95% confidence intervals are reported (dashed blue). Details are given in section A.3.

FIGURE 1.22: Time-varying variances of GDP growth



Notes: In each panel of the figure we show the series of squared detrended GDP growth (black) and the time-varying variance of detrended GDP growth (solid blue) implied by the stochastic volatility model. In addition, 95% confidence intervals are reported (dashed blue). Details are given in section A.3.

## Alternative country samples

In this section we examine whether an alternative composition of the country sample changes our results. Recall that we included only 14 of the G20 countries to be able to start estimation in 1991. Adding the remaining five countries<sup>6</sup> requires to postpone the sample start to 1996Q2 for data availability. Using the shorter sample, we re-estimate the three-factor FSVAR including 19 countries as a robustness check. The variance decomposition under this alternative country sample is very similar to the baseline G14-FSVAR in terms of the G7 factors and spillovers (see row “G19”). As expected, the share that is due to spillovers from the OIC increases notably and for all countries. While estimation precision may be an issue here, this result strengthens our main finding that spillovers from the OIC are a relevant source of business cycle fluctuations for the G7.

In a final step we examine whether excluding single OIC countries from the G14 sample makes a difference. To this end, we re-estimate the three factor FSVAR using 13 instead of 14 countries, leaving everything else equal. In most cases, the results from the baseline G14-FSVAR remain qualitatively and quantitatively unchanged (see rows “Drop *country XY*” in Table 1.7). There are two exceptions. First, when we drop South Korea or Brazil factor 3 becomes a kind of Japanese factor, accounting for a much higher share of the Japanese forecast error variance, while the relevance of the idiosyncratic Japanese shock decreases by the same amount. This is plausible because in the baseline G14-FSVAR the third factor loads most strongly on South Korea or Brazil. Dropping one of these countries lets Japan fill the gap. Second, dropping Mexico affects the rotation of the first and, due to orthogonality, also of the third factor so that the third factor becomes a kind of UK factor similar as discussed for Japan above. These cases show that it is important to include a large enough set of non-G7 countries in order to be able to identify a non-G7 factor. Nevertheless, the results for the G7 countries other than the UK and Japan are almost unaffected by the restrictions on the country sample. In addition, the OIC spillover shares remain robust for all G7 countries, so our main result that OIC spillovers are quantitatively relevant for the G7 business cycle remains intact.

## 1.7 Conclusion

Based on a sample of 14 countries out of the G20, this paper documents the empirical relevance of countries that are often referred to as small or emerging for both the global business cycle and the national business cycles of the G7. Output innovations originating outside the G7 contribute noticeably, relative to G7 output innovations, to fluctuations in important global macroeconomic indicators. In addition, they account for shares of almost 25 percent in the business cycle fluctuations of national G7 GDP growth, mainly due to spillovers of idiosyncratic shocks. The shares are even higher when other national G7 variables such as employment, the current account balance, inflation, and inflation volatility are considered. Finally, the spillovers appear to be transmitted particularly

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<sup>6</sup>These are Argentina, India, Indonesia, Russia, and Saudi Arabia. We leave out the European Union because its major four member countries are already included.

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through world market returns and prices, and their volatilities. The results indicate that the narrative that regional and group-specific factors dominate the international business cycle is not the complete story. In a globalized world spillovers from emerging markets and industrial countries other than the G7 play a relevant role for major aspects of the G7 and world business cycle.

## **1.8 Coauthor contributions**

Kai Carstensen had the idea for the research question and the factor identification scheme. Besides, he proposed the augmentation of the FSVAR by world and national business cycle indicators to obtain a more detailed picture of the propagation of shocks.

Leonard Salzmänn had the idea of using the FSVAR as empirical framework and was mainly responsible for the coding work in Matlab. He also collected the data, prepared them for estimation, and performed the econometric analysis.

Kai and Leonard were equally involved in drafting the manuscript. Whereas Leonard wrote the first version and was responsible for the methodology and data section and the results section 1.4, Kai had a leading role in writing the introduction, the results section 1.5, and the conclusion. Both authors substantially contributed to revising and refining all parts of the manuscript.

A declaration on our respective contributions signed by both co-authors can be found at the end of the dissertation.

## Chapter 2

# China's Economic Slowdown and International Inflation Dynamics

This chapter of the dissertation is single-authored and has been published as Econstor in 2018. The paper included was awarded by the INFER Research Prize 2018.

**Abstract**

I examine the impact of the Chinese economic slowdown that started after the Great Recession on global inflation dynamics. To this end, I fit a high-dimensional data set comprising macroeconomic indicators of 41 countries to a structural factor-augmented vector autoregressive model. My main findings are the following: (i) Business cycle shocks and especially demand shocks in China significantly spill over to inflation rates in the US, Europe, Asia, and Oceania and are transmitted by global oil, commodity, and steel prices. (ii) The decline in Chinese growth rates can be attributed to a combination of negative aggregate demand and supply shocks. (iii) Historical decompositions indicate that after 2014, these shocks lowered PPI inflation rates outside of China by up to 0.3 percentage points per quarter, resulting in a cumulative effect on the PPI of six percent. Hence, they markedly contributed to the decline in global inflation rates and hampered the recent upward trend. (iv) The Chinese influence is also reflected in interest rates outside of China by a reduction of yields at the current edge.

*Keywords:* China's Economic Slowdown, Global inflation, Spillovers, Factor Augmented Vector Autoregressive Model

*JEL classification:* E31, E32, E43

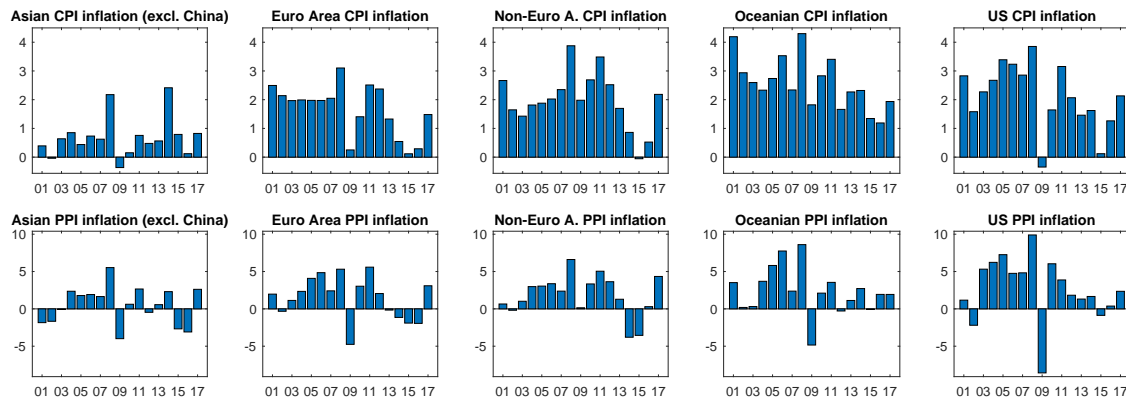


## 2.1 Introduction

It is widely known that inflation rates have been globally declining after the Great Recession, reaching values close to zero. Figure 2.1 shows that from 2011 to 2015, they fell in all economic areas of the world and increased again only recently. In the US, for example, CPI inflation fell from 3.2 percent in 2011 to 0.1 percent in 2015.

While this decline can be partly explained by domestic factors (Ciccarelli et al., 2017 and Bobeica et al., 2017), there is also evidence pointing to influence from the emerging economies, especially from China. Aastveit et al. (2015), for example, show that the demand from emerging economies has become twice as important as the demand from developed countries in accounting for the fluctuations in oil prices. Besides, Eickmeier and Kühnlenz (2016) find that aggregate demand shocks from China account for eleven percent in the variance of crude oil prices and five percent in the variance of US consumer prices.

FIGURE 2.1: Global inflation indicators

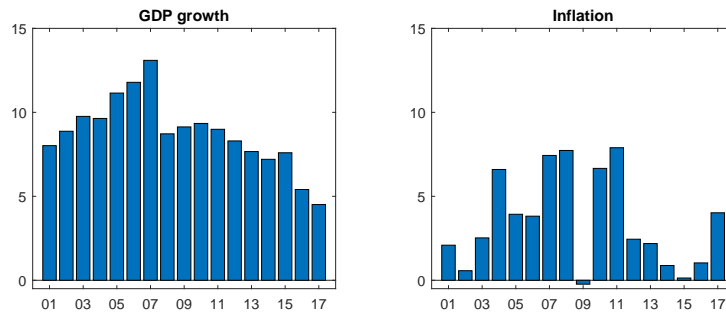


Notes: The panels show four-quarter averages of year-on-year inflation rates (in percentages). The national inflation rates are averaged over countries in Asia (Japan and South Korea), the eleven original Euro Area countries, eight non-Euro countries, and Oceania (Australia and New Zealand). The averages are weighted according to the countries' shares in the group-specific nominal GDP aggregates. Source: OECD and own calculations.

In light of these findings, the question arises which role China played for global inflation rates during the last decade, notably since the Chinese business cycle experienced a marked slowdown after the Great Recession. Figure 2.2 illustrates this slowdown in terms of Chinese GDP growth and inflation. After very high GDP growth rates of up to 13.1 percent in the period 2001-2007, the Great Recession kicked in and reduced GDP growth to 8.7 percent in 2008. The subsequent, weak recovery in 2009 and 2010 is followed by repeatedly falling growth rates, from 9.3 percent in 2010 to 4.5 percent in 2017<sup>1</sup>. China's inflation rate lags behind output, dropping to -0.2 percent only in 2009. Afterwards, it increased again to 7.8 percent in 2011 and then continuously fell to 0.1 percent in 2015. In 2016, it increased once more and reached 4.0 percent in 2017.

<sup>1</sup>The GDP growth rate published by the World Bank slightly differs from that of Chang et al. (2016) in 2016 and 2017. However, I show in section 2.5.4 that the choice between the two indicators does not play a role in my conclusions.

FIGURE 2.2: Chinese business cycle indicators



Notes: The panels show four-quarter averages of year-on-year growth rates of Chinese real GDP and the Chinese GDP deflator (in percentages). Source: Chang et al. (2016) and own calculations.

As a result, we observe a substantial and persistent decline in Chinese GDP growth and inflation rates after 2011 and a trend reversal of inflation rates in 2016. Furthermore, China's business cycle was significantly correlated with inflation rates worldwide during this period.

The aim of this work is to quantify the Chinese contribution to the decline in global inflation rates. To the best of my knowledge, this issue has not been examined in the literature yet. Dizioli et al. (2016) only consider the impact of the Chinese business cycle on real activity in five major Asian economies. They find that the Chinese influence is larger in economies which are commodity exporters and have strong trade links with China, namely Malaysia, Singapore, and Thailand. Metelli and Natoli (2017) investigate the effects on inflation in the Euro Area and the United States using the NiGEM multi-country model. They show that China's economic downturn has led to a significant disinflation in both regions. However, these results are based on different slowdown scenarios imposed on a theoretical model and not on the data.

To empirically identify the Chinese business cycle, I use the factor-augmented vector autoregressive model (FAVAR) suggested by Bernanke et al. (2005). The FAVAR allows flexible economic modeling while keeping dimensionality manageable. I proceed as follows: First, I estimate a set of factors from a large data set of 749 national and international macroeconomic time series covering nominal and real indicators of 41 major economies, including all OECD countries. These factors are added to a classical VAR model of the Chinese GDP growth rate and the Chinese inflation rate serving as business cycle controls. Subsequently, I identify aggregate supply and demand shocks in China by imposing sign restrictions on the impulse response functions of the domestic indicators. To examine the international propagation of these shocks, I compute impulse response functions of global price indicators and national price indicators in the US, Europe, Asia, and Oceania. Using historical decompositions, I additionally assess their role during the period of China's cyclical downturn. I present the Chinese structural shock series over the course of the last decade and quantify their impact on inflation indicators worldwide. Finally, I examine the implications for long-term interest rates in the tradition of the Fisher effect.

The results show that business cycle shocks and especially aggregate demand shocks in China significantly spill over to global oil, commodity, and steel prices and national inflation

rates in the US, Europe, Asia, and Oceania. The international effects are most substantial in the US and generally translate more in terms of producer prices than consumer prices. The decline in Chinese growth rates after the Great Recession can be attributed to a combination of adverse aggregate demand and supply shocks. From 2014 onwards, these shocks lowered CPI inflation rates outside of China by up to 0.1 percentage points and PPI inflation rates by up to 0.3 percentage points per quarter. They cumulatively reduced oil prices by twelve percent and foreign national PPis by up to six percent. In accordance with the Fisher effect and monetary policy rules, the shocks are also reflected in interest rates and thus financial indicators outside of China. As a result, the Chinese economic slowdown markedly contributed to the global decline in inflation and interest rates and hampered the recent upward trend.

The rest of the paper is organized as follows: In sections 2.2 and 2.3, I present the FAVAR framework and details on the data. In section 2.4, I describe the identification and estimation approach. In section 2.5, I discuss the results of an impulse response analysis, the series of structural shocks, historical decompositions, and extensive robustness checks. Section 2.6 concludes.

## 2.2 Factor-augmented vector autoregressive model

To assess the impact of Chinese business cycle shocks on global inflation dynamics, I employ a time series vector  $X_t$  comprising a large number of macroeconomic indicators and countries. The large cross-section has the clear advantage that it allows analyzing different world regions and inflation categories and includes lots of information on global business cycle dynamics. However, the number of time observations of macroeconomic time series is typically small, hence I cannot include all series in a standard VAR jointly with Chinese indicators. Instead, I estimate a two-variable VAR for the Chinese economy that I augment by a latent but estimable common component of the series in  $X_t$ . Here I assume that macroeconomic indicators are strongly driven by global and regional business cycle fluctuations and therefore can be reduced to a handful of common factors. By including these factors in the VAR I keep the model parsimonious and, at the same time, I control for international business cycle movements. This approach goes back to Bernanke et al. (2005) who augmented a VAR of the US economy by international factors to study the effects of monetary policy shocks on real variables.

I start with a classical structural VAR:

$$A_0 F_t = \sum_{i=1}^p A_i F_{t-i} + \varepsilon_t \quad (2.1)$$

that can be transformed into the reduced form

$$F_t = \sum_{i=1}^p B_i F_{t-i} + u_t \quad (2.2)$$

where  $B_i = A_0^{-1}A_i$ ,  $i = 1, \dots, p$ , and  $u_t = A_0^{-1}\varepsilon_t$ .  $F_t = [H_t', \Delta cgdpt_t, \Delta cdefl_t]'$  is  $k \times 1$ -dimensional and consists of  $r$  (latent) international factors  $H_t = [H_{1,t}, \dots, H_{r,t}]'$ , the Chinese GDP growth rate ( $\Delta cgdpt_t$ ), and the logarithmic difference of the Chinese GDP deflator ( $\Delta cdefl_t$ ). As usual, it holds for the structural shocks  $\varepsilon_t$  and the reduced-form shocks  $u_t$  that  $E(u_t) = E(\varepsilon_t) = 0$ ,  $E(u_t u_t') = \Sigma$  and  $E(\varepsilon_t \varepsilon_t') = I_k$ . The structural shocks  $\varepsilon_t$  are identified by imposing sign restrictions on the reduced-form residuals  $u_t$  (see, e.g., Faust, 1998; Canova and De Nicolò, 2003; Peersman, 2005; Uhlig, 2005). More details on the identification and estimation of  $H_t$  and  $\varepsilon_t$  are described in section 2.4.

The relationship between  $F_t$  and  $X_t$  follows an approximate factor model along the lines of Bai and Ng (2002) and Stock and Watson (2002):

$$X_t = \Lambda F_t + \Xi_t \quad (2.3)$$

$\Lambda$  denotes the  $n \times k$ -dimensional loading matrix of the factors  $F_t = [f_{1t}, \dots, f_{kt}]'$  and  $\Xi_t = [\xi_{i,t}, \dots, \xi_{N,t}]'$  is the vector of idiosyncratic components. The  $\xi_{i,t}$ 's are orthogonal to the factors  $F_t$  but are allowed to be weakly correlated between each other and over time in the tradition of Chamberlain and Rothschild (1983).

## 2.3 Data and detrending

The data vector  $X_t$  comprises  $n = 749$  national macroeconomic time series of 41 countries, namely all OECD countries plus Brazil, Indonesia, India, Russia, and South Africa. For every country I include, if available, GDP, investment, consumption, exports, imports, bilateral exports/imports to/from China, consumer prices, producer prices, the GDP deflator, a broad monetary aggregate M3, overnight interest rates, 3-month and 10-year rates, wages, unit labor costs, real effective exchange rates, employment, and unemployment rates. I also include the following international series: oil prices, fuel prices, steel prices, commodity prices (excluding fuels), manufacturing prices, stock market returns and their variance, inflation variance, world GDP, world industrial production, trade volumes, and the composite OECD leading indicator. The series are either taken from the OECD databases or national statistics offices.

The Chinese indicators are taken from Chang et al. (2016), who construct a standard set of macroeconomic time series comparable to those commonly used in the macroeconomic literature on Western economies. Their main data source is the CEIC's China Premium Database, which compiles China's official macroeconomic time series<sup>2</sup>.

The series are at quarterly frequency and span the period 2000Q1-2017Q4, resulting in  $T = 72$  observations. All of them except unemployment rates, interest rates, real effective exchange rates, and variances are stationarized by taking logarithmic first differences. To prevent my results from being driven by outliers, I follow Carstensen and Salzmann (2017)

<sup>2</sup>In the baseline specification of the FAVAR, the Chinese economy is represented by the (mean-adjusted) GDP growth rate and the (mean-adjusted) inflation rate. To account for the possibility that these rates do not fluctuate around a constant mean but, e.g. exhibit a secular productivity trend, I check in section 2.5.4 if detrending them with the local-level filter suggested by Stock and Watson (2005) alters my results. Since this is not the case I refrain from using the filter in the baseline setup.

and Stock and Watson (2005) in trimming any observation that is further than five times the interquartile range away from its median to the respective threshold.

Although the sample covers the Great Recession, I assume a constant volatility regime in my model. I base parts of my conclusions on historical decompositions, which are a function of both the variance matrix of the structural shocks  $E(\varepsilon_t \varepsilon_t')$ , and the VAR coefficient matrices  $B_i$ . On the one hand, shifts in the relative variance of two structural shocks change their relative importance. On the other hand, Carstensen and Salzmann (2017) found only mild heteroskedasticity in a factor structural VAR of the G20 countries over the sample period 1991-2014. Since relaxing the assumption of a constant volatility regime did not change their results, I conclude that heteroskedasticity is not a significant issue in my model, too.

## 2.4 Identification and Estimation

The first step of estimating the FAVAR involves finding  $H_t$ . Extracting principal components of  $X_t$  would be the standard practice here but might be problematic if  $H_t$  is supposed to represent the international non-Chinese business cycle in the FAVAR system (2.1)-(2.3). It is quite likely that the first principal components of  $X_t$  do not only mirror the international business cycle but also contain a share associated with the Chinese economy. In a FAVAR that comprises Chinese GDP growth and inflation and the principal components of  $X_t$  it is therefore hard to distinguish Chinese shocks from international ones.

To account for this issue, I apply a “cleaning” procedure proposed by Bernanke et al. (2005) that isolates the international business cycle from the Chinese observables  $\Delta cdefl_t$  and  $\Delta cgdp_t$ . The cleaning is executed as follows: First, I extract the first principal components of  $X_t$  and take them as a first estimate for the unobserved factors  $H_t$ , defined as  $\hat{H}_t^0$ . The number of principal components is determined by the *IC2* criterion proposed by Bai and Ng (2002) and accordingly set to  $r = 5$  (see Table 2.1). The share in the variance of  $X_t$  explained by these five principal components amounts to 79 percent. In the next step, I model  $\hat{H}_t^0$  as a linear combination of Chinese and non-Chinese business cycle components:

$$\hat{H}_t^0 = b_{H^*} \hat{H}^* + b_{cdefl} \Delta cdefl_t + b_{cgdp} \Delta cgdp_t \quad (2.4)$$

where  $\hat{H}^*$  represents the non-Chinese component. If this linear combination and especially  $\hat{H}^*$  was known, the Chinese share could be removed from  $\hat{H}_t^0$  by subtracting  $b_{cdefl} \Delta cdefl_t + b_{cgdp} \Delta cgdp_t$  from it. Since this is not the case, I need to find  $\hat{H}^*$  to estimate equation (2.4) in a multiple regression. One way to obtain  $\hat{H}^*$  is to extract principal components from the subset of  $X_t$  of slow-moving variables<sup>3</sup>, which by assumption are predetermined concerning  $\Delta cdefl_t$  and  $\Delta cgdp_t$ . I follow Bernanke et al. (2005) in assuming that real quantities and composite price indices are slow-moving. The remaining subset of fast-moving variables accordingly consists of the monetary aggregate M3, interest rates, stock market variables, exchange rates, and prices of oil, steel, and commodities. Hence, real

<sup>3</sup>The number of slow-moving variables amounts to 67 percent of all variables in  $X_t$ . I again rely on the *IC2* criterion of Bai and Ng (2002) in choosing the number of factors, which suggests four factors.

TABLE 2.1: Number of factors selection

Number of factors	1	2	3	4	5	6	7
Bai and Ng criterion IC2	-0.11	-0.18	-0.23	-0.26	<b>-0.28</b>	-0.27	-0.26
Explained variance in %	26.1	19.5	14.0	10.8	8.4	5.8	4.6

Notes: The upper row shows the Bai and Ng criterion IC2 for different numbers of factors. The factors are the first principal components of  $X_t$ . The lower row shows the variance shares of  $X_t$  explained by the respective factors.

economic indicators and composite price indices outside of China need at least one quarter to react to Chinese business cycle shocks, while financial variables and commodity prices react instantaneously<sup>4</sup>. To obtain the “cleaned” estimate  $\hat{H}_t^1$ , I estimate equation (2.4) by ordinary least squares and subtract  $b_{cdefl}\Delta cdefl_t + b_{cgdp}\Delta cgdp_t$  from  $\hat{H}_t^0$ .

Next, I turn to estimating the actual FAVAR system (2.1)-(2.3). I estimate the loadings  $\Lambda$  by regressing  $X_t$  on  $\hat{F}_t = [\hat{H}_t^1, \Delta cgdp_t, \Delta cdefl_t]'$ . This procedure is valid since the principal components of  $X_t$  estimate the unobserved common component of  $X_t$   $n$ -consistently, hence I do not face the problem of generated regressors. To examine domestic effects of Chinese business cycle shocks, I also include key indicators of the Chinese economy as dependent variables in this regression. The results are presented in section 2.5.1. Subsequently, I estimate the VAR system (2.1)-(2.2) by ordinary least squares, which gives me the reduced form residuals  $u_t$  and the residual covariance matrix  $\Sigma$ . I follow Eickmeier (2010) in setting the VAR lag length  $p = 2^5$ .

