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CESIFO WORKING PAPER NO. 5980
CATEGORY 6: FISCAL POLICY, MACROECONOMICS AND GROWTH
JUNE 2016

ISSN 2364-1428

CESifo
Center for Economic Studies & Ifo Institute

CESifo *Working Paper No. 5980*

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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.

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June 28, 2016
We are grateful to Ruediger Bachmann, Lutz Kilian, and various seminar participants for many helpful comments and discussions.

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 and stock market returns, and in inflation 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 2 presents the data and outlines the detrending procedure. Section 3 introduces the FSVAR and describes how we identify the common international factors. Section 4 presents the results of the FSVAR. In Section 5 we report the results of supplementary regressions of world and G7 business cycle indicators on the factors and shocks extracted by the FSVAR. We check the robustness of our main findings to changes in the setup of the analysis in Section 6. Section 7 concludes.

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.[1]

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

[1]These shares are based on the World Development Indicators published by the World Bank.

observations, it would also mean to neglect some important business cycle movements like the euro area trough of 1993.

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 below that this adjustment scheme does not drive our results, see section 6.

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):

$$y_t = \mu_t + u_t \tag{1}$$

$$\mu_t = \mu_{t-1} + \tau\eta_t \tag{2}$$

$$u_t = \sum_{i=1}^{4} \alpha_i u_{t-i} + w_t \tag{3}$$

where η_t and w_t are serially and mutually uncorrelated mean-zero disturbances. The measurement equation (1) decomposes GDP growth, y_t, into a slowly evolving mean, μ_t, and a stationary cycle, u_t. According to (2) μ_t follows a random walk, while (3) models u_t as an AR(4) process. The relative importance of the trend innovations, η_t, compared to the cyclical shocks, w_t, is reflected by the scaling factor τ.

We estimate the local level model using an asymptotically median unbiased estimator of τ 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 τ. Then we use the Kalman smoother to remove μ_t. This yields detrended GDP growth as shown in Figures 1 and 2.

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.

3.1 Choice of the lag order

We start from the unrestricted VAR model

$$Y_t = \sum_{i=1}^{p} A_i Y_{t-i} + v_t, \tag{4}$$

where Y_t is a n-dimensional vector of detrended GDP growth rates, v_t is a vector of reduced-from 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.[2]

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 ma-

[2] In the robustness analysis below, we demonstrate that choosing $p = 1$ as selected by information criteria does not qualitatively change our results. We prefer a higher lag order to be sure that we do not miss important higher-order dynamics and because an overly restrictive specification could lead to inconsistent parameter estimates.

trix of the residuals. In the second step, we estimate the VAR as a system, plugging the estimated covariance matrix into the FGLS estimator.

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:

$$v_t = \Gamma f_t + \xi_t, \tag{5}$$

where ξ_t denotes the n-dimensional vector of country-specific shocks, f_t denotes the k-dimensional vector of factors, and Γ is a $(n \times k)$ matrix of factor loadings. We assume that both f_t and ξ_t are uncorrelated with each other and over time, with diagonal covariance matrices. We estimate the decomposition of the reduced form covariance matrix into the factor structure (5) 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 et al. (2010) for fiscal policy shocks.

A similar factor structure is used by Altonji and Ham (1990), Norrbin and Schlagenhauf (1996), and Stock and Watson (2005). The main advantage of it 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). 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).[3] 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.

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 Γ. 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

[3]Stock and Watson (2005) and Helbling and Bayoumi (2003) use G7 output data for the time periods 1960-2002 and 1973-2001, respectively

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 can be found in Appendix A.) 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 sensitivity analysis below that such an approach yields very similar results.

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.

4.1 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 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 co-movements, 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).

4.2 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 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 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 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 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 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.

4.3 Historical decompositions

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 3 to 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, Germany, 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 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 3 to 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.

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 Appendix B).