To identify the structural shocks  $\varepsilon_t$ , I impose two theory-based sign restrictions on the reduced-form shocks  $u_t$ . First, I orthogonalize them by the inverse of the Cholesky factor of  $\Sigma$ . Here I order the Chinese variables behind  $\hat{H}_t^1$  such that they react contemporaneously to all variables, whereas  $\hat{H}_t^1$  reacts to the Chinese shocks only after one quarter. This ordering is consistent with the assumptions on the slow-moving variables in  $X_t$  in the cleaning equation (2.4). Since the fast-moving variables are assumed to react instantaneously to Chinese shocks, I checked if ordering the Chinese variables before  $\hat{H}_t^1$  alters my results. It turned out, however, that this reordering does not play a significant role. Further details are described in section 2.5.4. Second, I rotate the two orthogonalized Chinese shocks to identify an aggregate supply (AS) shock and an aggregate demand (AD) shock in China. The identification of the shocks rests upon sign restrictions imposed on the impulse response profile of the Chinese indicators. The restriction scheme is the following: the AD shock is defined as a shock that drives Chinese GDP growth and inflation in the same direction.

<sup>4</sup>Although these assumptions are widely accepted in the literature (see, e.g., Bernanke et al., 2005 and Cesa-Bianchi, 2013), I tested different classifications of the variables as “slow-moving” and “fast-moving” and checked the robustness of my results. As it turns out, the results are not significantly affected and my conclusions remain intact.

<sup>5</sup>Whereas the BIC and the HQ point to  $p = 1$  the AIC suggests  $p = 3$ . To check if my results hinge on a higher lag order I re-estimate the model with  $p = 3$ . It turns out, however, that my conclusions are not affected. Details are presented in section 2.5.4.

The AS shock, by contrast, is a shock that drives the same variables in opposite directions<sup>6</sup>. These assumptions are consistent with a large number of theoretical models such as the IS-LM model or New-Keynesian models à la Smets and Wouters (2003) and have often been applied in the empirical literature (e.g., Peersman, 2005 and Eickmeier, 2010).

I implement the restrictions by means of a  $k$ -dimensional identity matrix  $R$  whose lower-right  $2 \times 2$  submatrix is replaced by a Given's rotation matrix. Hence,  $R$  has the property  $R'R = R^{-1}R = I_k$ . Using the definition  $A_0^{-1} = \text{chol}(\Sigma)R$  in equation (2.1), I obtain the structural shocks  $\varepsilon_t$  as follows:

$$u_t = A_0^{-1}\varepsilon_t \quad (2.5)$$

$$\Leftrightarrow \varepsilon_t = R'\text{chol}(\Sigma)^{-1}u_t \quad (2.6)$$

I choose the angle of  $R$  by randomly drawing candidates from a domain between 0 and  $2\pi$ . In case the sign restrictions described above are met, I keep the draw and otherwise discard it. I stop the search once I have collected 200 accepted angles.

This identification has the clear disadvantage that the 200 accepted angles imply 200 observationally equivalent but different and possibly conflictive models. To circumvent this problem and find a “representative” model, I follow the “Median Target Approach” by Fry, Pagan, et al. (2007): I compute the impulse response functions implied by all 200 accepted angles and choose the one that minimizes the squared distance from the median impulse responses.

## 2.5 Results

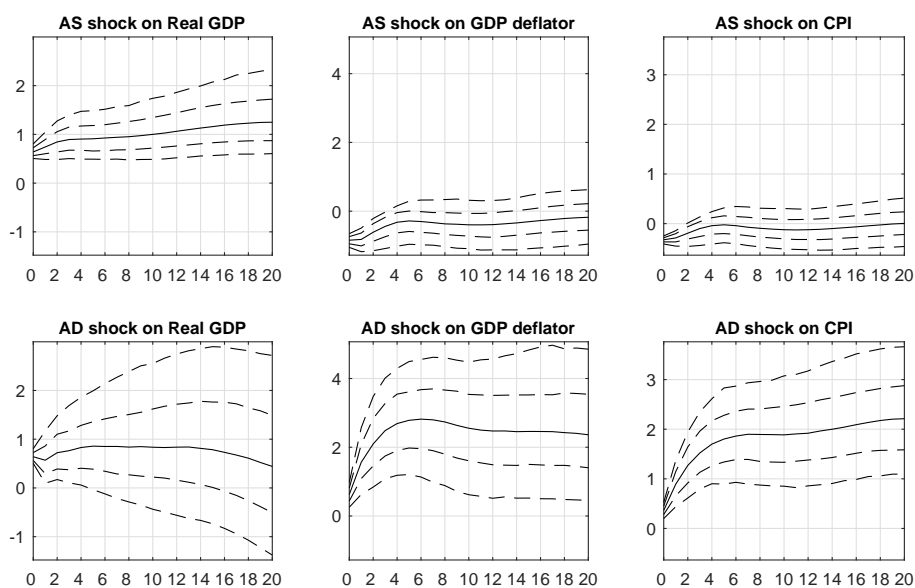
In this section, I present key results implied by the FAVAR. First, I perform an impulse response analysis to learn about the domestic and international effects of the Chinese structural shocks. Then I show the estimated shock series to depict the Chinese business cycle of the last decade in terms of AS and AD innovations. Finally, I assess the international effects of these innovations from 2012 onward using historical decompositions of inflation and interest rates outside of China.

### 2.5.1 Impulse response functions

Figure 2.3 shows cumulative median impulse responses of Chinese GDP growth and inflation to a positive AS shock and a positive AD shock. Both shocks are scaled such that Chinese GDP growth increases on impact by one standard deviation, which is 0.6 percent. To account for measurement uncertainty, I add 68 and 95 percent confidence intervals to the median impulse responses resulting from the bootstrap-after-bootstrap method of Kilian (1998). I set the number of bootstrap replications to 1000. Since  $n \gg T$  the uncertainty associated with the factor estimation can be neglected, as shown by Bai, Ng, et al. (2006).

<sup>6</sup>The time horizon for which the sign restrictions are imposed on the impulse response functions is set to four quarters. Hence, after that period the impulse responses are unrestricted. I tried different horizons but the estimation results did not significantly change.

FIGURE 2.3: Impulse response functions - Chinese indicators



Notes: The panels show cumulative impulse response functions of economic indicators to a Chinese AD shock and an AS shock, displayed in percentages. Both shocks are scaled such that Chinese GDP growth increases on impact by one standard deviation (0.6 percent). The impulse responses are constructed using the “Median Target Approach” suggested by Fry, Pagan, et al. (2007). The dashed graphs are 68 and 95 percent confidence intervals resulting from the bootstrap-after-bootstrap method proposed by Kilian (1998) and 1000 re-estimations.

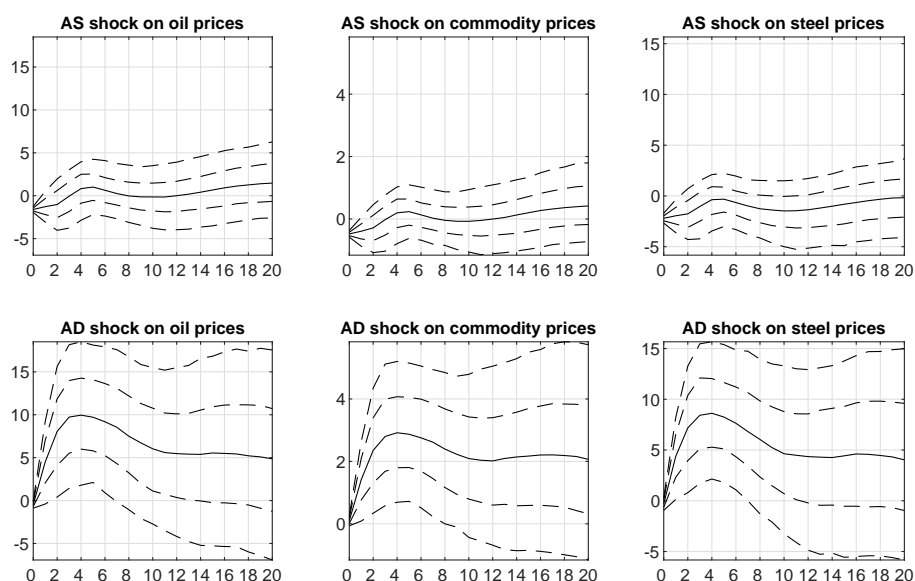
As expected, the AS shock drives GDP and prices in China in opposite directions. It increases GDP by 0.6 percent on impact and by 1.3 percent in the long run, and it lowers the GDP deflator by up to 0.8 percent. The AD shock, by contrast, drives GDP and prices in the same direction. GDP again increases by 0.6 percent on impact and slowly fades out afterwards. Prices react more sluggishly to the AD shock than to the AS shock: The GDP deflator appreciates by 0.8 percent on impact and reaches its maximum of 2.9 percent only six quarters after the shock.

Figures 2.4 and 2.5 show how global oil, commodity, and steel prices and national price indicators outside of China react to the Chinese shocks. As national reference measures I use consumer and producer prices (CPI and PPI). Since it is impossible to comment on the impulse response functions of all 41 countries in the dataset I compute weighted averages over countries for Asia (Japan and South Korea), the eleven original Euro Area countries, eight non-Euro countries (Czech Republic, Denmark, Hungary, Norway, Poland, Sweden, Switzerland, and the UK), and Oceania (Australia and New Zealand). The weights are based on the country shares in the group-specific nominal GDP aggregates.

The figures show that the impulse response functions have qualitatively similar features across price categories and country groups. Most impulse responses are close to zero or insignificant at small horizons, which implies that international spillovers of Chinese business cycle shocks are sluggish. They reach their maximum after approximately four quarters and become insignificant again at large horizons. Hence, the Chinese shocks do not have long-run effects on international prices.



FIGURE 2.4: Impulse response functions - Global price indicators



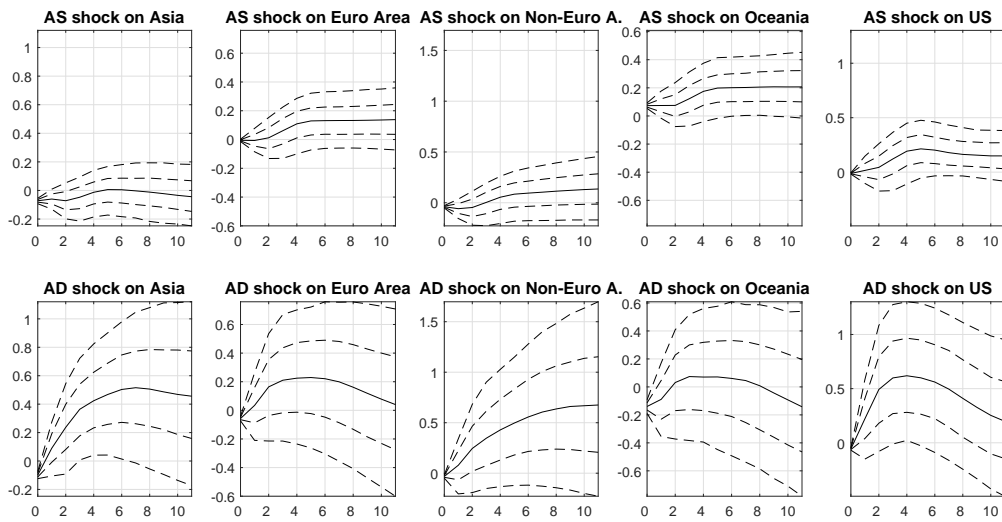
Notes: See figure 2.3 for a detailed description of the graphs.

The figures also show that the AS shock tends to have a lowering on-impact effect on prices outside of China, which either fades out or turns slightly positive after approximately one year. This finding might be the result of two countervailing mechanisms: By definition, a positive AS shock lowers inflation but raises real activity in China. Through international price competition this should also lower prices outside of China. However, if higher real activity comes along with higher demand for commodities and thus raises their prices, the net effect of the AS shock is unclear.

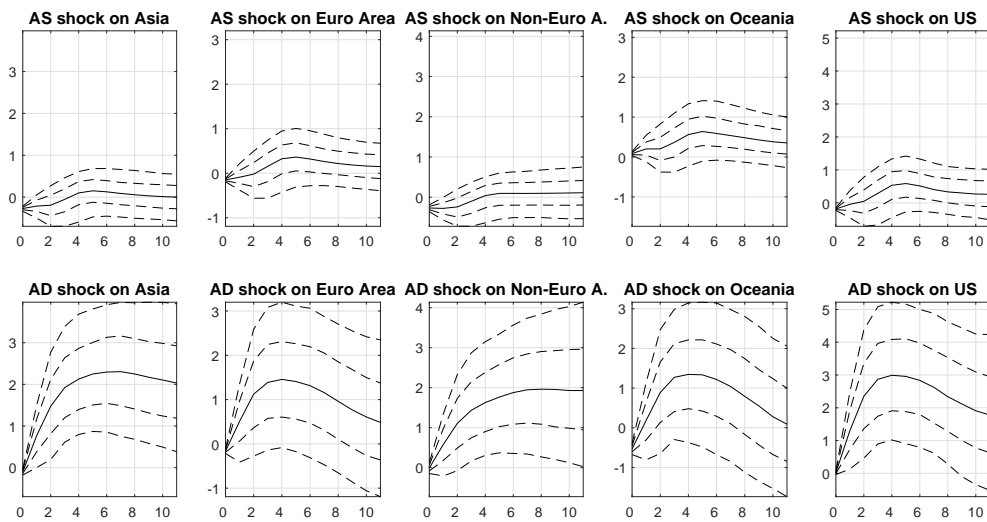
By contrast, the AD shock has a considerable and significantly positive effect on global prices. The effects are particularly large for oil, commodity, and steel prices, which respectively increase by ten, three, and eight percent. Hence, globally traded raw materials are important transmission channels of Chinese demand shocks. We also see that the national PPIs react considerably stronger to a Chinese AD shock than the CPIs, a finding which is in line with Eickmeier and Kühnlenz (2016). Overall, the effect is most pronounced in the US, where the PPI increases by three percent in response to a Chinese AD shock. In Asia, the Euro Area, the non-Euro countries, and Oceania the effects are also non-negligible and amount to 2.3, 1.4, 2.0, and 1.3 percent, respectively. The greater importance of external shocks for the PPIs might be explainable by the fact that the PPI contains more tradeable and manufactured goods than the CPI. Furthermore, Bacchetta and Wincoop (2003) show that if domestic firms import intermediate goods priced in foreign currency and sell final goods in domestic currency, the pass-through of external shocks to the CPI is incomplete.

FIGURE 2.5: Impulse response functions - National price indicators outside of China

(A) CPI



(B) PPI



Notes: See figure 2.3 for a detailed description of the graphs.

### 2.5.2 Structural shock estimates

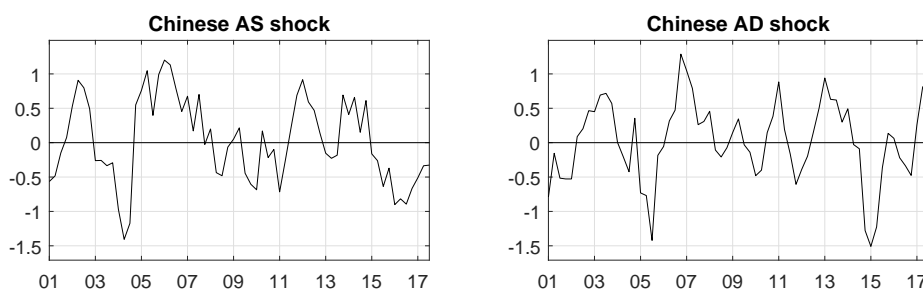
Figure 2.6 displays 3-quarter averages of the estimated Chinese AS and AD shock series. The series indicate for each point in time whether the shocks are expansive or contractionary and which magnitude they have.

The Great Recession that affected China already in 2008 is preceded by positive AS and AD shocks from 2006 until the beginning of 2008. The shock sizes in 2008 and 2009 are rather moderate, which is expected since the Great Recession is largely explained by the international component  $H_t$ . The recovery of 2010, however, also shows up as positive demand innovations in China.

Afterwards, we observe a further expansion in demand in 2012 and 2013, followed by a sharp downturn from mid-2014 until 2015Q1. The AD component then recovers slightly in 2015 and 2016 and turns positive again in 2017. The AS component persistently stays at low levels after the Great Recession and turns positive only in mid-2011. After an expansive period until the end of 2014, it becomes contractionary again and remains so until the end of the sample.

To sum up, China's cyclical downturn from 2012 until 2015 can be attributed to a mixture of negative AS and AD shocks. The further fall in real activity and the trend reversal in the inflation rate in 2016 and 2017 is mainly due to negative AS shocks.

FIGURE 2.6: Structural shocks



Notes: The panels show 3-quarter averages of the estimated Chinese AS and AD shocks.

### 2.5.3 Historical decompositions

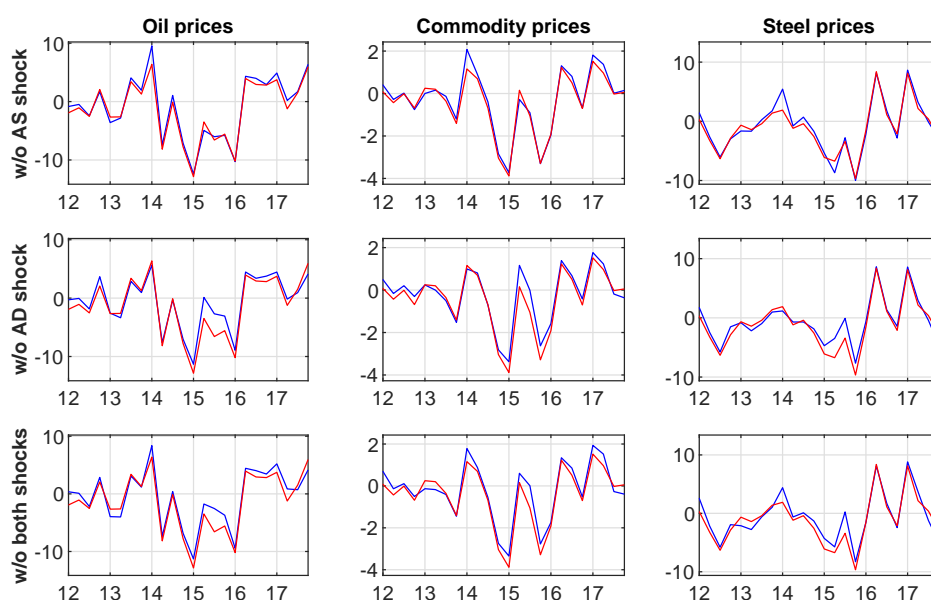
In this section, I quantify the global influence of the Chinese shocks on inflation and interest rates after 2012. The figures 2.7 and 2.8 show historical decompositions of several inflation indicators. Each panel shows the realized inflation rate (red) and a hypothetical rate (blue) that results from a counterfactual analysis. In that counterfactual analysis, I maintain the idiosyncratic and common shocks in the FAVAR but shut down one of the two Chinese shocks or both shocks. Hence, the difference between the realized and the hypothetical rates indicates how relevant China's influence was for global inflation. To examine the financial implications, I perform the same historical decompositions for interest rates (see Figure 2.10). As region-specific aggregate measures I again take the weighted averages of the national indicators.

### 2.5.3.1 Inflation

The Figures 2.7 and 2.8 indicate a non-negligible impact of the Chinese business cycle on global inflation dynamics during the last decade. The hypothetical inflation rates without the influence of one of the two Chinese shocks are to a moderate but significant degree different from the realized rates. The same holds for the hypothetical rates where both shocks are shut down at a time.

Figure 2.7 shows that after 2014, the Chinese shocks tended to lower global oil, commodity, and steel prices since the hypothetical inflation rates are higher than the realized rates. Before 2014, the Chinese shocks had negligible or even positive effects since the hypothetical rates are lower than the realized rates. This finding again confirms that commodity prices are important transmission channels of Chinese business cycle shocks.

FIGURE 2.7: Historical decompositions - Global inflation indicators

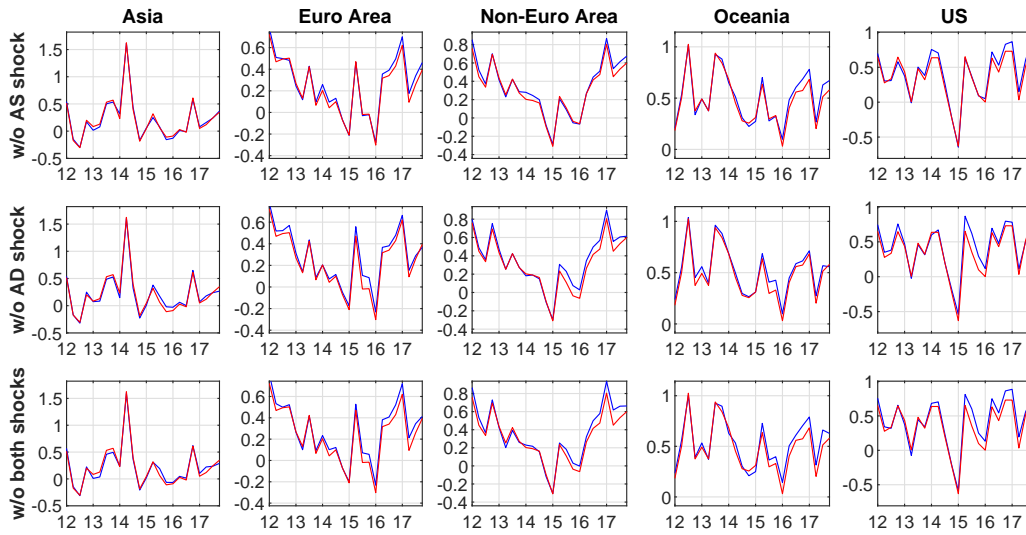


Notes: Each panel shows the realized quarterly inflation rate (red) and a hypothetical inflation rate that is implied by the FAVAR (blue). The hypothetical rates in the upper two rows result from a counterfactual analysis in which one Chinese shock is shut down and all other shocks are maintained. The hypothetical rates in the bottom row result from shutting down both Chinese shocks and maintaining all other shocks. The inflation rates are displayed in percentages.

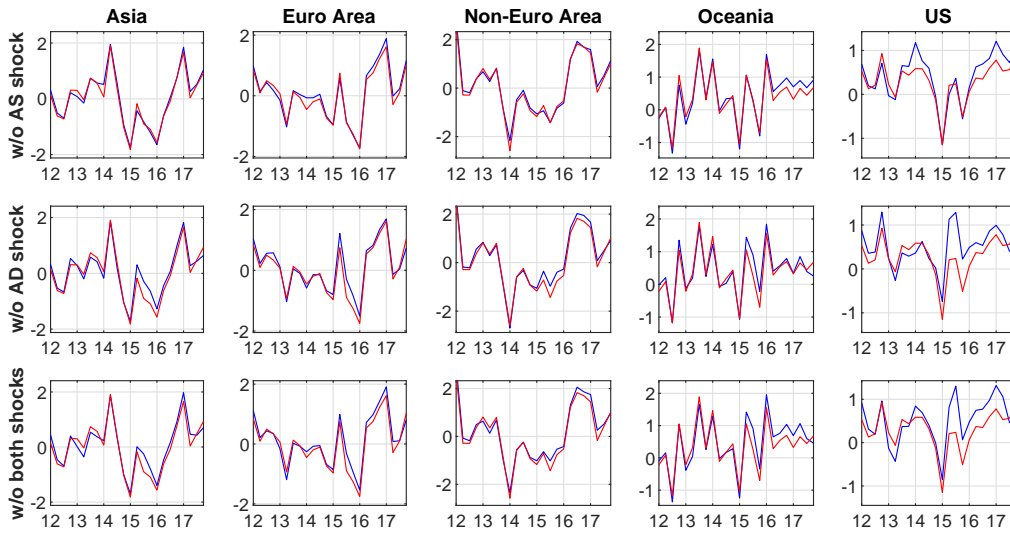
If we look at national CPI and PPI inflation outside of China, displayed in Figure 2.8, the results are similar. Until 2014, the effects of the Chinese shocks are ambiguous or economically insignificant. After 2014, the negative AS and AD shocks take effect and markedly lower inflation rates in all country groups. The results confirm the findings from section 2.5.1: first, the effects are most pronounced in the US. Second, AD shocks have slightly larger effects than AS shocks, and third, the PPIs react stronger to both Chinese shocks than the CPIs. Between 2014Q1 and 2017Q4, the realized quarterly PPI inflation rates in Asia, the Euro Area, the non-Euro countries, Oceania, and the US were on average 0.16, 0.18, 0.16, 0.19, and 0.33 percentage points lower than the hypothetical rates without the two Chinese shocks. These numbers are considerable given that the standard deviations

FIGURE 2.8: Historical decompositions - National inflation indicators outside of China

(A) CPI inflation



(B) PPI inflation



See figure 2.7 for a detailed description of the graphs.

of the quarterly PPI inflation rates over the entire sample are 0.99, 1.04, 1.17, 1.33, and 1.74 percent, respectively. In terms of CPI inflation rates the differences are slightly smaller in the same period. The realized CPI inflation rates were on average 0.01, 0.06, 0.06, 0.06, and 0.10 percentage points lower than the hypothetical rates in Asia, the Euro Area, the non-Euro-Area countries, Oceania, and the US, respectively. The country group-specific standard deviations of CPI inflation amount to 0.34, 0.29, 0.32, 0.34, and 0.53 percent.

These effects are clearly linked to the positive AD shocks in 2012 and 2013 and the negative AD shocks in 2014 and 2015. It is striking that the Chinese influence on international prices was particularly significant in the second half of 2015, hence about one year after the period of large negative AD shocks from 2014Q2 until 2015Q1. This time lag is due to the sluggishness of the international effects that I found in section 2.5.1.

To assess the cumulative effect of the Chinese shocks, I also compute price levels implied by the historical decompositions. Figure 2.9 displays the price levels implied by the hypothetical inflation rates that include all shocks but the two Chinese in the FAVAR. Besides, it shows the realized price levels. I normalize all prices in 2014Q1 to an index value of 100<sup>7</sup>. Table 2.2 additionally reports the gaps between the realized and the hypothetical prices in 2015Q4, 2016Q4, and 2017Q4.

The results show that in the first half of 2014, China's global influence on prices was still small. Afterwards, however, the contractionary Chinese shocks become increasingly visible since realized and hypothetical prices start to diverge. The effect on the price of raw materials is especially pronounced: In terms of steel prices it amounted to -8.3 percent already in 2015Q4. The national price indicators reacted a bit later but still noticeably. In the US, for example, the CPI and the PPI fell by up to 1.8 and 5.7 percent in response to the Chinese shocks, respectively. In the Euro Area and Asia, China's influence was strong enough to turn (hypothetically) positive dynamics of the PPI into negative. Whereas the realized PPI in these regions dropped by 0.7 and 1.0 percent, the counterfactual PPIs without the Chinese shocks would have increased by 2.5 and 1.2 percent, respectively.

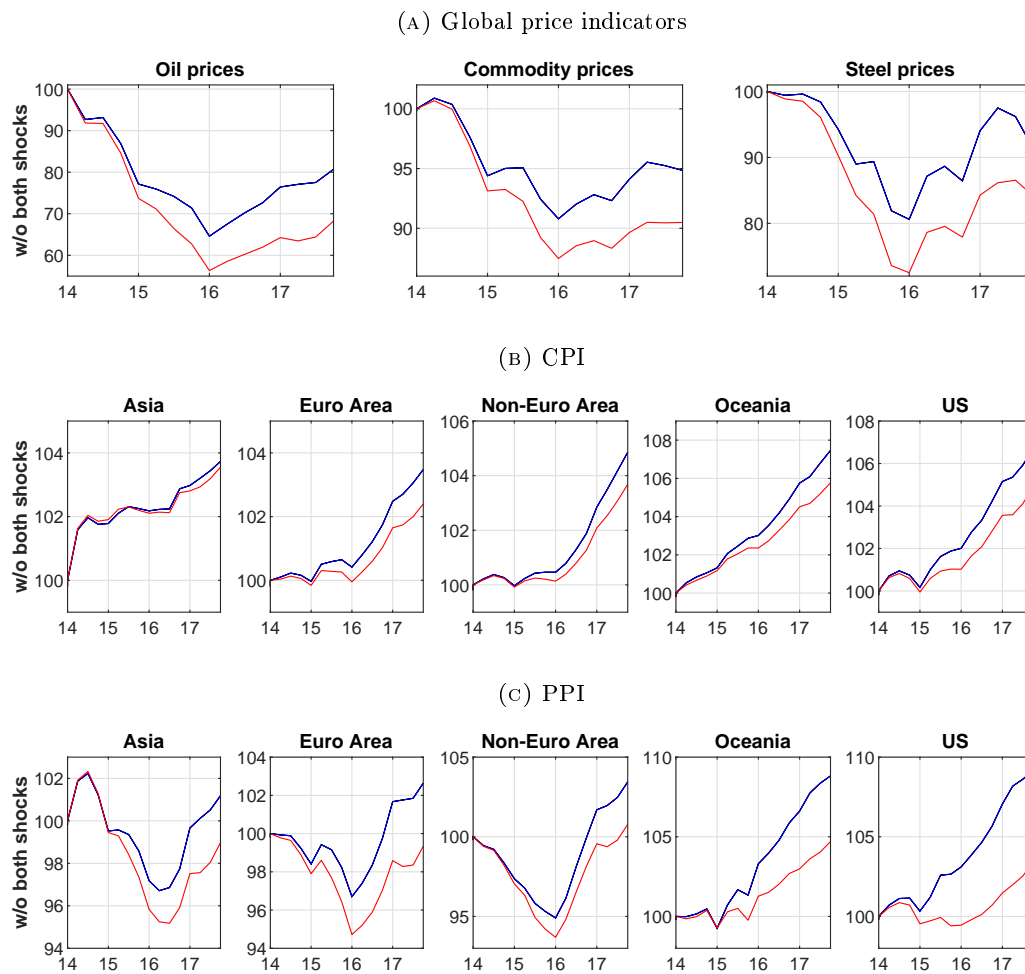
### 2.5.3.2 Interest rates

In this section, I examine to which degree the Chinese shocks spilled over to interest rates outside of China. Similarly like inflation rates, interest rates experienced a pronounced and persistent decline after the Great Recession. While parts of this decline can be explained by a lower real interest rate (Holston et al., 2017), monetary policy rules and the Fisher effect create a direct link to domestic inflation (Taylor, 1999; Clarida et al., 1999; Mishkin, 1992). Moreover, since the findings from sections 2.5.1 and 2.5.3.1 suggest a significant contribution of Chinese shocks to the global downturn in inflation rates, I conclude that these shocks should also have lowered interest rates internationally.

I conduct the same historical decomposition of interest rates as in the case of inflation rates. Figure 2.10 displays 10-year government bond rates in the considered regions and

<sup>7</sup>I choose this date as base period because in 2014Q2 the Chinese AD shock fell sharply below zero, reaching its lowest level in 2015Q1. Furthermore, in 2014 at the latest the Chinese shocks started to markedly lower inflation rates outside of China, as the figures 2.7 and 2.8 show.

FIGURE 2.9: Cumulative effects of Chinese shocks on prices outside of China



Notes: Each panel shows the realized price level (red) and the price level implied by a hypothetical quarterly inflation rate (blue). The hypothetical inflation rate results from a counterfactual analysis in which both Chinese shocks are shut down and all other shocks in the FAVAR are maintained. The price levels are normalized to 100 in the base period 2014Q1.

TABLE 2.2: Cumulative effects of Chinese shocks on prices outside of China

Global prices	Oil prices	Commodity prices			Steel prices
2015Q4	-8.7		-3.2		-8.3
2016Q4	-10.7		-4.0		-8.5
2017Q4	-12.4		-4.4		-7.2
National prices	Asia	Euro Area	Non-Euro	Oceania	US
CPI					
2015Q4	-0.06	-0.39	-0.26	-0.51	-0.85
2016Q4	-0.12	-0.72	-0.61	-1.08	-1.40
2017Q4	-0.17	-1.08	-1.17	-1.69	-1.77
PPI					
2015Q4	-1.23	-1.79	-1.11	-1.58	-3.24
2016Q4	-1.82	-2.71	-1.79	-3.18	-4.96
2017Q4	-2.21	-3.30	-2.66	-4.12	-5.70

Notes: The table displays the difference between the realized price level and the price level implied by a hypothetical quarterly inflation rate. The hypothetical inflation rate results from a counterfactual analysis in which both Chinese shocks are shut down and all other shocks in the FAVAR are maintained. The price levels are normalized to 100 in the base period 2014Q1.

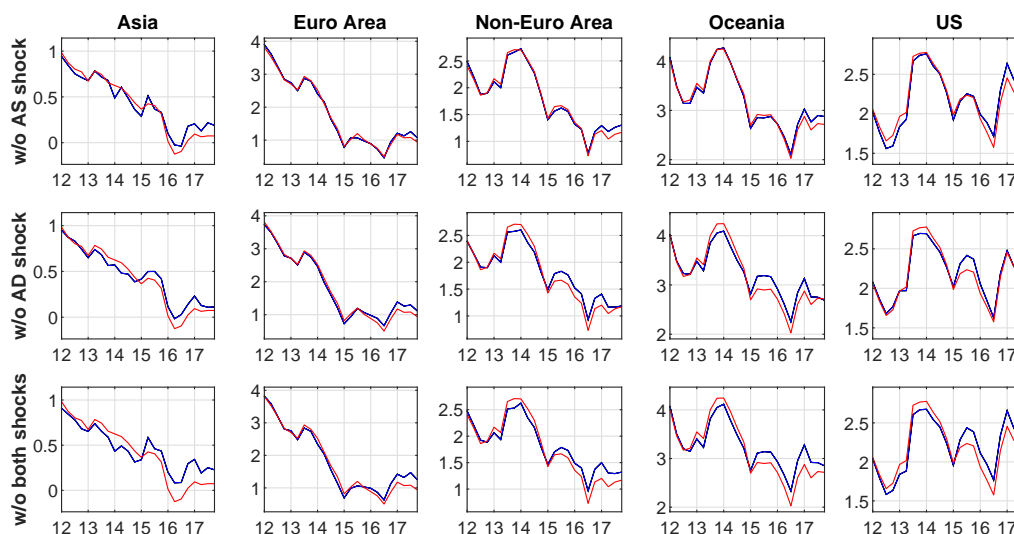
their respective counterfactuals without the influence of the two Chinese shocks<sup>8</sup>. The comparison between both series shows that the Chinese business cycle noticeably affected long-term interest rates outside of China. Between 2012 and 2017, the average absolute deviation between the realized interest rate and the hypothetical rate amounted to 12, 13, 14, 18, and 12 basis points in Asia, the Euro Area, the non-Euro countries, Oceania, and the US, respectively. From 2013Q1 until 2015Q1, the realized rates tended to be higher than the hypothetical rates, which implies a positive effect of the Chinese shocks during this time. After 2015Q1, the effect becomes negative. This reversal follows the qualitative turn of the Chinese AD shock from positive to negative in 2014Q2 and is consistent with the effects on inflation described in section 2.5.3.1. The lowering impact is most visible in the last observations. In the Euro Area, for instance, the difference between the realized 10-year rate and the counterfactual without the Chinese influence amounted to 28 basis points in 2017Q4.

To sum up, China's cyclic downturn also spilled over to interest rates and thus the financial sector outside of China. In particular, it reinforced the decline in financial yields during the last decade, resulting in a significant reduction at the current edge.

<sup>8</sup>I conducted the same analysis using interest rates with shorter maturity (e.g., 3-month rates) but did not find significantly different results.



FIGURE 2.10: Historical decompositions - National interest rates outside of China



Notes: Each panel shows the realized 10-year government bond rate (red) and a hypothetical rate that is implied by the FAVAR (blue). The hypothetical rates in the upper two rows result from a counterfactual analysis in which one Chinese shock is shut down and all other shocks are maintained. The hypothetical rates in the bottom row result from shutting down both Chinese shocks and maintaining all other shocks. The rates are displayed in percentages.

### 2.5.4 Robustness checks

As customary in empirical papers, I perform several sensitivity checks to strengthen the credibility of my results. In the following subsections, I present results from modifying a single property of the baseline FAVAR and re-estimating it. In every modification the respective other estimation settings remain unchanged. I check the sensitivity of the baseline setup by comparing the cumulative effects of the Chinese shocks on global inflation in 2016Q4. All results are reported in Table 2.3.

#### Ordering of variables

To orthogonalize the VAR residuals in the baseline setup, I set the Chinese variables below the international factors. Hence, I assume that the international factors react to shocks from China only with a delay of one quarter whereas the Chinese variables immediately react to international shocks. In a first experiment, I check if this ordering plays a role for my results and conclusions. I estimate a version of the FAVAR in which I set the Chinese variables above the international factors and again compute the cumulative effects of the Chinese shocks on international prices. The results are reported in the second row of Table 2.3, together with the baseline results. As it turns out, the new ordering leads to higher cumulative effects of the Chinese shocks on prices outside of China. These findings are not unexpected since the alternative ordering allows international factors to react to the shocks on impact. As a result, my conclusion that China's economic slowdown has lowered prices globally is confirmed.

## Detrending

As the data showed, the slowdown in China's economic performance markedly contrasts with the very high and stable growth rates before the Great Recession. The stark difference between both periods raises the question whether not only China's business cycle has slowed down but also its long-term potential growth. If this is the case, however, the Chinese series need to be cleaned by a time-varying trend prior to using them in the FAVAR. Up to this point, I only adjusted the growth rates by their means, implicitly assuming constant potential growth.

To allow for a secular growth trend, I apply the local-level model suggested by Stock and Watson (2005) to the Chinese GDP growth rate and the inflation rate. The model yields a smooth time-varying trend for both series, which I subtract from these. Then I plug the detrended series into the FAVAR and carry out the estimation as described. The estimated trend is shown jointly with the other series in the FAVAR in Figure B.1.

The effects of the Chinese shocks under this modification are presented in row two of Table 2.3. As it turns out, they are barely distinguishable from the baseline results, which suggests that time-variation in the growth trend does not play a role in this paper.

## Long-run restrictions

In section 2.4, I described and justified the identification of AD and AS shocks in China by means of short-run sign restrictions. To check if my results hinge on this scheme, I apply long-run restrictions to identify both shocks. Blanchard and Quah (1989) introduced this method relying on the idea that AD shocks should have no long-run effects on real economic activity. I follow their assumption and impose on the Chinese AD shock that it does not affect Chinese GDP in the long run. By contrast, the effect of the AS shock is left unrestricted. The estimated impact of both shocks on international prices are displayed in row four of Table 2.3. They are slightly smaller in absolute values but still very similar to those of the baseline setup. I conclude from this that the identification of structural shocks plays a subordinate role in my conclusions.

## Control for oil prices

Here I address the argument that oil market developments might not be sufficiently accounted for in the model, especially during the sharp decline in oil prices in 2014. Between June and December of that year, the Brent oil price dropped by 44 percent of its original value. According to Baumeister and Kilian (2016), half of this decline can be attributed to a fall in global aggregate demand, whereas one third was due to oil supply shocks. Since oil supply shocks should have opposite effects on GDP and inflation, I need to rule out the risk that they are confused with Chinese AS shocks. To control for oil supply shocks, I replace the factor space by  $F_t = [\hat{H}_t', \Delta cgdpt, \Delta cdeflt, \Delta oilpt]'$  where  $oilpt$  denotes the real price of crude oil, and re-estimate the model. The fact that oil prices are ordered last follows the assumption that they are fast-moving and is consistent with the discussion in section 2.4.

The estimation results under this setup are reported in the fifth row of Table 2.3. It turns out that controlling for oil price shocks slightly increases the effect of China's growth slowdown on global inflation. This finding is to a considerable degree due to the third and fourth quarters of 2014, hence the period in which the oil price drop occurred. However, the total effects are still comparable to those in the baseline setup and therefore do not affect my conclusions.

TABLE 2.3: Robustness checks

Modification	Asia (excl. China)	Euro Area	Non-Euro Area	Oceania	US
CPI					
1. <b>Baseline</b>	-0.12	-0.72	-0.61	-1.08	-1.40
2. Ordering of variables	-0.09	-1.45	-2.03	-1.80	-1.54
3. Detrending	-0.08	-0.70	-0.56	-1.06	-1.41
4. Long-run restrictions	-0.10	-0.67	-0.55	-1.02	-1.35
5. Control for oil prices	-0.12	-1.26	-1.14	-1.61	-2.17
6. Control for Euro crisis	-0.13	-0.63	-0.53	-0.99	-1.27
7. Regional factors	-0.06	-0.80	-0.84	-1.00	-1.21
8. Value-added	-0.10	-0.65	-0.52	-1.05	-1.41
9. VAR(3)	-0.40	-1.06	-1.08	-0.93	-1.55
PPI					
1. <b>Baseline</b>	-1.82	-2.71	-1.79	-3.18	-4.96
2. Ordering of variables	-1.64	-3.44	-3.74	-2.36	-3.48
3. Detrending	-1.69	-2.60	-1.65	-3.06	-4.92
4. Long-run restrictions	-1.74	-2.58	-1.67	-3.04	-4.83
5. Control for oil prices	-2.87	-3.86	-3.17	-4.03	-7.63
6. Control for Euro crisis	-1.69	-2.43	-1.61	-2.97	-4.55
7. Regional factors	-1.51	-2.67	-2.02	-1.68	-4.52
8. Value-added	-1.69	-2.44	-1.70	-3.00	-4.97
9. VAR(3)	-2.34	-4.49	-6.31	-2.01	-5.07

Notes: The table displays the difference between the realized price level and the price level implied by a hypothetical quarterly inflation rate in 2016Q4. The hypothetical inflation rate results from a counterfactual analysis in which both Chinese shocks are shut down and all other shocks in the FAVAR are maintained. The price levels are normalized to 100 in the base period 2014Q1.

### Control for the Euro crisis

I also address the possibility that the global factors  $\hat{H}_t$  do not sufficiently control for the Euro crisis, which kicked in between 2012 and 2013 in terms of Euro Area GDP and thus overlapped with China's economic slowdown. To account for this issue, I add Italian real GDP growth ( $\Delta itagdp_t$ ) as a slow-moving variable to the factor space such that  $F_t = [\hat{H}_t', \Delta itagdp_t, \Delta cgdpt, \Delta cdefl_t]'$ , and re-estimate the model then. I choose Italian GDP growth for two reasons: First, Italy is the third-largest economy of the Euro zone. Second, Italy was severely and persistently affected by the crisis: National GDP

growth was -2.8 percent in 2012 and -1.7 percent in 2013. It turns out, however, that re-running the estimation based on this specification yields only negligible changes (see row six of Table 2.3).

### Regional factors

It is a popular narrative in the literature that regional factors are important drivers of the international business cycle (see, e.g., Artis and Zhang, 1999 and Stock and Watson, 2005). To account for this issue, I modify my model setup as follows: I estimate a total of ten regional factors, namely four for North America and Europe and two for Asia (excluding China). The factors are estimated by extracting principal components from the region-specific subsamples of  $X_t$ <sup>9</sup>. Then I set up the factor space  $F_t = [\hat{H}_t^{EU'} \hat{H}_t^{NA'} \hat{H}_t^{AS'} \Delta cgdp_t \Delta cdefl_t]'$  and re-estimate the FAVAR. I tried different orderings of the regional factors, but the results were barely distinguishable from those presented here. The cumulative effects of the Chinese shocks in the historical decomposition are reported in row seven of Table 2.3. Again, except for a few cases, the numbers are very similar to those of the baseline estimation.

### Measuring real activity

Since the quality of Chinese data is often subject to criticism, I check if using Chinese value-added instead of real GDP in the FAVAR yields different results. I again rely on the data constructed by Chang et al. (2016), which matches the series published by the World Bank. The growth rate of value-added is generally very similar to GDP growth but slightly differs in 2016 and 2017. In 2016, GDP growth amounted to 5.4 percent, but value-added grew by 6.5 percent. In 2017, GDP growth added up to 4.5 percent, while the growth rate of value added was 6.6 percent. However, if I take value-added in the FAVAR I obtain cumulative effects of the Chinese shocks that are very similar to those of the baseline setup. The results are reported in row eight of Table 2.3.

### Lag order

Finally, I check if a higher lag order in the VAR changes my results. I re-estimate the model with  $p = 3$ , as suggested by the AIC. However, I find that both the impulse responses and the structural shock series are very similar to those of baseline setup with  $p = 2$ . The same holds for the cumulative effects of the Chinese shocks on global inflation, which are reported in row nine of Table 2.3. As it turns out, they are slightly larger in absolute values than those of the baseline setup. Hence, my conclusions remain intact.

## 2.6 Conclusion

I fit a factor-augmented vector autoregressive model to a large-dimensional macroeconomic data set covering 41 countries over the period 2000-2017 to examine the impact of China's

<sup>9</sup>The number of factors is determined by the IC2 criterion by Bai and Ng (2002). I cleaned the regional factors from the Chinese component using the procedure described in section 2.4.

economic downturn on inflation outside of China. I identify and estimate Chinese AS and AD innovations and compute impulse responses of global price indicators and national prices in the US, Europe, Asia, and Oceania in response to these innovations. Furthermore, I compute historical decompositions to identify the Chinese economic slowdown in terms of structural shocks and assess their contributions to international inflation dynamics.