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 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 indicator z_{it} is

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

where f_t denotes the (3×1) dimensional vector of global factors, ξ_t denotes the (14×1) dimensional vector of idiosyncratic shocks, and ε_t takes up all additional shocks. By assumption, f_t, ξ_t, and ε_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^2_{OIC}, 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^{OIC} denotes the OIC factor, and ξ_t^{OIC} denotes the (7×1) dimensional vector of idiosyncratic OIC shocks. Similarly, for the G7 we compute the R-squared, R^2_{G7}, 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^{G7} denotes the two G7 factors, and ξ_t^{G7} denotes the (7×1) 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

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

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 5 we report the variance shares of detrended global macro indicators accounted for by all shocks extracted from the G14-FSVAR (computed as $R^2_{\mathrm{G7}} + R^2_{\mathrm{OIC}}$) and the relative importance of the OIC factor and shocks (computed as $R^2_{\mathrm{OIC}}/(R^2_{\mathrm{G7}} + R^2_{\mathrm{OIC}})$). 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 13 and 39 percent for world market prices and price volatilities. For example, all G14 shocks explain 80 percent of the one-quarter ahead variance and 63 percent of the two-quarter ahead variance of the Brent oil price, of which 20 percent and 37 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 26 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 (2013) 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 $h = 8$.

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 $R^2_{\mathrm{OIC}}/(R^2_{\mathrm{G7}} + R^2_{\mathrm{OIC}})$, in Table 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.[4] Similarly, at the one and two

[4]Since we use the same detrended GDP growth here as in the G14-FSVAR above, this

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.

6 Robustness checks

In this section we report the results of an extensive robustness analysis. Table 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.

6.1 Clustered factor loadings

In the baseline three factor 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 Γ 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

is an expected outcome. In fact, the results are, up to approximation error, quantitatively identical.

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 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 these 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.

6.2 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”).

6.3 Alternative lag order

In section 3.1 we argued why we consider a VAR(4,1) to be appropriate in our analysis. However, it is possible that a different choice of the lag order may change our conclusions. In fact, the AIC, BIC and HQ information criteria prefer a more parsimonious VAR(1,1) specification. In the baseline, we nevertheless used a VAR(4,1) because choosing too small a lag order may lead to inconsistent parameter estimation. However, re-running the G14-FSVAR using a VAR(1,1) specification yields only negligible changes in the results (see row “Alt. lag order”).

6.4 Restricted country samples

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*”). 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 on 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.

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 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.