My main findings are the following: (i) Business cycle shocks and especially AD shocks in China significantly spill over to national inflation rates in the US, Europe, Asia, and Oceania and are transmitted by global oil, commodity, and steel prices. (ii) The slowdown in the Chinese business cycle after the Great Recession can be attributed to a combination of contractionary AS and AD shocks in China. (iii) From 2014 onward, these shocks had a lowering effect on quarterly PPI inflation rates outside of China of up to 0.3 percentage points. They cumulatively lowered global oil prices by twelve percent and national PPIs outside of China by up to six percent. Hence, the Chinese business cycle noticeably contributed to the worldwide decline in inflation rates and hampered the recent upward trend. (iv) Adverse Chinese shocks also spilled over to interest rates and hence the financial sector outside of China, resulting in a lowering impact on the current level of yields.



## Chapter 3

# The Impact of Uncertainty and Financial Shocks in Recessions and Booms

This chapter of the dissertation is single-authored and has been published as Econstor working paper in 2019.

**Abstract**

The literature has widely discussed the role of financial and uncertainty shocks for the macroeconomy. However, it has turned out to be difficult to isolate these shocks from financial market indicators and uncertainty proxies because any identifying restriction on their response profile requires strong assumptions. To obtain more robust results, I model financial and uncertainty shocks jointly in a state-dependent FAVAR setup for the U.S. and provide agnostic identification bounds on their effects. I document that (i) uncertainty shocks are of limited relevance for real activity and asset prices in boom periods but have contractionary effects in recessions. (ii) By comparison, adverse financial shocks are contractionary in both states of the economy. (iii) Identifying assumptions play a significant role in recessions, reflected by wide identification bounds on the macroeconomic effects. (iv) Financial shocks exhibit tighter bounds than uncertainty shocks considering the impact on asset prices, hence the impact can be determined more precisely.

*Keywords:* Macroeconomic tail events, nonlinear FAVARs, financial shocks

*JEL classification:* E32, E37, E44



## 3.1 Introduction

The unprecedented disruptions of the Great Recession, its depth and duration have led to the question of whether traditional sources of business cycle fluctuations are sufficient in times of economic stress. Therefore, more recently theorists and empiricists have increasingly focused on the role of uncertainty and financial conditions and, in particular, the interplay between both (Bachmann et al., 2013; Bloom, 2009; Curdia and Woodford, 2010; Ajello, 2016). There is strong evidence that periods of elevated financial stress are associated with higher volatility in economic indicators, and the combination of these factors leads to significant real effects. Caldara et al. (2016), for instance, find that the Great Recession was likely a result of the toxic interaction between uncertainty and financial shocks. Alessandri and Mumtaz (2018) moreover document that the impact of exogenous increases in uncertainty is six times larger during times of financial stress.

The connection between financial indicators and uncertainty suggests that it is essential to model them jointly to separate autonomous changes from endogenous reactions. Indeed, parts of the literature question uncertainty as an exogenous driver of the business cycle but instead emphasize its endogeneity to financial and other disturbances. For example, Ludvigson et al. (2015) find that sharply higher macroeconomic uncertainty in recessions is often an endogenous response to output shocks, while shocks that originate in the financial market are a likely source of output fluctuations. As a result, exogenous disturbances in macroeconomic uncertainty play a minor role once financial shocks are controlled for (Popescu and Smets, 2010).

However, the empirical isolation of uncertainty shocks from financial shocks is difficult, as Stock and Watson (2012) show in their analysis of the channels of the Great Recession. Under the nonexistence of valid instruments we need identifying restrictions on the shocks' response profile, and these are typically strong. To give an example, financial and uncertainty indicators are assumed to react to each other on impact, which precludes plausible contemporaneous zero restrictions in an SVAR setup. Popescu and Smets (2010) accordingly document that the coexistence of both indicators raises identification issues if a recursive ordering is used.

In this paper, I use a set identification scheme based on the penalty function approach of Uhlig (2005) to estimate the impact of financial and uncertainty shocks on real economic activity and asset prices in the United States. I apply the identification to a state-dependent factor-augmented VAR model in which I include a large panel of macroeconomic and financial indicators. To measure uncertainty, I use a set of proxies capturing different categories, namely macroeconomic, financial, and economic policy uncertainty. As an indicator of financial stress I use the excess bond premium introduced by Gilchrist and Zakrajšek (2012).

I contribute in several ways to the literature. First, the penalty function approach yields identification bounds on the effects of uncertainty and financial shocks that reflect views stressing uncertainty as an exogenous source of business cycle fluctuations (e.g., Bachmann et al., 2013 and Bloom, 2009) as well as conservative views (e.g., Popescu and Smets, 2010 and Ludvigson et al., 2015). The bounds are constructed by defining a “large” and a “small”

version of both shocks. The large uncertainty shock is defined as an innovation that induces the maximal increase in a given uncertainty proxy. By the same token, the large financial shock is characterized as an innovation which yields the largest possible increase in the excess bond premium. I define the small uncertainty shock as the empirical residual of the uncertainty indicator that is not explained by the large financial shock. The analogous definition applies to the small financial shock. As it will turn out, the large versions of both shocks yield a sharper macroeconomic contraction than the small versions and thus the lower bound of the corridor of possible impacts. The small versions consequently generate the upper bound.

Second, the identification bounds indicate how financial disturbances and uncertainty innovations are transferred to the business cycle. Following the view of Bloom (2009), uncertainty has real implications since investment projects are partially irreversible. This means that when business conditions are uncertain, entrepreneurs defer real capital expenditures or recruiting until the outlook becomes clearer, a behavior that is commonly referred to as “wait-and-see business cycles” (Bachmann et al., 2013). These “real option effects” serve as explanation for both versions of the uncertainty shock since each of them induces an increase in uncertainty proxies. However, since the large uncertainty shock produces a rise in the excess bond premium it also echoes the financial perspective shaped by Gilchrist et al. (2014), Christiano et al. (2014), and Alessandri and Mumtaz (2018). The narrative here is that uncertainty shocks raise risk premia on external finance and thus marginal costs, which results in lower real activity.

Third, I distinguish between recessions and boom periods in the empirical framework and hence provide further evidence on the state-dependence of uncertainty and financial shocks. Besides, I account for the proposition that both these shocks were a major driving force of the Great Recession (e.g., Stock and Watson, 2012 and Caldara et al., 2016). To my knowledge, there are no other contributions that address their role in a joint setup and distinguish between recessions and boom periods at the same time.

My findings can be summarized as follows: Exogenous increases in uncertainty have a highly state-dependent influence on real activity and asset prices. While they are of limited significance in boom periods, they have contractionary effects in recessions. However, identifying assumptions play a non-negligible role for the effect sizes since the identification bounds are generally wide. This implies that the impact of uncertainty shocks cannot be precisely determined and is potentially small if financial shocks are simultaneously accounted for. By comparison, financial shocks have relatively tight bounds, albeit only in terms of their impact on asset prices. The bandwidths of the possible effects on real activity are considerable for both shocks. Hence, the interaction between uncertainty and financial conditions plays a pivotal role in the shock transmissions.

The paper is organized as follows. Sections 3.2 and 3.3 describe the model setup and the estimation approach. Section 3.4 presents the data and their transformations. In section 3.5, I discuss impulse responses and forecast error variance decompositions of macroeconomic indicators in response to financial and uncertainty shocks and a robustness analysis. Section 3.6 concludes.

## 3.2 Empirical setup

As empirical framework I employ a state-dependent version of the factor-augmented vector autoregressive (FAVAR) model for the United States. I augment a VAR of a financial indicator and an uncertainty proxy by a limited number of latent but estimable factors. This approach has two advantages: first, it circumvents the curse of dimensionality if a large panel of economic variables is of interest by reducing the panel to a small set of common factors. Hence, I do not need to restrict the variables entering the analysis to a few key measures. Second, the common factors concentrate a broad set of real, financial, and price indicators and are consequently informative enough to serve as business cycle controls (Bernanke et al., 2005 and Forni and Gambetti, 2010). To account for state-dependence in the FAVAR, I distinguish between a recessionary and a non-recessionary state (which I henceforth refer to as boom state). The states are identified by the recession chronology of the National Bureau of Economic Research (NBER).

### 3.2.1 State-dependent FAVAR

The starting point of the state-dependent FAVAR is a recession indicator  $R_t$ , defined as

$$R_t = \begin{cases} 1 & \text{if period } t \text{ is an NBER recession} \\ 0 & \text{otherwise.} \end{cases}$$

$R_t$  assigns an  $n \times 1$ -dimensional vector  $X_t$  of  $n = 101$  macroeconomic variables for the United States either a recession or a boom subsample. Both subsamples are assumed to follow a factor structure, thus each  $X_{i,t}$ ,  $i = 1, \dots, n$  is driven by a common component and an idiosyncratic component. The state-specific observation equation of the FAVAR is accordingly given by

$$X_t = \Lambda'_{R_t} Y_t + \xi_t \tag{3.1}$$

where  $\Lambda'_{R_t} Y_t$  represents the common component and  $\xi_t \sim N(0, \Omega_{R_t})$  the idiosyncratic component with diagonal covariance matrix  $\Omega_{R_t} = \text{Var}(\xi_t) = \text{diag}(\omega_{1,R_t}^2, \dots, \omega_{n,R_t}^2)$ . The term  $\Lambda_{R_t} = [\Lambda_{1,R_t}, \dots, \Lambda_{n,R_t}]$  denotes the loading matrix and  $\omega_{i,R_t}^2$ ,  $i = 1, \dots, n$  the variance of the idiosyncratic component of  $X_{i,t}$ .  $Y_t = [F'_t, EBP_t, UN_t]'$  is  $k \times 1$  and contains a set of  $m$  latent but estimable factors  $F_t = [F_{1,t}, \dots, F_{m,t}]'$  and a finance-uncertainty bloc consisting of two observable variables, namely the excess bond premium  $EBP_t$  and a proxy for economic uncertainty  $UN_t$ . In section 3.4, I describe further details on the indicators in the finance-uncertainty bloc and the series in  $X_t$ <sup>1</sup>.

<sup>1</sup>The indicators in the finance-uncertainty bloc are mean adjusted for the purpose of estimation. The series in  $X_t$  are additionally standardized. The identification of the latent factors  $F_t$  follows the scheme suggested by Bernanke et al. (2005): in case of  $m$  factors the first  $m$  variables in  $X_t$  have identity as loading matrix. In addition, I set their loadings on the finance-uncertainty bloc to zero. Since the factors only serve as control variables in my analysis, I refrain from using any rotations on top of the just-identification. However, I impose further zero restrictions on the loadings of slow-moving variables in  $X_t$  on the finance-uncertainty bloc. I assume that variables such as industrial production, employment, and price indices do not instantaneously react to financial or uncertainty shocks but adjust with a delay of at least one month

The dynamic relationship between the finance-uncertainty bloc and  $F_t$  follows a structural VAR, which forms the transition equation of the FAVAR:

$$Y_t = \sum_{k=1}^p B_{R_t,k} Y_{t-k} + u_t \quad (3.2)$$

$$u_t = P_{R_t,j} \epsilon_t \quad (3.3)$$

$p$  denotes the lag order,  $u_t \sim N(0, \Sigma_{R_t})$  the vector of reduced-form residuals and  $\epsilon_t \sim N(0, I_k)$  the structural shocks. The matrix  $P_{R_t,j}$  with property  $P_{R_t,j} P'_{R_t,j} = \Sigma_{R_t}$  describes the contemporaneous relationship between the reduced-form residuals and the structural shocks of interest, namely the uncertainty shock and the financial shock, under identification scheme  $j$ . The identifying restrictions are discussed in the following.

To isolate the finance-uncertainty bloc as a whole from the latent factors  $F_t$ , I initially assume a recursive chain. Hence, the EBP can react instantaneously to the latent factors but not vice versa, a scheme that mimics Bernanke et al. (2005) and Forni and Gambetti (2010). I follow Popescu and Smets (2010) and Jurado et al. (2015) in setting uncertainty below the latent factors, relying on the assumption that uncertainty shocks should not affect the business cycle on impact because of various information or decision lags.

### 3.2.2 The penalty function approach

The isolation of financial shocks *from* uncertainty shocks and thus the determination of  $P_{R_t,j}$  is a key issue of my contribution. I refrain from using contemporaneous zero restrictions since the EBP and the uncertainty proxy are assumed to react to each other on impact. I instead employ a version of the penalty function approach (PFA) proposed by Uhlig (2005) and Caldara et al. (2016), which leaves the mutual impact responses of the EBP and the uncertainty proxy unrestricted. In brief, the PFA selects a structural (FA)VAR shock that maximizes a criterion function subject to inequality constraints. Uhlig (2005), for example, isolates a monetary policy shock by maximizing the shock's contribution to the forecast error variance of the federal funds rate<sup>2</sup>.

In this paper, the criterion function consists of the sum of impulse response functions (IRFs) of selected variables from horizon 0 to  $h$ , while the inequality constraints correspond to sign restrictions on these IRFs. Using this design of the PFA, I choose two different identification schemes  $j = 1, 2$ , labeled as “EBP-max” and “UN-max” scheme. The EBP-max scheme defines the financial shock as the one which maximizes the  $h$ -step cumulative IRF of the EBP. I henceforth call it the “large” financial shock because it has a maximal effect on the EBP. The UN-max scheme defines the uncertainty shock as the one which maximizes the  $h$ -step cumulative IRF of the uncertainty proxy. I call it the “large” uncertainty shock.

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through the factors. Accordingly, the loadings of fast-moving variables such as asset prices, interest rates, and the money supply are left unrestricted.

<sup>2</sup>My version of the PFA and that of Caldara et al. (2016) slightly differs from that of Uhlig (2005). Instead of maximizing the forecast error variance of a target variable in response to a specific structural shock, I maximize the cumulative IRF. This approach has the advantage that it prevents the target variable from switching signs over the forecast horizon.

To implement these assumptions, I define the impact matrix  $P_{R_t,j}$  as follows:

$$P_{R_t,j} = \text{chol}(\Sigma_{R_t}) \begin{pmatrix} I_m & \mathbf{0}_{m \times 2} \\ \mathbf{0}_{2 \times m} & Q_{R_t,j} \end{pmatrix}',$$

where  $Q_{R_t,j}$  is a two-dimensional Given's rotation matrix for which holds  $Q'_{R_t,j}Q_{R_t,j} = Q_{R_t,j}^{-1}Q_{R_t,j} = I_2$ . To find the rotations  $Q_{R_t,j}$  of each scheme, I initially compute the Cholesky decomposition of the residual covariance matrix  $\Sigma_{R_t}$ . Then I rotate the lower-right  $2 \times 2$  submatrix of the Cholesky factor such that  $Q_{R_t,j}$  satisfies the identifying assumption of scheme  $j$ . As a result, I obtain the impact matrix of the EBP-max scheme,  $P_{R_t,1}$ , and the impact matrix of the UN-max scheme,  $P_{R_t,2}$ <sup>3</sup>.

Apart from the large versions of both shocks the PFA implicitly also defines “small” versions. They arise from the fact that after controlling for the factors in the FAVAR, the uncertainty proxy and the EBP are still positively correlated. For that reason the (large) financial shock of the EBP-max scheme is associated with a rise in the uncertainty proxy. The uncertainty shock, in turn, is the residual component of uncertainty that is not explained by the EBP under this scheme. As a result, it turns out small in size relative to the uncertainty shock of the UN-max scheme. The analogous definition applies to the UN-max scheme: since the large uncertainty shock is inflated with financial components (measured by the EBP), the financial shock is the residual part of the EBP that is not explained by the uncertainty proxy, and thus relatively small.

### 3.2.3 Identification bounds

A valuable property of the PFA is that it provides identification bounds on the impact of uncertainty and financial shocks. Since the large versions of both shocks induce a more substantial decline in real activity and asset prices than the small versions, they will always yield the lower of both IRFs. The small shocks accordingly generate the upper IRF. As a result, the PFA restricts a corridor for the possible effects on macroeconomic variables.

This corridor is useful from an agnostic point of view since it reflects different perspectives in the literature. On the one hand, theories and findings emphasizing uncertainty shocks as driving forces of the business cycle and financial conditions (Alessandri and Mumtaz, 2018; Bloom, 2009; Christiano et al., 2014) are mirrored by the UN-max scheme, hence the lower bound of uncertainty shocks and the upper bound of financial shocks. On the other hand, views emphasizing the endogeneity of uncertainty to other shocks rather than its exogeneity (Ludvigson et al., 2015; Popescu and Smets, 2010; Carriero et al., 2018) are echoed by the EBP-max scheme, hence the upper bound of uncertainty shocks and the lower bound of financial shocks.

Moreover, the bounds refer to different implicit transmission channels. Uncertainty shocks, for instance, act through at least two mechanisms. First, partial irreversibility

<sup>3</sup>This design of the PFA is a generalization of the Cholesky identification since it collapses to Cholesky if the IRF horizon  $h$  is zero. Moreover, the PFA implies that depending on the chosen IRF horizon, contractionary financial and uncertainty shocks induce a prolonged period of elevated financial stress and uncertainty, respectively. I follow Caldara et al. (2016) in choosing  $h = 6$  months. However, the robustness checks in section 3.5.5 show that other horizons yield similar results.

of investment decisions creates a real option effect, as described by Bloom (2009) and Bachmann and Bayer (2013). Specifically, more uncertain business conditions make entrepreneurs defer real capital expenditures or recruiting and wait until prospects become clearer. This narrative applies to both versions of the uncertainty shock since each of them induces an increase in uncertainty. An uncertainty shock arising from the UN-max scheme, however, also works through a financial transmission channel. Since it produces a rise in the EBP it increases the price of external finance, resulting in further macroeconomic contraction. This mechanism underlies the financial view on uncertainty shocks discussed by Alessandri and Mumtaz (2018) and Christiano et al. (2014).

Financial shocks can be considered analogously. In general, they increase the EBP and thus the cost of external financing, leading to a decline in real activity and asset prices. In the EBP-max scheme, however, they also induce a rise in uncertainty that intensifies the overall effects. Firms might be uncertain about how severely business conditions worsen in response to the financial shock and to which degree monetary and fiscal authorities counteract, and accordingly keep a low profile. Baker et al. (2016), for example, document that economic policy uncertainty increases during times of financial turmoil and that economic policy uncertainty, in turn, has notable real effects<sup>4</sup>.

### 3.3 Estimation

The estimation of the reduced-form FAVAR (equations (3.1) and (3.2)) is Bayesian, and I implement it using a Gibbs sampling routine<sup>5</sup>. Since I measure uncertainty by three different proxies, I also estimate the FAVAR three times. Each time the FAVAR incorporates the EBP and one of the three uncertainty proxies forming the finance-uncertainty bloc. The estimation settings are otherwise identical. I describe the uncertainty proxies in section 3.4.

Before I start the estimation, I split the observations into a recession and a boom subsample according to the chronology of the NBER. The sequence of regimes is presented in Figure C.2. Since I carry out the Gibbs sampling steps for each regime separately using only its specific observations, I omit the regime subindex  $R_t$  in the following.

The sampling of the observation equation coefficients  $\Lambda_i$  and  $\omega_i^2$  is conducted for each  $X_{i,t}$  separately, i.e., equation-wise. The priors are (independent) Normal and inverse-Gamma, respectively. The prior of the VAR parameters  $B$  and  $\Sigma$  is normal inverse-Wishart. Further details on the priors and hyperparameters can be found in section C.2.

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<sup>4</sup> However, the existing evidence on the propagation of financial shocks through uncertainty does not account for regime-specific dynamics. Caldara et al. (2016) and Baker et al. (2016) base their conclusions on constant-parameter VARs.

<sup>5</sup>In the baseline estimation setup, the number of lags in the VAR part and the number of latent factors are set to  $p = 6$  months and  $m = 4$ , respectively. However, the robustness checks in section 3.5.5 show that other choices of  $p$  and  $m$  do not affect my conclusions.

Given the two subsamples and the priors, the Gibbs sampling steps are the following:

1. I sample from the conditional posterior distributions of the coefficients  $\Lambda_i$  and  $\omega_i^2$  of the observation equation (3.1), which are given by

$$\Lambda_i|X_i, \omega_i^2 \sim N(\bar{\Lambda}_i, \bar{\Sigma}_{\Lambda_i}), \quad \omega_i^2|X_i, \Lambda_i \sim IG(\bar{\phi}, \bar{\theta}_i)$$

2. I sample from the conditional posterior distributions of the coefficients  $B$  and  $\Sigma$  of the transition equation (3.2), i.e., the VAR part. They are given by

$$\text{vec}(B)|Y, \Sigma \sim N(\text{vec}(\bar{B}), \bar{\Sigma}_B), \quad \Sigma|Y \sim IW(\bar{S}, \bar{\alpha})$$

3. I run the Kalman filter and then the Carter-Kohn algorithm to find the factors  $F_t$ . The filtering is conditional on the regime-specific estimates of  $\Lambda$ ,  $\Omega$ ,  $B$ , and  $\Sigma$ . Hence, it switches between the recession regime and the boom regime.

To ensure convergence, I repeat these steps 10,000 times from which I discard the first 5,000 repetitions. Details on the conditional posteriors of the observation equation and the transition equation can be found in section C.2.

## 3.4 Data

The time series I use in the analysis are at monthly frequency and span the period 1975:m1-2016:m8. This time window contains  $T = 500$  observations of which 61 are NBER recessions. The series contained in  $X_t$  and the finance-uncertainty bloc are described in more detail in the following.

I take the excess bond premium (EBP) introduced by Gilchrist and Zakrajšek (2012) as a proxy for financial stress. The EBP is based on a credit spread index comprising a large number of prices of corporate bonds trading in the secondary market. It forms the component of the index that is not explained by the available firm-specific information on expected defaults, hence it approximates the *pricing* of default risk in the corporate bond market. The authors show that an increase in the EBP reflects a lower capacity or willingness of taking risk in the financial sector and, consequently, a reduction in the supply of credit.

Since uncertainty is a wide concept and hard to measure, I use three different indicators as proxies. To measure macroeconomic uncertainty, I rely on the uncertainty measure proposed by Jurado et al. (2015). It is based on the conditional volatility of the unpredictable component of real economic activity derived from a factor model that comprises a large number of macroeconomic series<sup>6</sup>. I call it the “JLN” measure in the following.

To highlight the role of financial uncertainty, I use the VXO volatility index published by the Chicago Board Options Exchange. For the period from January 1986 onward,

<sup>6</sup>Jurado et al. (2015) use different forecast horizons to construct the series. I choose one month as horizon in my analysis, but choosing three or twelve months does not alter the results.

this index corresponds to the implied volatility of S&P100 options 30 days to expiration. For the Pre-1986 period I follow Bloom (2009) in using realized stock return volatility<sup>7</sup>, measured by monthly standard deviations of the S&P500. I call the compound series the “Bloom” measure hereafter.

As a proxy for economic policy uncertainty I use the newspaper-based index by Baker et al. (2016), which I call the “BBD” measure in the following. This index rests upon the frequency of newspaper references to policy-related economic uncertainty. Details can be found in the paper.

The vector  $X_t$  contains 101 key macroeconomic and financial variables for the United States. The selection of series is orientated at the data set by Forni and Gambetti (2010) and a list of them is presented in Table C.2. Since I extract factors, I standardize every series in  $X_t$  to obtain a zero mean and a variance of one. Series which exhibit a seasonal pattern are seasonally adjusted. To prevent my results from being driven by outliers, I follow Carstensen and Salzmann (2017) and Stock and Watson (2005) in trimming any observation that is further than five times the interquartile range away from its median to the respective threshold. The data is taken from the webpage of the Federal Reserve Bank of St. Louis.

## 3.5 Results

I base my conclusions on state-dependent impulse responses of real economic indicators and asset prices to uncertainty and financial shocks and forecast error variance decompositions. In addition, I present cross-effects between the EBP and uncertainty, that is to say, the reaction of uncertainty proxies to a financial shock and that of the EBP to an uncertainty shock. I rely on three estimated versions of the FAVAR, each of which includes the EBP and one of the three uncertainty proxies. I present the results from the EBP-max and the UN-max identification jointly in one figure or table to depict them as identification bounds.

### 3.5.1 Cross-effects of uncertainty and financial shocks

Figure 3.1 shows state-dependent IRFs of the EBP and the uncertainty proxies to exogenous innovations in financial conditions and uncertainty. The labels “JLN”, “Bloom”, and “BBD” above the panels stand for the uncertainty measure used in the FAVAR. In each panel, the solid graphs result from the EBP-max scheme and thus depict the effects of the large financial shock and the small uncertainty shock. The dashed graphs result from the UN-max scheme and accordingly represent the effects of the large uncertainty shock and the small financial shock<sup>8</sup>.

<sup>7</sup>For the pre-1986 period the VXO index is unavailable, so Bloom (2009) takes the monthly standard deviation of the daily S&P500 index normalized to the same mean and variance as the VXO index when the series overlap from 1986 onward.

<sup>8</sup>I adjust the shock magnitudes to obtain a predetermined response of the uncertainty proxies and the EBP. In particular, I scale the large uncertainty shock such that the corresponding uncertainty proxy jumps on impact by one regime-specific standard deviation. I adjust the size of the small uncertainty



As the panels A) and C) show, financial and uncertainty shocks induce a persistent rise in their respective indicators. Moreover, except for the hump-shaped reaction of the JLN measure all effects peak on impact. The differences between the small and large shock versions are generally significant but slightly larger in terms of uncertainty shocks.

The panels B) and D) show the cross-effects of both shocks. We see that in general, they are larger in recessions and have wider identification bounds than in boom periods. Moreover, they are considerably smaller if the shocks arise from the residual components of the indicators derived from the PFA. In the UN-max scheme, the EBP jumps on impact by up to 2.5 standard deviations in response to an uncertainty shock, a result which confirms the transmitting role of credit conditions (e.g., Christiano et al., 2014 and Alessandri and Mumtaz, 2018). In the EBP-max scheme, however, only shocks to the JLN measure have a positive and significant impact on the EBP. The cross-effects of financial shocks differ from those of uncertainty shocks since the effect magnitudes tend to be smaller and the identification bounds tighter.

These findings imply three conclusions: first, the optimization setup in the PFA and thus identifying assumptions play a pivotal role for uncertainty shocks. By comparison, financial shocks exhibit a slightly better identifiability since the bandwidth of possible effects is tighter. Second, large uncertainty shocks are associated with a considerable tightening in credit conditions, while large financial shocks only induce a moderate increase in uncertainty. The small versions of both shocks generally have limited cross-effects. Third, cross-effects between the EBP and uncertainty and the identification scheme play a greater role in the recession regime.

### 3.5.2 Macroeconomic impact of uncertainty shocks

Figure 3.2 shows the IRFs of the percentage 3-month growth rates of industrial production, employment, stock prices, and house prices to adverse uncertainty shocks.

The IRFs confirm the contractionary character of uncertainty that has been found by other contributions (e.g., Caldara et al., 2016). The impacts of the shocks are larger in recessions than in boom periods and hence state-dependent, albeit to a different extent depending on the chosen uncertainty measure. Shocks to the JLN measure reduce industrial production growth by up to 1.5 percentage points in recessions but have insignificant effects in boom periods<sup>9</sup>. In contrast, innovations in the BBD measure exhibit a considerably milder state-dependence. Interestingly, house prices fall during recessions but tend to increase in booms, a result that might arise from a flight-to-safety mechanism (Brogaard and Detzel, 2015).

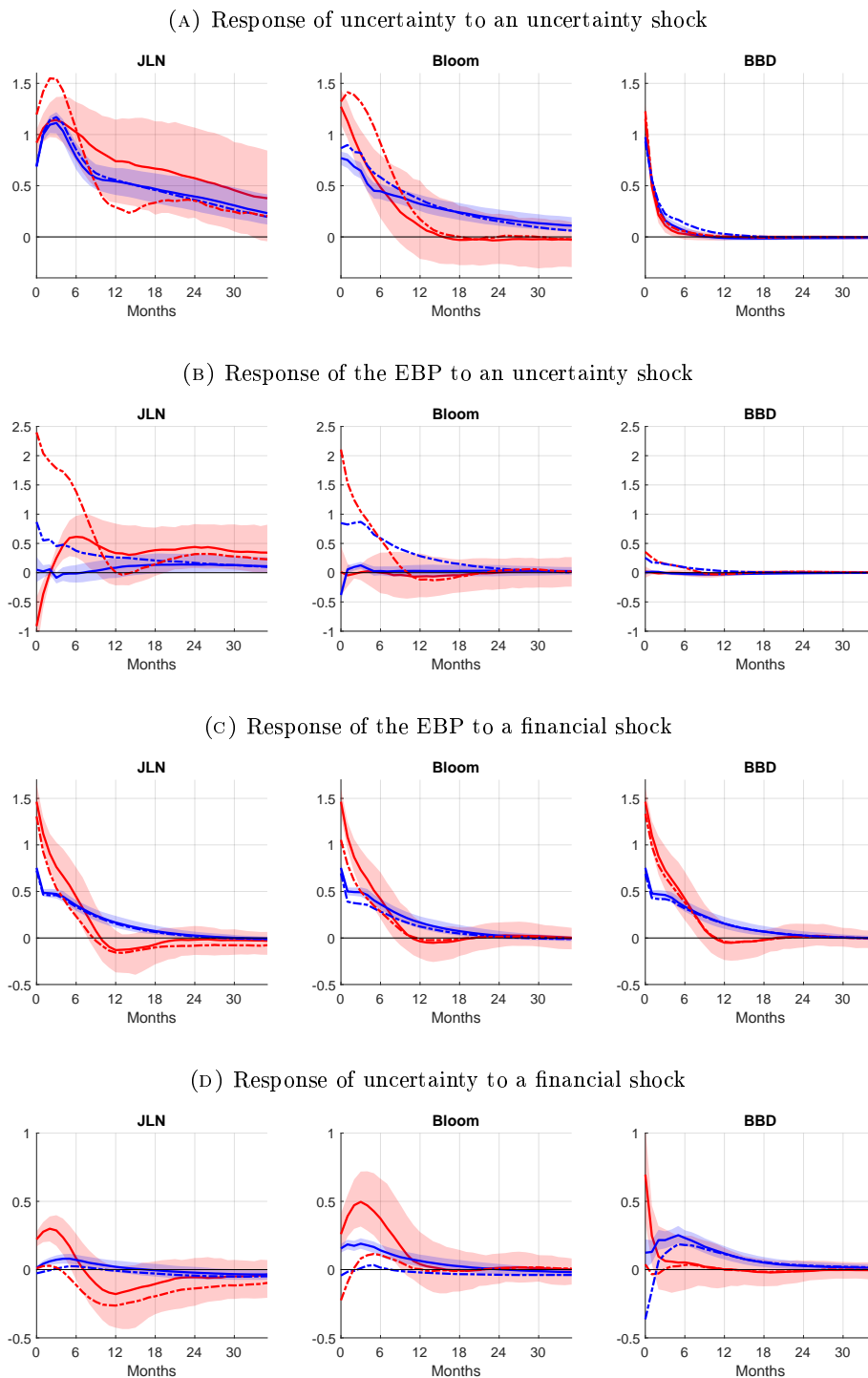
The IRFs exhibit wide identification bounds in recessions. Whereas a shock to the Bloom measure reduces stock returns by up to 15 percentage points in the UN-max scheme,

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shock proportionally. I repeat this procedure for the financial shock: its large version raises the EBP by one regime-specific standard deviation and the size of the small version adapts accordingly.

<sup>9</sup>This finding draws a picture of the role of uncertainty which is more differentiated than what other empirical works have found so far. Jurado et al. (2015), for example, show in a constant-parameter VAR that uncertainty has an adverse and considerable impact on real activity. My findings, however, indicate that the observations in the recession regime are primarily relevant in this proposition.

FIGURE 3.1: Cross-effects of uncertainty and financial shocks



Notes: The panels show regime-specific impulse response functions (IRFs) of uncertainty and the EBP to a contractionary uncertainty shock and a financial shock. The headings “JLN”, “Bloom”, and “BBD” stand for the uncertainty measure used in the FAVAR. The units on the y-axis are standard deviations of the responding variables. The red graphs depict the IRFs in the recession regime and the blue graphs those in the boom regime. The solid and dashed graphs are median IRFs resulting from the EBP-max and the UN-max identification, respectively. The shaded areas are 68 percent confidence intervals on the IRFs of the EBP-max identification. The uncertainty shocks are scaled such that the large shock induces a rise in the corresponding uncertainty proxy by one regime-specific standard deviation. The analogous scaling is applied to the financial shocks.

it has insignificant effects in the EBP-max scheme. Hence, the identification entirely accounts for the state-dependence in this case. The effects on the real indicators tend to be more robust. The IRFs of the EBP-max scheme amount to about 50 percent of those implied by the UN-max scheme, which implies that small uncertainty shocks are likewise contractionary. Taking this result together with the limited impact of small uncertainty shocks on credit conditions (section 3.5.1), I conclude that financial conditions play an essential role in transmitting uncertainty shocks but real option effects are also at work.

To account for the relative importance of uncertainty shocks for the considered indicators, I compute variance decompositions after 24 months<sup>10</sup>, displayed in Table 3.1. I follow Bernanke et al. (2005) in assessing the importance of the shocks relative only to the portion of the indicators explained by the common factors, hence I focus on cyclical fluctuations<sup>11</sup>. The decompositions confirm the findings from the impulse response analysis. In general, uncertainty shocks are of limited importance in boom periods but contribute significantly to macroeconomic fluctuations in recessions. Moreover, the higher relevance of uncertainty shocks in recessions comes along with broader identification bounds. These often include variance shares close to zero, only the JLN measure exhibits significant fractions in the EBP-max specification.

Both the IRFs and the variance decompositions show that among the considered uncertainty measures, the Bloom index exhibits the widest identification bounds. For example, its relative contribution to cyclical fluctuations of stock returns ranges between zero and 46 percent (!). On the one hand, this could indicate that a (large) financial uncertainty shock leads to a tightening in credit conditions, which in turn affects real indicators and asset prices. On the other hand, it may also reflect the difficulty of distinguishing between first and second-moment financial disturbances. Accordingly, Stock and Watson (2012) find in their analysis of the channels of the Great Recession that credit spreads and proxies for financial uncertainty do not identify distinct shocks.

Another striking result is that shocks to the BBD measure are of limited relevance since they only pertain to stock returns. This contrasts Baker et al. (2016), who find in a classical VAR that an adverse economic policy uncertainty shock reduces industrial production and employment to a moderate but significant degree. There are multiple reasons for this discrepancy, but one is presumably due to the conditioning on the EBP in the empirical setup<sup>12</sup>.

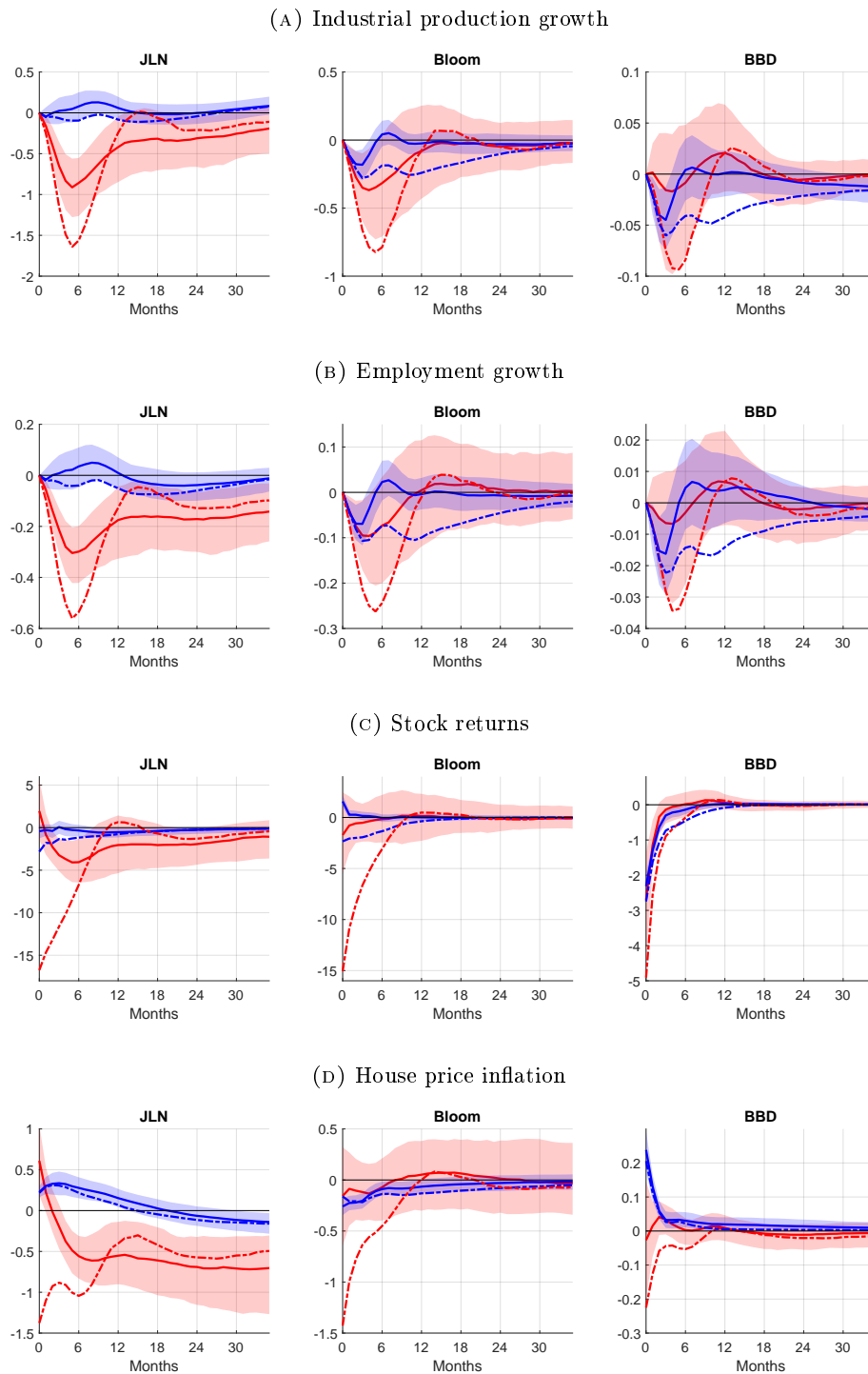
As a result, I rely on the JLN measure of macroeconomic uncertainty for the remainder of this paper. I base this choice not only on the identification issues of the Bloom index

<sup>10</sup>I omitted variance decompositions at other horizons since they do not affect my conclusions.

<sup>11</sup>As a result, I ignore the idiosyncratic component here. Bernanke et al. (2005) justify this approach by the assumption that the idiosyncratic component reflects in part measurement error and thus should not react to business cycle determinants.

<sup>12</sup>Baker et al. (2016) find that a shock of two standard deviations in the BBD index lowers industrial production by 1.1 percent and employment by 0.35 percent nine months after the shock. Under the UN-max setup, I find slightly smaller corresponding effects, namely between 0.27 percent (recessions) and 0.31 percent (boom periods) on industrial production and between 0.1 percent (recessions) and 0.12 percent (boom periods) on employment. Apart from the conditioning on financial stress, the Bayesian estimation setup might also play a role for the different results since the mean parameters are shrunk towards zero. Moreover, Baker et al. (2016) order uncertainty first in a Cholesky identification with real economic indicators, implying that uncertainty shocks potentially contain business cycle components.

FIGURE 3.2: Macroeconomic effects of an uncertainty shock



Notes: The panels show regime-specific impulse response functions (IRFs) of the percentage 3-month growth rates of industrial production, employment, stock prices, and house prices to a contractionary uncertainty shock. The headings “JLN”, “Bloom”, and “BBD” stand for the uncertainty measure used in the FAVAR. The red graphs depict the IRFs in the recession regime and the blue graphs those in the boom regime. The solid and dashed graphs are median IRFs resulting from the EBP-max and the UN-max identification, respectively. The shaded areas are 68 percent confidence intervals on the IRFs of the EBP-max identification. The shock magnitudes are adjusted such that the large uncertainty shock induces a rise in the corresponding uncertainty proxy by one regime-specific standard deviation.

TABLE 3.1: Forecast error variance decomposition - Uncertainty shock

Variable \ Identification + Regime	Recessions		Booms	
	EBP-max	UN-max	EBP-max	UN-max
<b>Uncertainty measure: JLN</b>				
Industrial production growth	8.0	17.1	0.6	2.0
Employment growth	10.1	18.2	1.6	3.4
Stock returns	4.6	30.3	2.4	11.5
House price inflation	14.1	22.3	7.2	6.3
<b>Uncertainty measure: Bloom</b>				
Industrial production growth	2.8	12.9	0.7	7.4
Employment growth	1.7	11.8	0.4	4.8
Stock returns	0.4	45.5	1.9	18.5
House price inflation	1.4	23.6	2.6	5.5
<b>Uncertainty measure: BBD</b>				
Industrial production growth	0.2	1.5	0.5	3.8
Employment growth	0.2	1.9	0.4	2.4
Stock returns	7.2	27.8	35.0	61.6
House price inflation	0.3	4.8	16.4	11.1

Notes: The table shows the percentage shares of the forecast error variance of the common component of key macroeconomic variables accounted for by an uncertainty shock. The forecast horizon is set to 24 months.

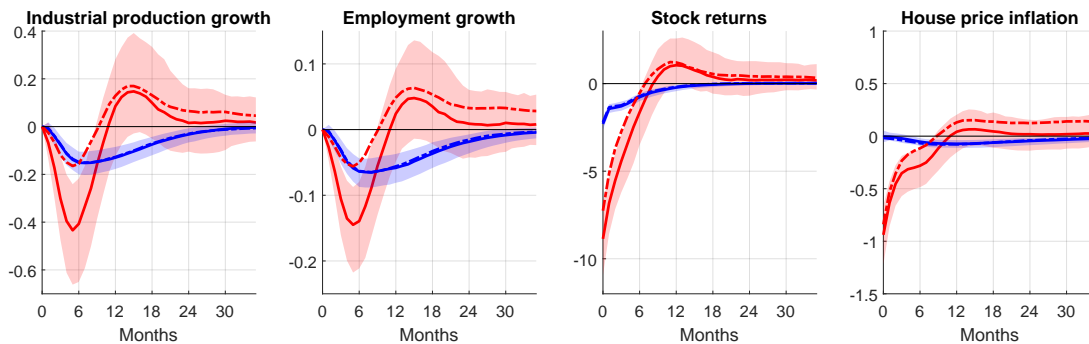
and the limited relevance of the BBD measure but also on the result by Caldara et al. (2016) that the JLN measure gives economic uncertainty the maximum role in explaining business cycle fluctuations out of a set of uncertainty measures, including those I use. I confirm this finding for the state-specific case since only the JLN measure significantly contributes to the cyclical components in both identification schemes<sup>13</sup>.

### 3.5.3 Macroeconomic impact of financial shocks

Figure 3.3 displays the IRFs of the real economic indicators and asset prices to an adverse financial shock using the JLN measure of uncertainty in the FAVAR. As in the case of uncertainty shocks, financial shocks are contractionary and state-dependent. The effects are more pronounced in recessions than in boom periods, especially if we consider asset returns. Stock returns, for example, fall by up to nine percentage points in recessions but only by two percentage points in boom periods. The real indicators moreover exhibit state-specific dynamic patterns. Whereas industrial production growth falls by 0.2 percentage points after six months and remains negative in boom periods, it falls by up to 0.4 percentage points in recessions, recovers within ten months and overshoots. The overshoot, however, is not statistically significant.

<sup>13</sup>For the sake of completeness and to review the robustness of the baseline results, I show the IRFs and variance shares of the financial shock using the other two uncertainty measures in Figure C.1 and Table C.1.

FIGURE 3.3: Macroeconomic effects of a financial shock



Notes: The panels show regime-specific impulse response functions (IRFs) of the percentage 3-month growth rates of industrial production, employment, stock prices, and house prices to a contractionary financial shock using the JLN measure of uncertainty. The red graphs depict the IRFs in the recession regime and the blue graphs those in the boom regime. The solid and dashed graphs are median IRFs resulting from the EBP-max and the UN-max identification, respectively. The shaded areas are 68 percent confidence intervals on the IRFs of the EBP-max identification. The shock magnitudes are adjusted such that the large financial shock induces a rise in the EBP by one regime-specific standard deviation.

The IRFs are more robust to identifying assumptions than those of uncertainty shocks. The dashed and solid graphs significantly differ only in the state of recession and in terms of the real indicators. In this case, however, the difference is sizeable since the real effect in the EBP-max scheme is twice as large as the effect in the UN-max scheme<sup>14</sup>.