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Figures and Tables

Figure 1: Detrended annualized quarterly GDP growth of the G7

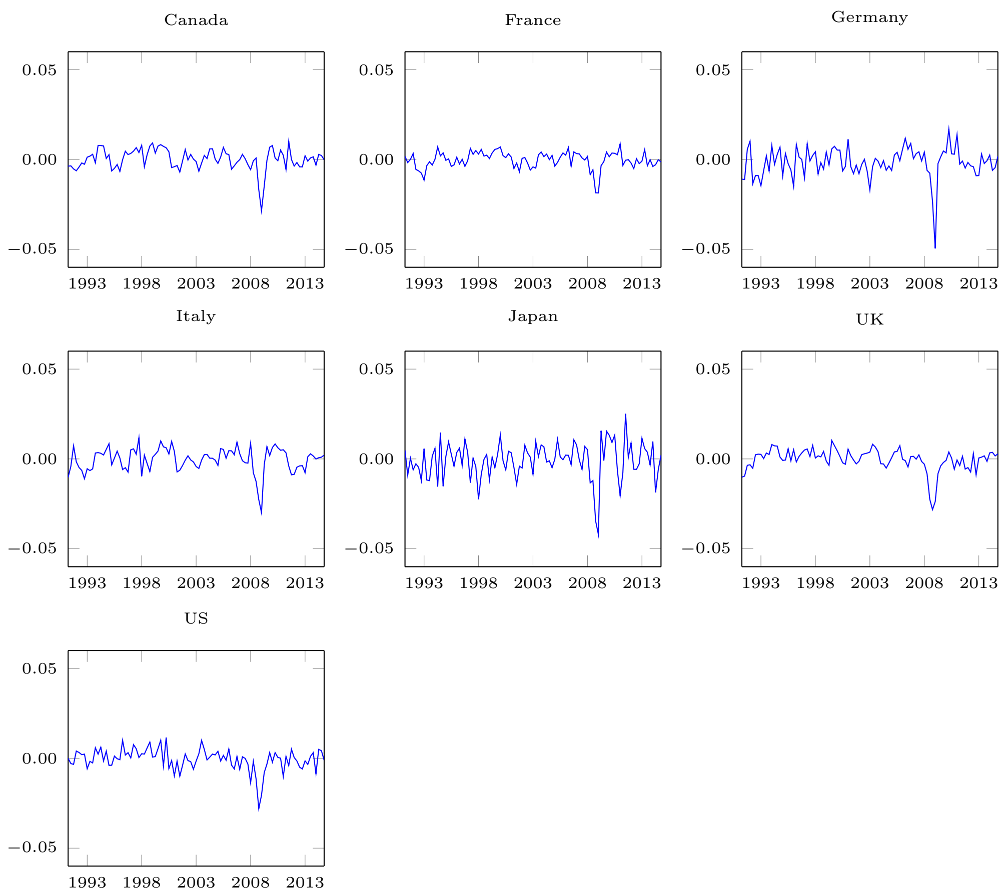


Figure 2: Detrended annualized quarterly GDP growth of the OIC

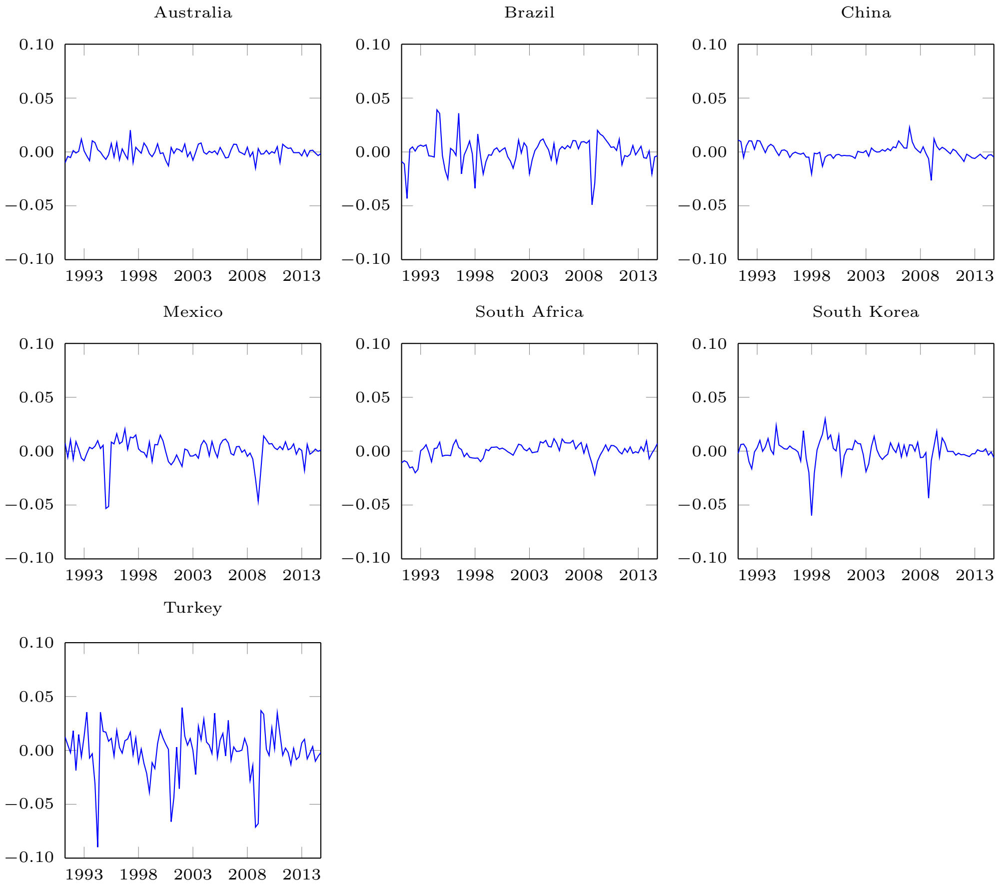


Table 1: Tests of k-factor FSVAR vs. unrestricted VAR

	G7-FSVAR			G14-FSVAR		
Number of factors k	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.

Table 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 FSVAR using G7 data. 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 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

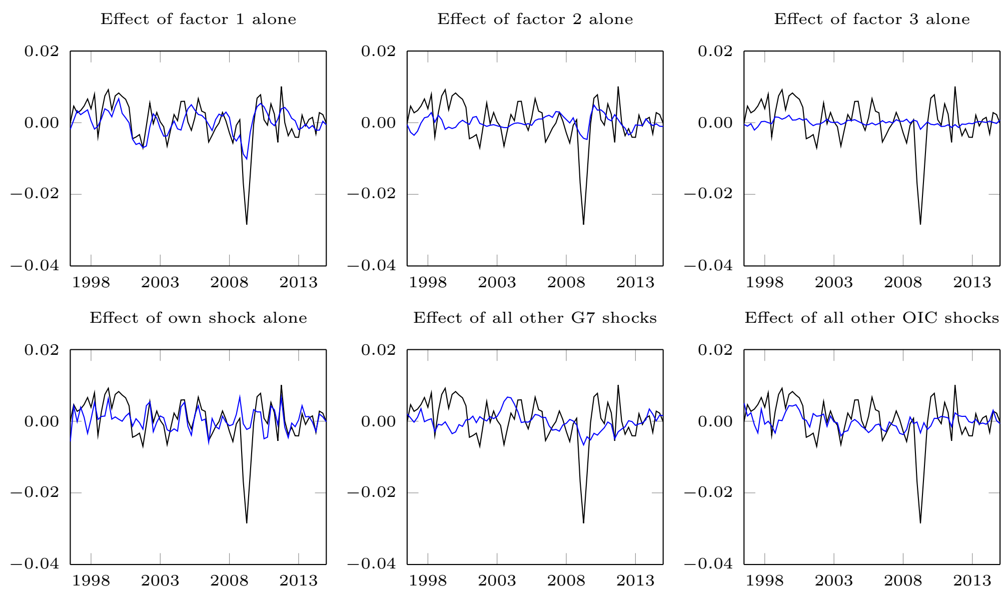
Notes: The table shows the square root of the forecast error variance of detrended GDP growth and its decomposition into factors, spillovers and own shocks. The results are based on the three factor FSVAR using G14 data. The standard deviations are in percentage points at an annual level, i.e. $400/h$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

Table 4: Forecast error variance decomposition based on the G14-FSVAR: Common shocks, spillovers and own-country shocks for the OIC

Country	h	Fore-cast error s.d.	Factor 1	Factor 2	Factor 3	Spill-overs from G7	Spill-overs 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