The forecast error variance shares of the financial shock are reported in Table 3.2. We see that they are significant in both states of the economy, a finding which contrasts Table 3.1 on uncertainty shocks. The identification bounds are again of considerable width in recessions. For instance, the shares of cyclical fluctuations of industrial production growth accounted for by financial shocks range between 6 and 16 percent. In booms, however, the limits are barely distinguishable, a result that reflects the limited impact of financial shocks on macroeconomic uncertainty discussed in section 3.5.1. Hence, whereas financial disturbances act through a purely financial transmission channel in boom periods, uncertainty noticeably transmits them in recessions. Interestingly, if we consider the UN-max scheme and the real indicators, the fractions of the financial shock are slightly smaller in recessions than in boom periods. At the same time, the shares in the EBP-max scheme are almost identical in both regimes. I conclude from this finding that compared to the boom regime, the financial channel shrinks in favor of the uncertainty channel in recessions.

This result highlights a property of financial shocks that is underrepresented in the related literature. Many contributions in this field still rely on constant-parameter models and consequently do not allow for different regimes of economic stress, for example Caldara et al. (2013) or Popescu and Smets (2010). Since the number of stressful periods is usually small relative to the total number of observations (61 recession periods vs. 439 boom periods in this paper), their conclusions are congruent with mine during boom periods, which is that uncertainty plays a negligible role in transmitting financial shocks.

<sup>14</sup>This finding hinges on the chosen uncertainty measure. As Figure C.1 and Table C.1 show, if I choose the BBD measure the identification bounds are barely distinguishable even in recessions. Hence, the transmission of financial shocks by economic policy uncertainty is negligible.

TABLE 3.2: Forecast error variance decomposition - Financial shock

Variable \ Identification + Regime	Recessions		Booms	
	EBP-max	UN-max	EBP-max	UN-max
Industrial production growth	15.6	6.2	14.8	13.4
Employment growth	16.2	7.8	13.4	11.5
Stock returns	63.2	36.9	77.7	68.5
House price inflation	40.5	31.7	6.6	7.5

Notes: The table shows the percentage shares of the forecast error variance of the common component of key macroeconomic variables accounted for by a financial shock. The JLN proxy is used as measure for uncertainty in the FAVAR. The forecast horizon is set to 24 months.

### 3.5.4 Impacts on sectoral employment

To further exploit the cross-sectional dimension of the FAVAR framework, I analyze the relevance of uncertainty and financial shocks for important macroeconomic disaggregates. Table 3.3 shows the relative contributions of both shocks to the cyclical fluctuations of sectoral employment growth. In general, the considered employment indicators confirm the conclusions of sections 3.5.2 and 3.5.3. Whereas uncertainty shocks account for significant variance shares only in recessions, financial shocks are relevant in both regimes. Moreover, financial shocks identified by the UN-max scheme are slightly more important in booms than in recessions.

However, the relevance of both shocks differs across sectors. Uncertainty shocks are generally important for employment fluctuations in the private sector and especially pertain to financial activities, trade, manufacturing, the goods producing sector, and the service sector. The shares in the EBP-max scheme are around half as large as those in the UN-max in most sectors, which again reflects a lack of identification robustness of uncertainty shocks. Interestingly, the bounds are very tight in terms of employment in the financial industries.

The ranking between the sectors is similar if we look at financial shocks. Again, the private sector is generally affected, but especially trade, manufacturing, the goods producing sector, and the service sector. Not unexpectedly, the government sector is little effected by both shocks.

Compared to uncertainty shocks, financial shocks exhibit a relatively low weight in the financial sector. This finding is puzzling at first sight but results from the fact that the EBP only contains bond prices of non-financial firms. Moreover, Prassas (2011) shows that historically, employment in financial activities has been little affected by economic downturns, thus times in which the EBP is typically high. The only exception was the period around the Great Recession of 2008/09 when housing-related financial industries lost 348,000 jobs.

TABLE 3.3: Forecast error variance decomposition - Sectoral employment growth

Sector	Identification +Regime	Recessions		Booms	
		EBP-max	UN-max	EBP-max	UN-max
<b>Uncertainty shocks</b>					
Total		10.1	18.2	1.6	3.4
Manufacturing		7.9	17.8	0.6	2.0
Construction		12.6	12.0	3.3	5.3
Total private industries		9.8	18.0	1.4	3.2
Government		2.4	3.1	4.2	4.4
Retail trade		10.9	17.7	1.0	2.4
Wholesale trade		11.5	20.0	1.0	2.7
Financial activities		22.2	20.3	1.7	2.8
Mining and logging		12.2	19.5	0.2	0.7
Durable goods		8.2	17.5	0.8	2.4
Nondurable goods		7.4	18.6	0.2	0.8
Goods-producing industries		10.3	17.4	1.3	3.1
Service-providing industries		12.0	20.0	1.8	3.5
Trade, transportation and utilities		10.2	18.6	1.2	2.9
<b>Financial shocks</b>					
Total		16.2	7.8	13.4	11.5
Manufacturing		16.8	6.6	14.9	13.4
Construction		7.5	7.9	10.9	8.8
Total private industries		15.9	7.4	13.9	12.1
Government		4.0	3.2	0.7	0.5
Retail trade		14.2	7.1	13.0	11.6
Wholesale trade		17.1	8.3	14.3	12.4
Financial activities		10.9	12.4	7.8	6.7
Mining and logging		17.1	9.5	8.0	7.4
Durable goods		16.3	6.7	15.0	13.3
Nondurable goods		18.0	6.5	13.7	13.0
Goods-producing industries		15.0	7.5	14.5	12.6
Service-providing industries		17.3	8.9	12.0	10.2
Trade, transportation and utilities		16.0	7.3	13.9	12.1

Notes: The table shows the percentage shares of the forecast error variance of the common component of sectoral employment growth accounted for by an uncertainty shock and a financial shock. The JLN proxy is used as measure for uncertainty in the FAVAR. The forecast horizon is set to 24 months.



### 3.5.5 Robustness checks

As customary in empirical papers, I perform several sensitivity checks to strengthen the credibility of my results. I re-estimate the FAVAR using a range of alternative settings in which I depart from a single property of the baseline setup while leaving all others unchanged. Figure 3.4 and Table 3.4 show the resulting IRFs and variance decompositions of employment growth after a shock to the JLN measure and a financial shock alongside the baseline results.

First, I check the robustness of the findings to changes in the VAR lag order. In the baseline setup, I allow for  $p = 6$  months which has been considered sufficient in various business cycle VARs, e.g., Eickmeier (2010). However, to account for potential serial correlation in the disturbance term  $u_t$  and since other applications such as Bachmann et al. (2013) use a lag order of 12 months, I re-estimate the FAVAR with  $p = 12$ . As Table 3.4 shows, this alternative specification yields slightly larger variance shares of the financial shock during boom periods. The remaining results and especially the IRFs are nevertheless very similar to those of the baseline setup, from which I conclude that the lag order does not play a significant role.

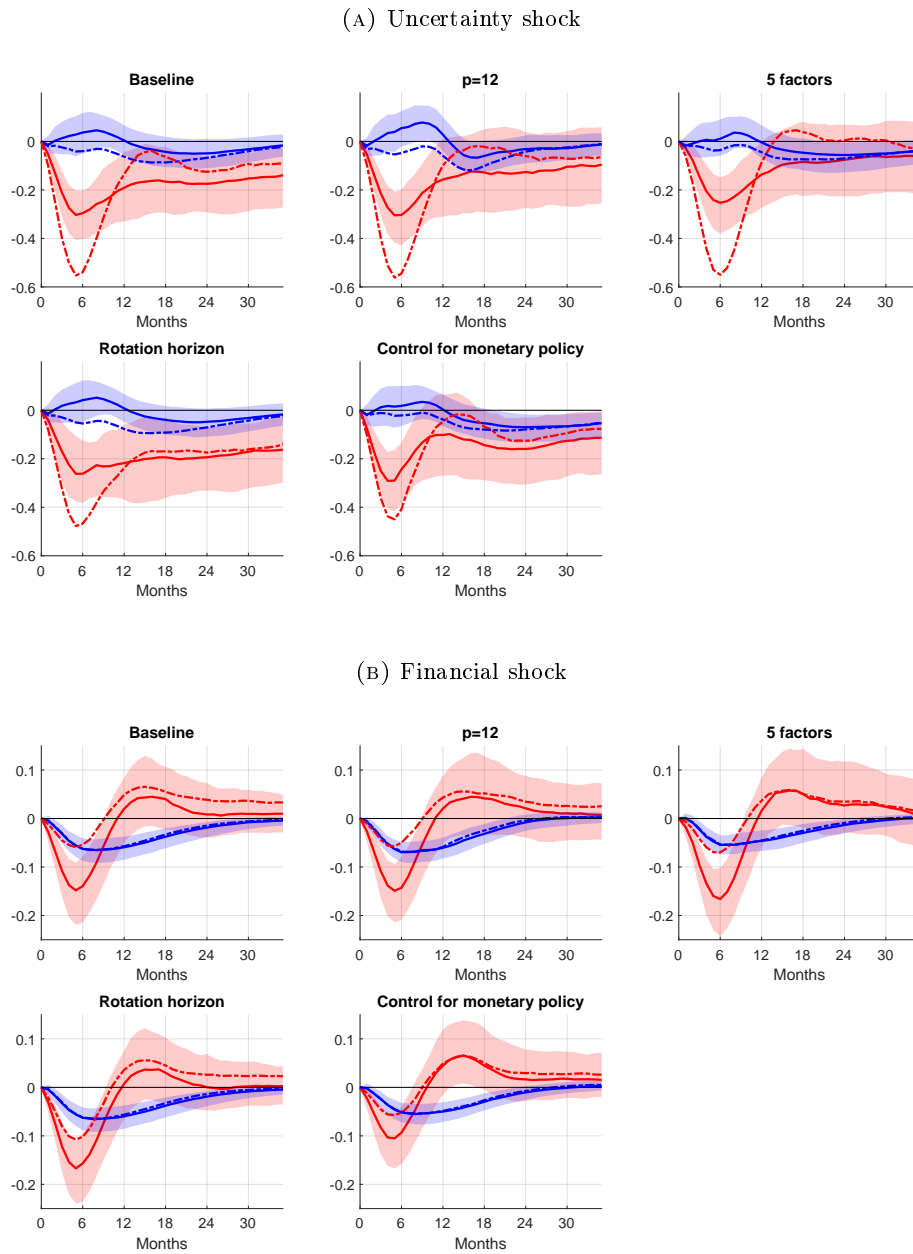
I also test if the number of latent factors in the FAVAR drives my results. I initially set it to  $m = 4$  to already capture 78 percent of the variance of  $X_t$ . Since a fifth factor accounts for another six percent, I check its relevance in a further estimation with  $m = 5$ . This alternative setting yields slightly smaller variance shares accounted for by financial shocks in boom periods. However, the overall picture of the results confirms the conclusions obtained from the baseline setup.

TABLE 3.4: Robustness checks

Modification	Identification +Regime	Recessions		Booms	
		EBP-max	UN-max	EBP-max	UN-max
<b>Uncertainty shocks</b>					
Baseline		10.1	18.2	1.6	3.4
12 lags		9.0	18.7	1.2	3.8
Number of factors		5.5	15.2	0.4	0.2
Rotation horizon		9.1	14.7	0.9	1.8
Control for monetary policy		6.6	9.5	0.2	0.4
<b>Financial shocks</b>					
Baseline		16.2	7.8	13.4	11.5
12 lags		16.8	6.7	19.9	17.4
Number of factors		16.4	6.5	8.2	8.3
Rotation horizon		18.3	11.4	13.7	12.7
Control for monetary policy		12.5	9.3	12.6	12.4

Notes: The table shows the percentage shares of the forecast error variance of the common component of employment growth accounted for by an uncertainty shock and a financial shock. The JLN proxy is used as measure for uncertainty in the FAVAR. The forecast horizon is set to 24 months.

FIGURE 3.4: Robustness checks



Notes: The panels show regime-specific impulse response functions (IRFs) of the percentage 3-month growth rates of employment to a contractionary uncertainty shock and a financial shock. The JLN proxy is used as measure for uncertainty in the FAVAR. The red graphs depict the IRFs in the recession regime and the blue graphs those in the boom regime. The solid and dashed graphs are median IRFs resulting from the EBP-max and the UN-max identification, respectively. The shaded areas are 68 percent confidence intervals on the IRFs of the EBP-max identification. The uncertainty shocks are scaled such that the large shock induces a rise in the corresponding uncertainty proxy by one regime-specific standard deviation. The analogous scaling is applied to the financial shocks.

The IRF horizon  $h$  in the PFA is an ingredient of my shock identification and thus another potential determinant of the results. I follow Caldara et al. (2016) in choosing six months since they find this horizon optimal for identifying uncertainty and financial shocks in a constant-parameter VAR. To check if this choice is relevant, I apply the PFA using  $h = 12$  months and the baseline estimates. Since the resulting IRFs and variance decompositions do not noticeably deviate from those of the baseline setup, I conclude that the identification horizon does not play a significant role either.

Finally, I include the federal funds rate (FFR) as observable variable into the FAVAR to control for the stance of monetary policy<sup>15</sup>. I place it at the bottom of the finance-uncertainty bloc and re-estimate the FAVAR, hence I treat the FFR as the most fast-moving variable (see, e.g., Prieto et al., 2016). This modification leads to slightly smaller variance shares accounted for by uncertainty shocks, but it again does not affect the overall picture of the results.

### 3.6 Conclusion

I analyze the effects of uncertainty and financial shocks based on a state-dependent FAVAR and U.S. data from 1975 to 2016. The FAVAR allows for a recession and a boom regime and includes a comprehensive set of macroeconomic and financial variables, different proxies for uncertainty, and a financial stress indicator. To identify exogenous innovations in financial conditions and uncertainty, I employ the penalty function approach proposed by Uhlig (2005). This approach enables constructing identification bounds that consider both shocks jointly and provide a corridor for their effects on macroeconomic indicators. The bounds are moreover agnostic since they unite various perspectives on the shocks in one framework and refer to different implicit transmission mechanisms.

I document that uncertainty shocks have highly state-dependent effects on real activity and asset prices. They are of limited relevance in boom periods but have a contractionary impact in recessions. By contrast, financial shocks result in significant macroeconomic effects in both regimes.

However, identifying assumptions play a non-negligible role in recessions. They tend to be more relevant for uncertainty shocks than for financial shocks, especially if we consider the impact on asset prices. In this case, the identification bounds of financial shocks are relatively tight. Those of uncertainty shocks, however, are broad and allow for large as well as negligible effects. As a result, uncertainty shocks are potentially of minor relevance for asset price fluctuations if they are modeled jointly with financial shocks. If we look at real activity, the bandwidth of possible effects is sizeable for both shocks. This implies that uncertainty shocks have real economic implications by worsening credit conditions and, conversely, financial shocks are transmitted by higher uncertainty.

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<sup>15</sup>Since the FFR fell to its zero lower bound during and after the Great Recession, namely from December 2008 until November 2015, I replace the observations in this period by the shadow short rates proposed by Krippner (2015).



## Appendix A

# Additional Material, Chapter 1

### A.1 Rotation of factors

We rotate the three factors of the full country sample as follows. We define the three-dimensional rotation matrix  $R$  with  $R'R = RR' = I$  such that the rotated factor decomposition remains observationally equivalent to the non-rotated model:

$$v_t = \Gamma f_t^{\text{G14}} + \xi_t = \Gamma R'R f_t^{\text{G14}} + \xi_t = \tilde{\Gamma} \tilde{f}_t^{\text{G14}} + \xi_t \quad (\text{A.1})$$

$$\mathbb{E} \left[ \tilde{f}_t^{\text{G14}} (\tilde{f}_t^{\text{G14}})' \right] = R \mathbb{E} \left[ f_t^{\text{G14}} (f_t^{\text{G14}})' \right] R' = RR' = I_k \quad (\text{A.2})$$

where  $f_t^{\text{G14}}$  denotes the unrotated and  $\tilde{f}_t^{\text{G14}} = R f_t^{\text{G14}}$  the rotated factors. Defining  $r_i$  as the  $i$ th row of  $R$ , the  $i$ th rotated factor is  $\tilde{f}_{it}^{\text{G14}} = r_i f_t^{\text{G14}}$ .

We choose  $R$  to maximize the correlation between the first two factors from the second stage (based on the G14 sample) with those from the first stage,  $f_t^{\text{G7}}$  (based on the G7 sample). To this end, we define the objective functions  $h_1$  and  $h_2$  which represent the correlation between the respective factors:

$$h_1 = \text{corr}(\tilde{f}_{1t}^{\text{G14}}, f_{1t}^{\text{G7}}) = \frac{\sum \tilde{f}_{1t}^{\text{G14}} f_{1t}^{\text{G7}}}{T-1} = r_1 \frac{\sum f_t^{\text{G14}} f_{1t}^{\text{G7}}}{T-1} = r_1 \begin{pmatrix} c_{11} \\ c_{21} \\ c_{31} \end{pmatrix} \quad (\text{A.3})$$

$$h_2 = \text{corr}(\tilde{f}_{2t}^{\text{G14}}, f_{2t}^{\text{G7}}) = \frac{\sum \tilde{f}_{2t}^{\text{G14}} f_{2t}^{\text{G7}}}{T-1} = r_2 \frac{\sum f_t^{\text{G14}} f_{2t}^{\text{G7}}}{T-1} = r_2 \begin{pmatrix} c_{12} \\ c_{22} \\ c_{32} \end{pmatrix} \quad (\text{A.4})$$

where  $c_{ij}$  denotes as the correlation between the  $i$ th unrotated second-stage factor and the  $j$ th first-stage factor.

Constructing  $R$  as

$$R = \begin{pmatrix} 1 & 0 & 0 \\ 0 & \cos(\alpha) & -\sin(\alpha) \\ 0 & \sin(\alpha) & \cos(\alpha) \end{pmatrix} \begin{pmatrix} \cos(\beta) & 0 & \sin(\beta) \\ 0 & 1 & 0 \\ -\sin(\beta) & 0 & \cos(\beta) \end{pmatrix} \begin{pmatrix} \cos(\gamma) & -\sin(\gamma) & 0 \\ \sin(\gamma) & \cos(\gamma) & 0 \\ 0 & 0 & 1 \end{pmatrix}$$

we choose  $\alpha$ ,  $\beta$  and  $\gamma$  such that these correlations are maximized. A closed-form solution is available upon request.

## A.2 Bayesian VAR Estimation

We estimate the VAR (1.4) with  $p = 4$  lags applying Bayesian methods following standard practice along the lines of Bańbura et al. (2010), Sims and Zha (1998), and Kadiyala and Karlsson (1997). The coefficients  $A_1, \dots, A_p$  are assumed to be a priori independent and normally distributed with moments

$$\mathbb{E}[(A_l)_{ij}] = \begin{cases} \delta_i, & j = i, l = 1 \\ 0, & \text{otherwise} \end{cases}, \quad \text{Var}[(A_l)_{ij}] = \begin{cases} \frac{\lambda^2}{l^2}, & j = i \\ \frac{\lambda^2 \sigma_i^2}{l^2 \sigma_j^2}, & \text{otherwise} \end{cases} \quad (\text{A.5})$$

where the hyperparameter  $\lambda$  governs the degree of shrinkage. Following Bańbura et al. (2010) we set  $\delta_i$  to the estimate of a univariate autoregression of  $y_{it}$  with lag length 1, and choose  $\sigma_i^2$  as the residual variance of a univariate autoregression of  $y_{it}$  with lag length  $p = 4$ . In order to implement the priors we write (1.4) in matrix form as

$$Y = XB + U \quad (\text{A.6})$$

where  $Y = (Y_1, \dots, Y_T)'$ ,  $X = (X_1, \dots, X_T)'$  with  $X_t = (Y'_{t-1}, \dots, Y'_{t-p})'$ ,  $U = (u_1, \dots, u_T)'$ , and  $B = (A_1, \dots, A_p)'$ . We follow Kadiyala and Karlsson (1997) and impose a Normal inverse-Wishart prior

$$\text{vec}(B) | \Sigma \sim N(\text{vec}(B_0), \Sigma \otimes \Omega_0) \quad \text{and} \quad \Sigma \sim iW(S_0, \alpha_0)$$

where the prior parameters  $B_0, \Omega_0, S_0$  and  $\alpha_0$  are set so that prior expectations and variances of  $B$  are consistent with (A.5) and the expectation of  $\Sigma$  is equal to a diagonal matrix with diagonal elements  $\sigma_i^2$ .

We compute the posterior means  $\tilde{B} = (\tilde{A}_1, \dots, \tilde{A}_p)'$  using dummy observations as proposed by Bańbura et al. (2010). Based on these means, we identify and estimate the factor model in exactly the same (frequentist) way as the FSVAR model (1.4) and (1.5). Hence, we use the Bayesian approach simply as a cheap shrinkage estimator of an unrestricted VAR model with four lags which is infeasible applying OLS.

## A.3 Time-varying variances of structural shocks

Suppose the variances of the factors,  $f_t$ , and the idiosyncratic shocks,  $\xi_t$ , are time-varying. Then their (diagonal) variance matrices  $\Sigma_{f,t}$  and  $\Sigma_{\xi,t}$  give rise to a time-varying variance structure of the factor model,

$$\Sigma_t = \Gamma \Sigma_{f,t} \Gamma' + \Sigma_{\xi,t}. \quad (\text{A.7})$$

Based on a sequence of estimates  $\Sigma_1, \dots, \Sigma_T$ , we can re-estimate the coefficient matrices  $A_1$  to  $A_4$  of the baseline G14-FSVAR by FGLS.

To this end, we have to estimate the diagonal elements of  $\Sigma_{f,t}$  and  $\Sigma_{\xi,t}$ . Since the shocks  $x_t = (f'_t, \xi'_t)'$  are mutually independent, we apply the univariate stochastic volatility model

proposed by Chan and Hsiao (2013) on which we impose a random walk structure:

$$x_{it} = e^{\frac{1}{2}h_{it}}\varepsilon_{it}, \quad \varepsilon_{it} \sim N(0, 1), \quad (\text{A.8})$$

$$h_{it} = h_{i,t-1} + \zeta_{it}, \quad \zeta_{it} \sim N(0, \omega_i^2), \quad (\text{A.9})$$

with effectively unrestricted initial observation  $h_{i1} \sim N(\mu, 50\omega_i^2)$ . We assume independent prior distributions for  $\mu$  and  $\sigma_h^2$ :

$$\mu \sim N(\mu_0, V_0), \quad \omega_i^2 \sim IG(\nu_0, S_0). \quad (\text{A.10})$$

We set  $\mu_0 = 0$ ,  $V_0 = 100$ ,  $\nu_0 = 2.1$ , and  $S_0 = 0.06^2(\nu_0 - 1)$ . The prior for  $\omega_i^2$  may deserve some comments. It gives rise to a prior mean of  $S_0/(1 - \nu_0) = 0.06^2 = 4 \cdot 0.03^2$ . Justiniano and Primiceri (2008) use an inverse Gamma prior with mean  $0.01^2$  for the log standard deviation  $\frac{1}{2}h_t$  which implies a mean of  $4 \cdot 0.01^2$  for the log variance  $h_t$  as in our specification. Hence, in terms of the standard deviation  $\omega_i$  our prior assumes a volatility that is three times larger than in Justiniano and Primiceri (2008). Since they analyze the U.S. while we include more volatile countries, we believe our prior is an appropriate ‘‘prior guess’’.<sup>1</sup>

Bayesian estimation is then performed by sampling from the joint posterior distribution via the Gibbs sampler. We take 20,000 draws and allow for a burn-in period of 1,000 draws to compute the posterior means of the standard deviations  $\exp(h_t/2)$ . The details of the estimation approach are described in Chan and Hsiao (2013).

## A.4 Data sources

We use quarterly GDP per capita series at constant prices which we download from Datastream (DS). A description of the data sources and their Datastream codes is given in Table A.1. Unfortunately, for Brazil and China there are no consistent GDP series available that cover the entire time period 1991-2014. Therefore we construct the series for these countries manually. In case of Brazil, the active series start in 1996 (DS code broexo03d), so we backdate it to 1991 using growth rates of a GDP volume index under constant prices (DS code broexp03h). For China, we use real GDP growth rates (DS code chgdp.%) for the period 1991-2014 from which we constructed an index that equals nominal GDP in 2005 (DS code chgdpcoma). Since the population data are at an annual frequency we log-linearly interpolate it to a quarterly frequency. Then we express real GDP in per-capita terms. The series are seasonally adjusted by the OECD. The only exception is Chinese GDP which we seasonally adjust by means of X-12 ARIMA in EViews. The sources for the global macro indicators are reported in Table A.2. ‘‘World industrial production’’, ‘‘CPB world trade’’, ‘‘CPB manufacturing prices’’, ‘‘World fuel prices’’, and ‘‘World commodity prices’’ are taken from the CPB World Trade Monitor November 2015, ‘‘OECD GDP’’ and ‘‘Brent oil price’’ stem from the OECD. The stock market volatility is based on the MSCI World stock price index which we source from the MSCI database. Both the exchange

<sup>1</sup>Our conclusions are robust to choosing a smaller or an even higher prior mean.

rate volatility and inflation volatility are based on weighted variances of national exchange rates and inflation rates. In most cases, they are downloaded from the FRED database.

TABLE A.1: Data sources for real GDP and population

Series	Datastream code	Source	Period
<i>A. Real GDP</i>			
Australia	auoexo03d	OECD	1991-2014
Brazil	broexp03h	OECD	1991-1995
	broexo03d	OECD	1996-2014
Canada	cnoexo03d	OECD	1991-2014
China	chgdpr..%c	NBS China	1991-2014
	chgdpcuma	NBS China	1991-2014
France	froexo03d	OECD	1991-2014
Germany	bdoexo03d	OECD	1991-2014
Italy	itoexo03d	OECD	1991-2014
Japan	jpoexo03d	OECD	1991-2014
Mexico	mxoexo03d	OECD	1991-2014
South Korea	kooexo03d	OECD	1991-2014
UK	ukoexo03d	OECD	1991-2014
US	usoexo03d	OECD	1991-2014
<i>B. Population</i>			
Australia	auoapopnp	OECD	1991-2014
Brazil	brpoptot	IGBE Brazil	1991-2014
Canada	cnoapopnp	OECD	1991-2014
China	choapopnp	OECD	1991-2014
France	froapopnp	OECD	1991-2014
Germany	bdoapopnp	OECD	1991-2014
Italy	itoapopnp	OECD	1991-2014
Japan	jpoapopnp	OECD	1991-2014
Mexico	mxoapopnp	OECD	1991-2014
South Africa	kooapopnp	OECD	1991-2014
South Korea	kooapopnp	OECD	1991-2014
Turkey	kooapopnp	OECD	1991-2014
UK	ukoapopnp	OECD	1991-2014
US	usoapopnp	OECD	1991-2014



TABLE A.2: Data sources: National macro indicators

National indicator	Canada	France	Germany	Italy	Japan	UK	US
Investment	OECD	OECD	OECD	OECD	OECD	OECD	OECD
Consumption	OECD	OECD	OECD	OECD	OECD	OECD	OECD
Exports	OECD	OECD	OECD	OECD	OECD	OECD	US Bureau of Economic Analysis
Imports	OECD	OECD	OECD	OECD	OECD	OECD	US Bureau of Economic Analysis
Employment	OECD	OECD	OECD	OECD	OECD	OECD	OECD
Unemployment rate	OECD	OECD	OECD	OECD	OECD	OECD	OECD
Current account balance	OECD	OECD	OECD	OECD	OECD	OECD	OECD
Real effective exchange rates	Bank for international settlements	Bank for international settlements	Bank for international settlements	Bank for international settlements	Bank for international settlements	Bank for international settlements	Bank for international settlements
Nominal effective exchange rates	Bank for international settlements	Bank for international settlements	Bank for international settlements	Bank for international settlements	Bank for international settlements	Bank for international settlements	Bank for international settlements
CPI inflation	OECD	OECD	OECD	OECD	OECD	OECD	US Bureau of Labor Statistics
10-year government bond rate	OECD	OECD	OECD	OECD	OECD	OECD	OECD
Stock market returns	S&P/TSX	MSCI	Deutsche Börse	MSCI	Nikkei	FTSE	Dow Jones

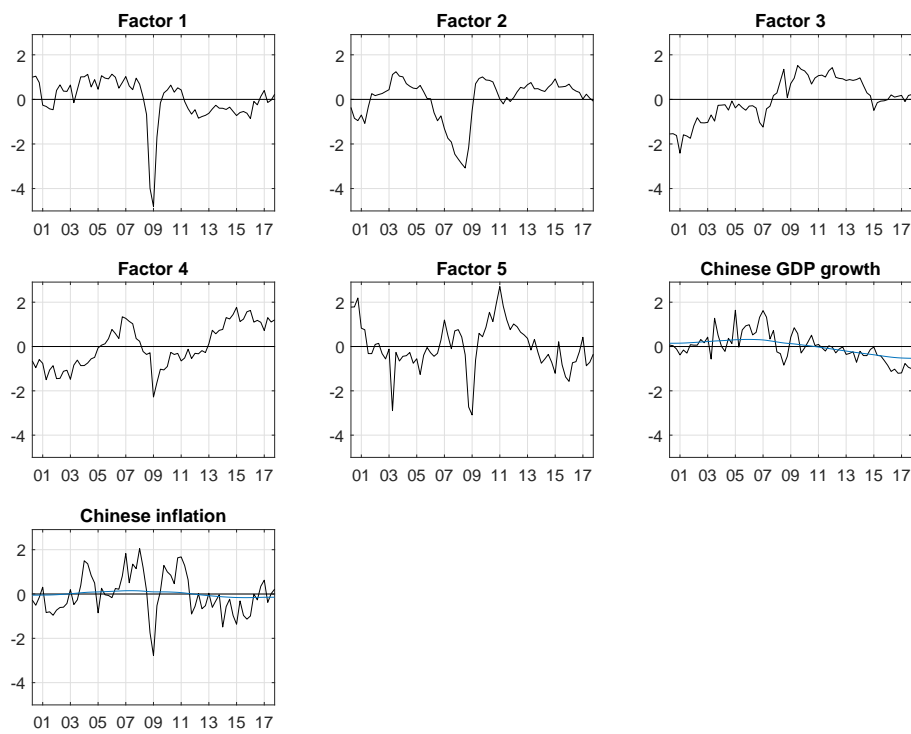


## Appendix B

# Additional Material, Chapter 2

### B.1 Data

FIGURE B.1: Factors



Notes: The panels show the series used in the baseline FAVAR. The Chinese GDP growth and inflation rates are mean-adjusted and displayed jointly with their trends. The estimation of the trends is outlined in section 2.5.4.



## Appendix C

# Additional Material, Chapter 3

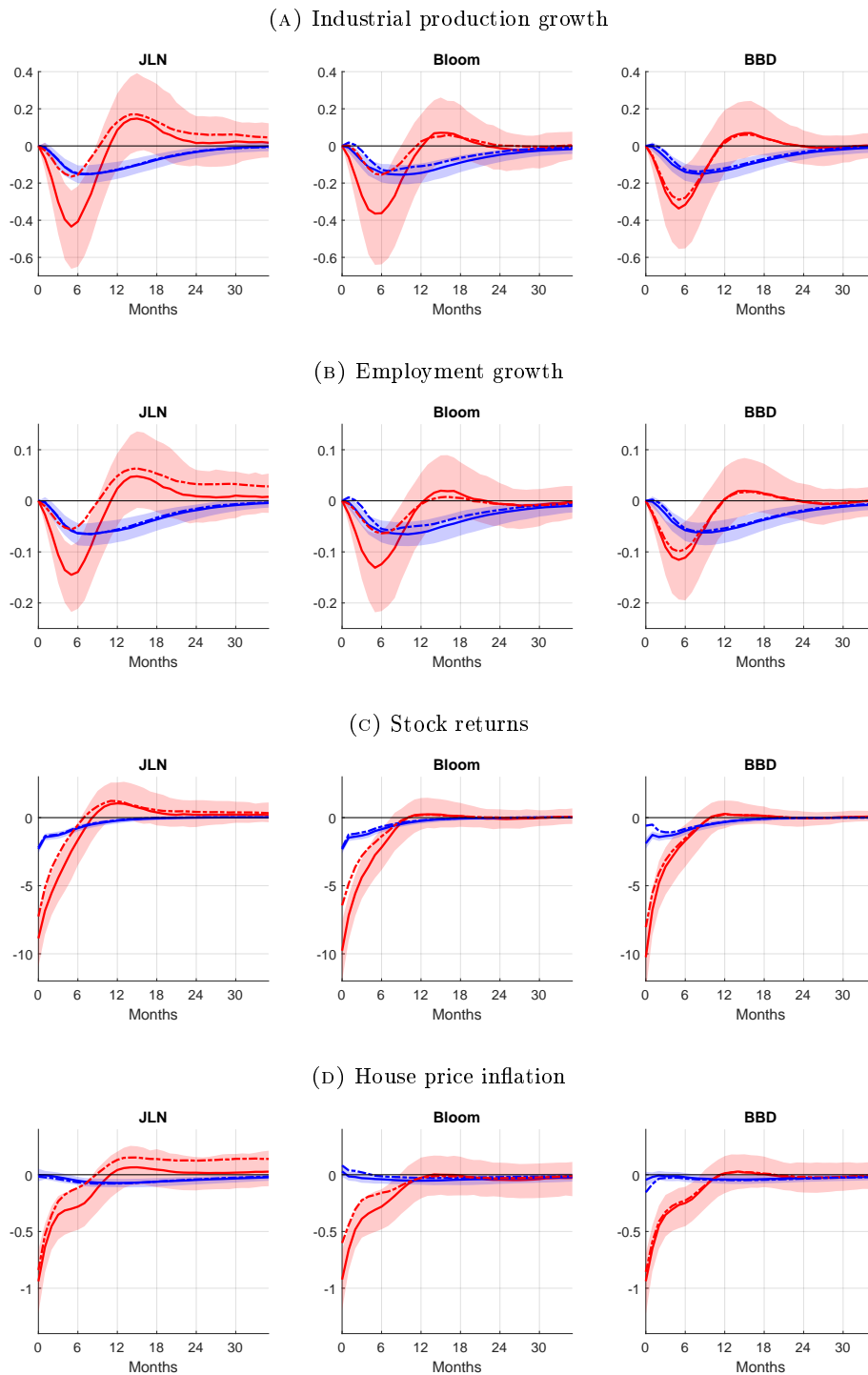
### C.1 Further results

TABLE C.1: Forecast error variance decomposition - Financial shock

Variable	Identification +Regime	Recessions		Booms	
		EBP-max	UN-max	EBP-max	UN-max
<b>Uncertainty measure: JLN</b>					
Industrial production growth		15.6	6.2	14.8	13.4
Employment growth		16.2	7.8	13.4	11.5
Stock returns		63.2	36.9	77.7	68.5
House price inflation		40.5	31.7	6.6	7.5
<b>Uncertainty measure: Bloom</b>					
Industrial production growth		12.0	2.3	16.8	10.1
Employment growth		13.1	3.4	12.2	7.7
Stock returns		83.2	38.2	77.3	60.6
House price inflation		39.1	17.1	5.2	2.3
<b>Uncertainty measure: BBD</b>					
Industrial production growth		8.9	7.3	18.3	14.9
Employment growth		10.1	8.1	17.8	15.7
Stock returns		72.3	51.3	50.7	24.1
House price inflation		39.9	34.4	6.9	8.4

Notes: The table shows the percentage shares of the forecast error variance of the common component of key macroeconomic variables accounted for by a financial shock. The forecast horizon is set to 24 months.

FIGURE C.1: Macroeconomic effects of a financial shock



Notes: The panels show regime-specific impulse response functions (IRFs) of the percentage 3-month growth rates of industrial production, employment, stock prices, and house prices to a contractionary financial shock. The headings “JLN”, “Bloom”, and “BBD” stand for the uncertainty measure used in the FAVAR. The red graphs depict the IRFs in the recession regime and the blue graphs those in the boom regime. The solid and dashed graphs are median IRFs resulting from the EBP-max and the UN-max identification, respectively. The shaded areas are 68 percent confidence intervals on the IRFs of the EBP-max identification. The shock magnitudes are adjusted such that the large financial shock induces a rise in the EBP by one regime-specific standard deviation.

## C.2 Priors and posteriors

### Transition equation

I impose normal inverse Wishart (natural conjugate) priors along the lines of Bańbura et al. (2010), Sims and Zha (1998), and Kadiyala and Karlsson (1997) for each of both regimes. For better readability, I omit the regime subindices in the matrices here.

The coefficients  $B_1, \dots, B_p$  are assumed to be a priori independent and normally distributed with moments

$$E[(B_l)_{ij}] = \begin{cases} \delta_i, & j = i, l = 1 \\ 0, & \text{otherwise} \end{cases}, \quad \text{Var}[(B_l)_{ij}] = \begin{cases} \frac{\lambda^2}{l^2}, & j = i \\ \frac{\lambda^2 \sigma_i^2}{l^2 \sigma_j^2}, & \text{otherwise} \end{cases} \quad (\text{C.1})$$

where the hyperparameter  $\lambda$  governs the degree of shrinkage. I follow Bańbura et al. (2010) in choosing  $\sigma_i^2$  as the residual variance of a univariate autoregression of  $Y_{i,t}$  with lag length  $p = 6$ . The parameter  $\delta_i$  is set to the estimate of a univariate autoregression of  $Y_{i,t}$  with lag length 1. By setting the overall tightness parameter  $\lambda$  to 0.1 I follow Chiu and Hacıoglu Hoke (2016), Carriero et al. (2015b), and Canova (2011).

To implement the priors, I write the VAR in matrix form as

$$Y = B'Z + U$$

where  $Y = (Y_1, \dots, Y_T)$ ,  $Z = (Z_1, \dots, Z_T)$  with  $Z_t = (Y'_{t-1}, \dots, Y'_{t-p})'$ ,  $U = (u_1, \dots, u_T)$ , and  $B = (B_1, \dots, B_p)'$ . I follow Kadiyala and Karlsson (1997) and impose a Normal inverse-Wishart prior

$$\text{vec}(B)|\Sigma \sim N(\text{vec}(\underline{B}), \Sigma \otimes \underline{\Psi}) \quad \text{and} \quad \Sigma \sim IW(\underline{S}, \underline{\alpha})$$

where the prior parameters  $\underline{B}$ ,  $\underline{S}$ ,  $\underline{\Psi}$ , and  $\underline{\alpha}$  are set so that they are consistent with equations (C.1). The expectation of  $\Sigma$  is equal to a diagonal matrix with diagonal elements  $\sigma_i^2$ . The conditional posterior distribution of the VAR parameters is given by

$$\text{vec}(B)|\Sigma, Y \sim N(\text{vec}(\overline{B}), \Sigma \otimes \overline{\Psi}) \quad \text{and} \quad \Sigma|Y \sim IW(\overline{S}, \overline{\alpha})$$

I compute the posterior parameters  $\overline{B}$ ,  $\overline{S}$ ,  $\overline{\Psi}$  and  $\overline{\alpha}$  using dummy observations as proposed by Bańbura et al. (2010).

## Measurement equation

For each measurement equation

$$X_{i,t} = \Lambda_i' Y_t + \xi_{i,t}$$

I assume an (independent) normal-inverse Gamma prior for  $\Lambda_i$  and  $\omega_i^2 = \text{Var}(\xi_{i,t})$ :

$$\Lambda_i \sim N(\underline{\Lambda}, \underline{\Sigma}_\Lambda) \quad \omega_i^2 \sim IG(\underline{\phi}, \underline{\theta})$$

where  $\underline{\Lambda}$  and  $\underline{\Sigma}_\Lambda$  are the prior moments of  $\Lambda_i$  and  $\underline{\phi}$  and  $\underline{\theta}$  are the prior degrees of freedom and scaling parameters of  $\omega_i^2$ , respectively. I follow Bernanke et al. (2005) in setting the priors  $\underline{\Lambda} = \mathbf{0}$ ,  $\underline{\Sigma}_\Lambda = I_k$ ,  $\underline{\phi} = 0.001$ , and  $\underline{\theta} = 3$ .

The conditional posterior distributions are derived in Koop (2003), p. 61:

$$\Lambda_i | X_i, \omega_i^2 \sim N(\bar{\Lambda}_i, \bar{\Sigma}_{\Lambda_i}) \quad \omega_i^2 | X_i, \Lambda_i \sim IG(\bar{\phi}, \bar{\theta}_i)$$

with the posterior parameters

$$\begin{aligned} \bar{\Lambda}_i &= \left( \underline{\Sigma}_\Lambda^{-1} + \frac{1}{\omega_i^2} Y Y' \right)^{-1} \left( \underline{\Sigma}_\Lambda^{-1} \underline{\Lambda} + \frac{1}{\omega_i^2} Y X_i' \right), & \bar{\Sigma}_{\Lambda_i} &= \left( \underline{\Sigma}_\Lambda^{-1} + \frac{1}{\omega_i^2} Y Y' \right)^{-1} \\ \bar{\theta}_i &= (X_i - \Lambda_i' Y)(X_i - \Lambda_i' Y)' + \underline{\theta}, & \bar{\phi} &= T + \underline{\phi}. \end{aligned}$$



## C.3 Data

TABLE C.2: Series in  $X_t$ 

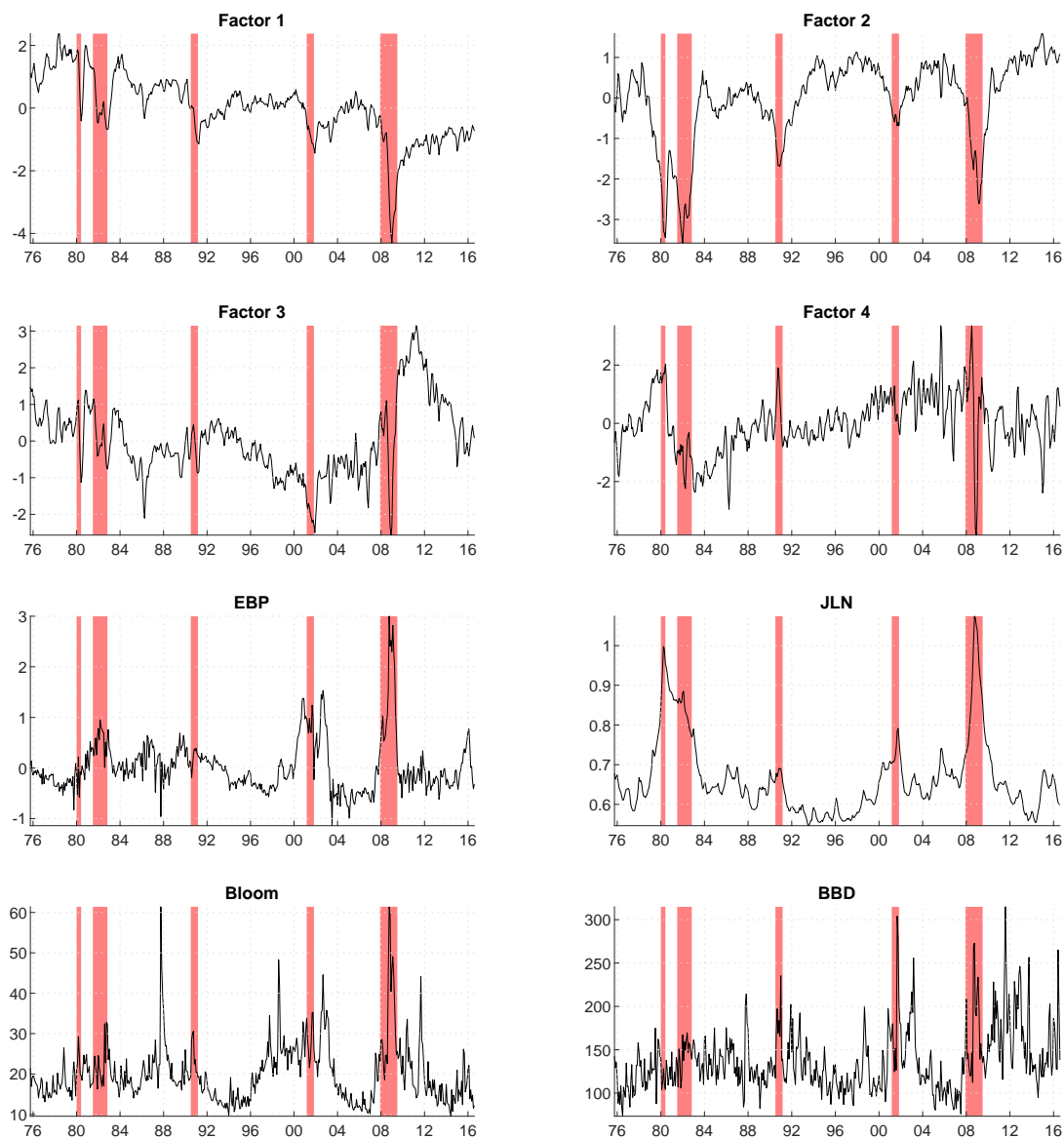
Variable	Transf.
Real Disposable Personal Income	1
Personal Income	1
Real Personal Consumption Expenditures	1
Capacity Utilization: Manufacturing (NAICS), Percent of Capacity	0
Real Manufacturing and Trade Inventories	1
Industrial Production Index	1
Industrial Production: Consumer Goods	1
Industrial Production: Durable Consumer Goods	1
Industrial Production: Nondurable Consumer Goods	1
Industrial Production: Business Equipment	1
Industrial Production: Final products	1
Industrial Production: Fuels	1
Industrial Production: Residential utilities	1
Industrial Production: Materials	1
Industrial Production: Durable goods materials	1
Industrial Production: Nondurable goods materials	1
Industrial Production: Manufacturing (SIC)	1
Number of Civilians Unemployed for 5 to 14 Weeks	0
Number of Civilians Unemployed for 15 Weeks and Over	0
Number of Civilians Unemployed for 15 to 26 Weeks	0
Number of Civilians Unemployed for 27 Weeks and Over	0
Number of Civilians Unemployed for Less Than 5 Weeks	0
Civilian Unemployment Rate	0
Civilian Employment Level	1
All Employees: Total Nonfarm Payrolls	1
All Employees: Manufacturing	1
All Employees: Construction	1
All Employees: Total Private Industries	1
All Employees: Retail Trade	1
All Employees: Government	1
All Employees: Wholesale Trade	1
All Employees: Financial Activities	1
All Employees: Mining and Logging	1
All Employees: Durable Goods	1
All Employees: Nondurable goods	1
All Employees: Goods-Producing Industries	1
All Employees: Service-Providing Industries	1
All Employees: Trade, Transportation and Utilities	1
Average Weekly Hours of Production and Nonsupervisory Employees: Total private	0
Average Weekly Hours of Production and Nonsupervisory Employees: Goods-Producing	0
Average Weekly Hours of Production and Nonsupervisory Employees: Manufacturing	0
Average Weekly Overtime Hours of Production and Nonsupervisory Employees: Manufacturing	0
New Private Housing Units Authorized by Building Permits in the Midwest Census Region	2
New Private Housing Units Authorized by Building Permits in the Northeast Census Region	2
New Private Housing Units Authorized by Building Permits, Thousands of Units	2
New Private Housing Units Authorized by Building Permits in the South Census Region	2
New Private Housing Units Authorized by Building Permits in the West Census Region	2
Housing Starts: Total: New Privately Owned Housing Units Started, Thousands of Units	2
Housing Starts in Midwest Census Region, Thousands of Units	2
Housing Starts in Northeast Census Region, Thousands of Units	2
Housing Starts in South Census Region, Thousands of Units	2
Housing Starts in West Census Region, Thousands of Units	2
M1 Money Stock	1
M2 Money Stock	1
Monetary Base	1

Notes: The table shows the series contained in the vector  $X_t$  of the FAVAR and their transformations. The codes have the following meaning: 0 = no transformation; 1 = 3-month log differences; 2 = logs. The transformations are orientated at Forni and Gambetti (2010).

TABLE C.2: Series in  $X_t$  ctd.

Variable	Transf.
Reserves of Depository Institutions, Nonborrowed	1
Total Reserves of Depository Institutions	1
Commercial and Industrial Loans	1
Total Consumer Credit Owned and Securitized, Outstanding	1
SP500	1
Effective Federal Funds Rate	0
3-Month Treasury Bill: Secondary Market Rate	0
6-Month Treasury Bill: Secondary Market Rate	0
10-Year Treasury Constant Maturity Rate	0
5-Year Treasury Constant Maturity Rate	0
1-Year Treasury Constant Maturity Rate	0
Moody's Seasoned Aaa Corporate Bond Yield	0
Moody's Seasoned Baa Corporate Bond Yield	0
Narrow Effective Exchange Rate for United States	1
Canada / U.S. Foreign Exchange Rate, Canadian Dollars to One U.S. Dollar	1
Japan / U.S. Foreign Exchange Rate, Japanese Yen to One U.S. Dollar	1
Switzerland / U.S. Foreign Exchange Rate, Swiss Francs to One U.S. Dollar	1
U.S. / U.K. Foreign Exchange Rate, U.S. Dollars to One British Pound	1
Producer Price Index by Commodity for Final Demand: Personal Consumption Goods	1
Producer Price Index by Commodity for Final Demand: Finished Goods	1
Producer Price Index for All Commodities, Index 1982=100	1
Producer Prices Index: Total Intermediate Goods for the United States	1
Consumer Price Index for All Urban Consumers: All Items	1
Consumer Price Index for All Urban Consumers: Apparel	1
Consumer Price Index for All Urban Consumers: Transportation	1
Consumer Price Index for All Urban Consumers: Medical Care	1
Consumer Price Index for All Urban Consumers: Commodities	1
Consumer Price Index for All Urban Consumers: Durables	1
Consumer Price Index for All Urban Consumers: Services	1
Consumer Price Index for All Urban Consumers: All Items Less Food	1
Consumer Price Index for All Urban Consumers: All items less medical care	1
Consumer Price Index for All Urban Consumers: All items less shelter	1
Average Hourly Earnings of Production and Nonsupervisory Employees: Construction	1
Average Hourly Earnings of Production and Nonsupervisory Employees: Manufacturing	1
Average Hourly Earnings of Production and Nonsupervisory Employees: Goods-Producing	1
Real Narrow Effective Exchange Rate for Switzerland	2
Real Narrow Effective Exchange Rate for Japan	2
Real Narrow Effective Exchange Rate for United Kingdom	2
Real Narrow Effective Exchange Rate for Canada	2
Long-Term Government Bond Yields: 10-year: Main (Including Benchmark) for the UK	0
Long-Term Government Bond Yields: 10-year: Main (Including Benchmark) for Canada	0
CPI less food and energy	1
CPI less energy	1
Crude oil spot price WTI	1
Case-Shiller House price index	1

Notes: The table shows the series contained in the vector  $X_t$  of the FAVAR and their transformations. The codes have the following meaning: 0 = no transformation; 1 = 3-month log differences; 2 = logs. The transformations are orientated at Forni and Gambetti (2010).

FIGURE C.2: Series in  $Y_t$ 

Notes: The panels show the series in the vector  $Y_t$  of the baseline FAVAR, i.e., the estimated factors, the excess bond premium and the JLN uncertainty index. In addition, it shows the Bloom and the BBD uncertainty proxy. The shaded areas depict NBER recessions. Details of the series are outlined in section 3.4.



# Bibliography

- Aastveit, Knut Are, Hilde C Bjørnland, and Leif Anders Thorsrud (2015). “What Drives Oil Prices? Emerging versus Developed Economies”. In: *Journal of Applied Econometrics* 30.7, pp. 1013–1028.
- Aguilar, Omar and Mike West (2000). “Bayesian Dynamic Factor Models and Portfolio Allocation”. In: *Journal of Business and Economic Statistics* 18, pp. 338–357.
- Ajello, Andrea (2016). “Financial Intermediation, Investment Dynamics, and Business Cycle Fluctuations”. In: *American Economic Review* 106.8, pp. 2256–2303.
- Alessandri, Piergiorgio and Haroon Mumtaz (2018). “Financial Regimes and Uncertainty Shocks.” In: *Journal of Monetary Economics*.
- Altonji, Joseph G and John C Ham (1990). “Variation in Employment Growth in Canada: the Role of External, National, Regional, and Industrial Factors”. In: *Journal of Labor Economics* 8.1, Part 2, S198–S236. DOI: 10.1086/298250.
- Artis, Michael J and Wenda Zhang (1997). “International Business Cycles and the ERM: Is There a European Business Cycle?” In: *International Journal of Finance & Economics* 2.1, pp. 1–16.
- Artis, Michael John and Wenda Zhang (1999). “Further Evidence on the International Business Cycle and the ERM: Is there a European Business Cycle?” In: *Oxford Economic Papers* 51.1, pp. 120–132.
- Bacchetta, Philippe and Eric Wincoop (2003). “Why do Consumer Prices React Less than Import Prices to Exchange Rates?” In: *Journal of the European Economic Association* 1.2-3, pp. 662–670.
- Bachmann, Rüdiger and Christian Bayer (2013). “‘Wait-and-See’ Business Cycles?” In: *Journal of Monetary Economics* 60.6, pp. 704–719.
- Bachmann, Rüdiger, Steffen Elstner, and Eric R Sims (2013). “Uncertainty and Economic Activity: Evidence from Business Survey Data”. In: *American Economic Journal: Macroeconomics* 5.2, pp. 217–49.
- Bai, Jushan and Serena Ng (2002). “Determining the Number of Factors in Approximate Factor Models”. In: *Econometrica* 70.1, pp. 191–221.
- Bai, Jushan, Serena Ng, et al. (2006). “Confidence Intervals for Diffusion Index Forecasts with a Large Number of Predictors”. In: *Econometrica* 74.4, pp. 1133–1150.
- Baker, Scott R, Nicholas Bloom, and Steven J Davis (2016). “Measuring Economic Policy Uncertainty”. In: *The Quarterly Journal of Economics* 131.4, pp. 1593–1636.
- Bañbura, Marta, Domenico Giannone, and Lucrezia Reichlin (2010). “Large Bayesian Vector Auto Regressions”. In: *Journal of Applied Econometrics* 25.1, pp. 71–92.

- Baumeister, Christiane and Lutz Kilian (2016). “Understanding the Decline in the Price of Oil since June 2014”. In: *Journal of the Association of Environmental and Resource Economists* 3.1, pp. 131–158.
- Bernanke, Ben S, Jean Boivin, and Piotr Elias (2005). “Measuring the Effects of Monetary Policy: a Factor-augmented Vector Autoregressive (FAVAR) Approach”. In: *The Quarterly Journal of Economics* 120.1, pp. 387–422.
- Bernanke, Ben S and Ilian Mihov (1998). “Measuring Monetary Policy”. In: *Quarterly Journal of Economics*, pp. 869–902.
- Blanchard, OJ and Danny Quah (1989). “The Dynamic Effects of Aggregate Demand and Supply Disturbances”. In: *American Economic Review* 79.4, pp. 655–673.
- Bloom, Nicholas (2009). “The Impact of Uncertainty Shocks”. In: *Econometrica* 77.3, pp. 623–685.
- Bobea, Elena et al. (2017). *Demographics and Inflation*. Tech. rep. ECB Working Paper.
- Brogaard, Jonathan and Andrew Detzel (2015). “The Asset-Pricing Implications of Government Economic Policy Uncertainty”. In: *Management Science* 61.1, pp. 3–18.
- Caldara, Dario et al. (2013). “On the Identification of Financial and Uncertainty Shocks”. In: *2013 Meeting Papers*. Vol. 965.
- Caldara, Dario et al. (2016). “The Macroeconomic Impact of Financial and Uncertainty shocks”. In: *European Economic Review* 88, pp. 185–207.
- Canova, Fabio (2011). *Methods for Applied Macroeconomic Research*. Princeton University Press.
- Canova, Fabio and Gianni De Nicolò (2003). “On the Sources of Business Cycles in the G-7”. In: *Journal of International Economics* 59.1, pp. 77–100.
- Carriero, Andrea, Todd E. Clark, and Massimiliano Marcellino (2015a). “Bayesian VARs: Specification Choices and Forecast Accuracy”. In: *Journal of Applied Econometrics* 30.1, pp. 46–73. ISSN: 1099-1255. DOI: 10.1002/jae.2315. URL: <http://dx.doi.org/10.1002/jae.2315>.
- Carriero, Andrea, Todd E Clark, and Massimiliano Marcellino (2015b). “Bayesian VARs: Specification Choices and Forecast Accuracy”. In: *Journal of Applied Econometrics* 30.1, pp. 46–73.
- Carriero, Andrea, Todd E Clark, and Massimiliano Giuseppe Marcellino (2018). “Endogenous Uncertainty”. In: FRB of Cleveland Working Paper.
- Carstensen, Kai and Leonard Salzmänn (2017). “The G7 Business Cycle in a Globalized World”. In: *Journal of International Money and Finance* 73, pp. 134–161.
- Cesa-Bianchi, Ambrogio (2013). “Housing Cycles and Macroeconomic Fluctuations: A Global Perspective”. In: *Journal of International Money and Finance* 37, pp. 215–238.
- Chamberlain, Gary and Michael Rothschild (1983). “Arbitrage, Factor Structure and Mean-Variance Analysis of Large Asset Markets”. In: *Econometrica (pre-1986)* 51.5, p. 1281.
- Chan, Joshua CC and Cody Yu-Ling Hsiao (2013). “Estimation of Stochastic Volatility Models with Heavy Tails and Serial Dependence”. CAMA Working Paper 74/2013.
- Chang, Chun et al. (2016). “Trends and Cycles in China’s Macroeconomy”. In: *NBER Macroeconomics Annual* 30.1, pp. 1–84.

- Chiu, Ching-Wai Jeremy and Sinem Hacıoglu Hoke (2016). “Macroeconomic Tail Events with Non-linear Bayesian VARs”. In: Bank of England working paper series.
- Christiano, Lawrence J, Roberto Motto, and Massimo Rostagno (2014). “Risk Shocks”. In: *American Economic Review* 104.1, pp. 27–65.
- Ciccarelli, Matteo et al. (2017). “Low Inflation in the Euro Area: Causes and Consequences”. In: *ECB occasional paper* 181.
- Clarida, Richard, Jordi Gali, and Mark Gertler (1999). “The Science of Monetary Policy: a New Keynesian Perspective”. In: *Journal of Economic Literature* 37.4, pp. 1661–1707.
- Crespo-Cuaresma, Jesús and Octavio Fernández-Amador (2013). “Business Cycle Convergence in EMU: A First Look at the Second Moment”. In: *Journal of Macroeconomics* 37, pp. 265–284.
- Crucini, Mario J, M Ayhan Kose, and Christopher Otrok (2011). “What Are the Driving Forces of International Business Cycles?” In: *Review of Economic Dynamics* 14.1, pp. 156–175.
- Curdia, Vasco and Michael Woodford (2010). “Credit Spreads and Monetary Policy”. In: *Journal of Money, Credit and Banking* 42, pp. 3–35.
- Del Negro, M and C Otrok (2003). “Dynamic Factor Models with Time-Varying Parameters: Measuring the Evolution of the European business cycle”. Federal Reserve Bank of Atlanta, manuscript.
- Diebold, Francis X and Kamil Yilmaz (2013). “Measuring the Dynamics of Global Business Cycle Connectedness”. PIER Working Paper 13-070.
- Dizioli, Allan et al. (2016). *Spillovers from China’s Growth Slowdown and Rebalancing to the ASEAN-5 Economies*. International Monetary Fund.
- Eickmeier, Sandra (2007). “Business Cycle Transmission from the US to Germany – A Structural Factor Approach”. In: *European Economic Review* 51.3, pp. 521–551.
- (2010). “Analyse der Übertragung US-amerikanischer Schocks auf Deutschland auf Basis eines FAVAR.” In: *Jahrbücher für Nationalökonomie & Statistik* 230.5.
- Eickmeier, Sandra and Markus Kühnlenz (2016). “China’s Role in Global Inflation Dynamics”. In: *Macroeconomic Dynamics*, pp. 1–30.
- Faust, Jon (1998). “The Robustness of Identified VAR Conclusions about Money”. In: *Carnegie-Rochester Conference Series on Public Policy*. Vol. 49. Elsevier, pp. 207–244.
- Forni, Mario and Luca Gambetti (2010). “The Dynamic Effects of Monetary Policy: A Structural Factor Model Approach”. In: *Journal of Monetary Economics* 57.2, pp. 203–216.
- Fry, Renée, Adrian Pagan, et al. (2007). “Some Issues in Using Sign Restrictions for Identifying Structural VARs”. In: *National Centre for Econometric Research Working Paper* 14, p. 2007.
- Gilchrist, Simon, Jae W Sim, and Egon Zakrajšek (2014). *Uncertainty, Financial Frictions, and Investment Dynamics*. Tech. rep. National Bureau of Economic Research.
- Gilchrist, Simon and Egon Zakrajšek (2012). “Credit Spreads and Business Cycle Fluctuations”. In: *American Economic Review* 102.4, pp. 1692–1720.

- Helbling, Thomas and Tamim Bayoumi (2003). “Are They All in the Same Boat? The 2000–2001 Growth Slowdown and the G-7 Business Cycle Linkages”. International Monetary Fund Working Paper 03/46.
- Hirata, Hideaki, M Ayhan Kose, and Christopher Otrok (2013). “Regionalization vs. Globalization”. In: *Globalization (February 2013). CAMA Working Paper 9*.
- Holston, Kathryn, Thomas Laubach, and John C Williams (2017). “Measuring the Natural Rate of Interest: International Trends and Determinants”. In: *Journal of International Economics* 108, pp. 59–75.
- Jurado, Kyle, Sydney C Ludvigson, and Serena Ng (2015). “Measuring Uncertainty”. In: *American Economic Review* 105.3, pp. 1177–1216.
- Justiniano, Alejandro and Giorgio E Primiceri (2008). “The Time-Varying Volatility of Macroeconomic Fluctuations”. In: *American Economic Review* 98.3, pp. 604–641.
- Kadiyala, K. Rao and Sune Karlsson (1997). “Numerical Methods for Estimation and Inference in Bayesian VAR-models”. In: *Journal of Applied Econometrics* 12.2, pp. 99–132.
- Keating, John and Victor Valcarcel (2012). “Greater Moderations”. In: *Economics Letters* 115.2, pp. 168–171.
- Kilian, Lutz (1998). “Small-sample Confidence Intervals for Impulse Response Functions”. In: *Review of Economics and Statistics* 80.2, pp. 218–230.
- (2009). “Not All Oil Price Shocks Are Alike: Disentangling Demand and Supply Shocks in the Crude Oil Market”. In: *American Economic Review* 99.3, pp. 1053–1069.
- Kilian, Lutz and Bruce Hicks (2013). “Did Unexpectedly Strong Economic Growth Cause the Oil Price Shock of 2003–2008?” In: *Journal of Forecasting* 32.5, pp. 385–394.
- Koop, Gary M (2003). *Bayesian Econometrics*. John Wiley & Sons Inc.
- Kose, M Ayhan, Christopher Otrok, and Eswar Prasad (2012). “Global Business Cycles: Convergence or Decoupling?” In: *International Economic Review* 53.2, pp. 511–538.
- Kose, M Ayhan, Christopher Otrok, and Charles H Whiteman (2003). “International Business Cycles: World, Region, and Country-Specific Factors”. In: *American Economic Review*, pp. 1216–1239.
- Krippner, Leo (2015). *Zero Lower Bound Term Structure Modeling: A Practitioner’s Guide*. Springer.
- Litterman, Robert B (1986). “Forecasting with Bayesian Vector Autoregressions: Five Years of Experience”. In: *Journal of Business & Economic Statistics* 4.1, pp. 25–38.
- Ludvigson, Sydney C, Sai Ma, and Serena Ng (2015). *Uncertainty and Business Cycles: Exogenous Impulse or Endogenous Response?* Tech. rep. National Bureau of Economic Research.
- Luginbuhl, Rob and Siem Jan Koopman (2004). “Convergence in European GDP Series: a Multivariate Common Converging Trend–Cycle Decomposition”. In: *Journal of Applied Econometrics* 19.5, pp. 611–636.
- Metelli, Luca and Filippo Natoli (2017). “The Effect of a Chinese Slowdown on Inflation in the Euro Area and the United States”. In: *Economic Modelling* 62, pp. 16–22.



- Mishkin, Frederic S (1992). “Is the Fisher effect for real?: A reexamination of the relationship between inflation and interest rates”. In: *Journal of Monetary economics* 30.2, pp. 195–215.
- Mumtaz, Haroon, Saverio Simonelli, and Paolo Surico (2011). “International Comovements, Business Cycle and Inflation: A Historical Perspective”. In: *Review of Economic Dynamics* 14.1, pp. 176–198.
- Norrbin, Stefan C and Don E Schlagenhauf (1996). “The Role of International Factors in the Business Cycle: A Multi-Country Study”. In: *Journal of International Economics* 40.1, pp. 85–104.
- Peersman, Gert (2005). “What Caused the Early Millennium Slowdown? Evidence Based on Vector Autoregressions”. In: *Journal of Applied Econometrics* 20.2, pp. 185–207.
- Popescu, Adina and Frank Smets (2010). “Uncertainty, Risk-taking, and the Business Cycle in Germany”. In: *CESifo Economic Studies* 56.4, pp. 596–626.
- Prassas, George (2011). “Employment in Financial Activities: Double Billed by Housing and Financial Crises”. In: *Monthly Labor Review* 4.1, pp. 40–44.
- Prieto, Esteban, Sandra Eickmeier, and Massimiliano Marcellino (2016). “Time Variation in Macro-Financial Linkages”. In: *Journal of Applied Econometrics* 31.7, pp. 1215–1233.
- Romer, Christina D and David H Romer (2010). “The Macroeconomic Effects of Tax Changes: Estimates Based on a New Measure of Fiscal Shocks”. In: *American Economic Review* 100.3, pp. 763–801.
- Sims, Christopher A and Tao Zha (1998). “Bayesian Methods for Dynamic Multivariate Models”. In: *International Economic Review* 39.4, pp. 949–968.
- Smets, Frank and Raf Wouters (2003). “An Estimated Dynamic Stochastic General Equilibrium Model of the Euro Area”. In: *Journal of the European Economic Association* 1.5, pp. 1123–1175.
- Stock, James H and Mark W Watson (1998). “Median Unbiased Estimation of Coefficient Variance in a Time-Varying Parameter Model”. In: *Journal of the American Statistical Association* 93.441, pp. 349–358.
- (2002). “Macroeconomic Forecasting using Diffusion Indexes”. In: *Journal of Business & Economic Statistics* 20.2, pp. 147–162.
- (2005). “Understanding Changes in International Business Cycle Dynamics”. In: *Journal of the European Economic Association* 3.5, pp. 968–1006.
- (2012). *Disentangling the Channels of the 2007-2009 Recession*. Tech. rep. National Bureau of Economic Research.
- Taylor, John B (1999). “A Historical Analysis of Monetary Policy Rules”. In: *Monetary policy rules*. University of Chicago Press, pp. 319–348.
- Uhlig, Harald (2005). “What are the Effects of Monetary Policy on Output? Results from an Agnostic Identification Procedure”. In: *Journal of Monetary Economics* 52.2, pp. 381–419.



## Declaration of Authorship

Ich, Leonard Salzmänn, erkläre hiermit, dass ich meine Doktorarbeit "Essays on the Business Cycle" selbstständig und ohne fremde Hilfe angefertigt habe und dass ich als Koautor maßgeblich zu den weiteren Fachartikeln beigetragen habe. Alle von anderen Autoren wörtlich übernommenen Stellen, wie auch die sich an die Gedanken anderer Autoren eng anlehnenden Ausführungen der aufgeführten Beiträge wurden besonders gekennzeichnet und die Quellen nach den mir angegebenen Richtlinien zitiert.

Signatur:

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Datum:

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