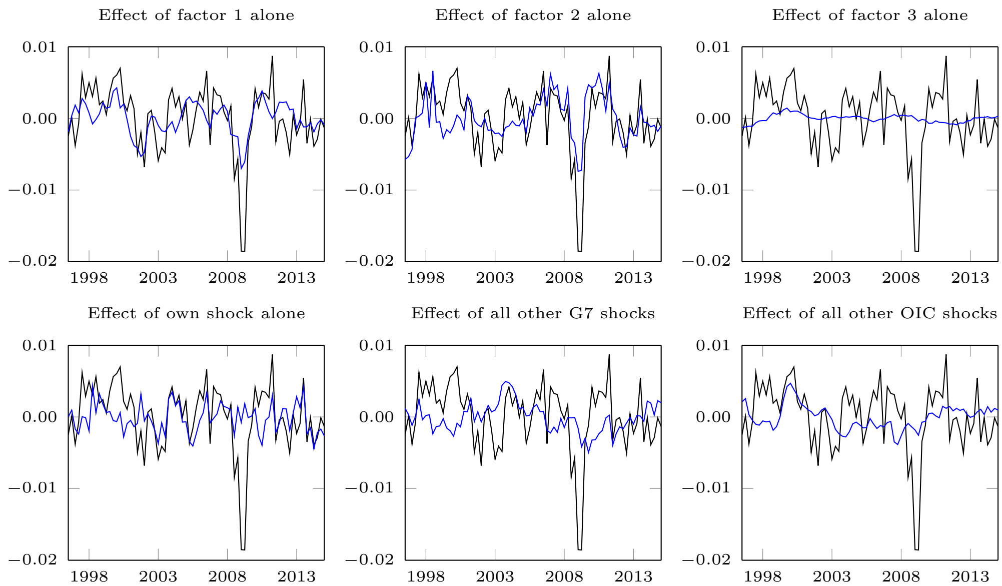
Notes: The table shows the square root of the forecast error variance of detrended GDP growth and its decomposition into factors, spillovers and own shocks. The results are based on the three factor FSVAR using G14 data. The standard deviations are in percentage points at an annual level, i.e. $400/h$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

Figure 3: Historical decompositions – Canada



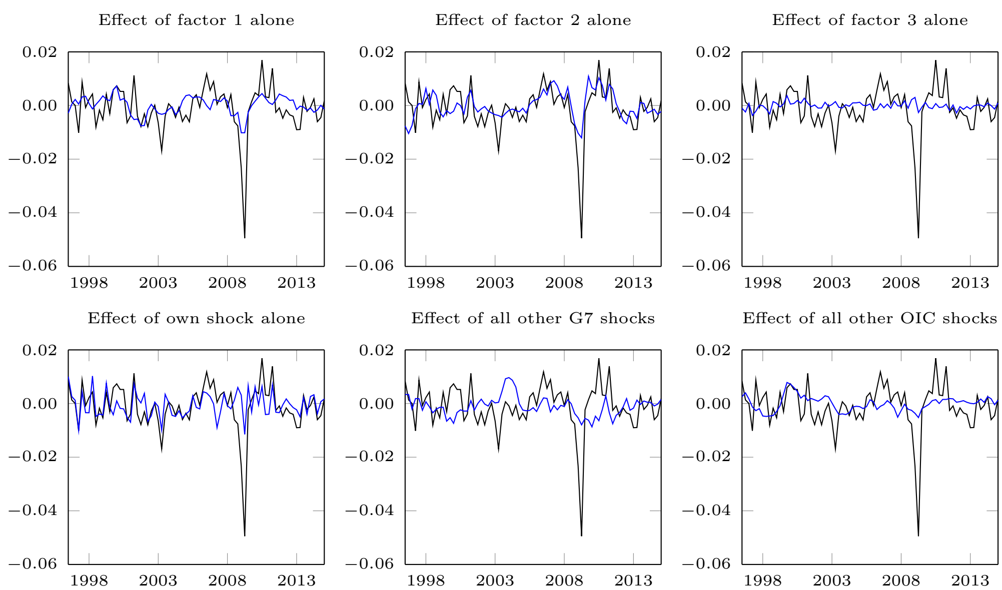
Notes: In each panel of the figure we show the realized series of detrended GDP growth (black) and a hypothetical series (blue) that is implied by the G14-FSVAR. The hypothetical series results from a counterfactual analysis in which one (set of) structural shock(s) is allowed for. Details are given in Section 4.3.

Figure 4: Historical decompositions – France



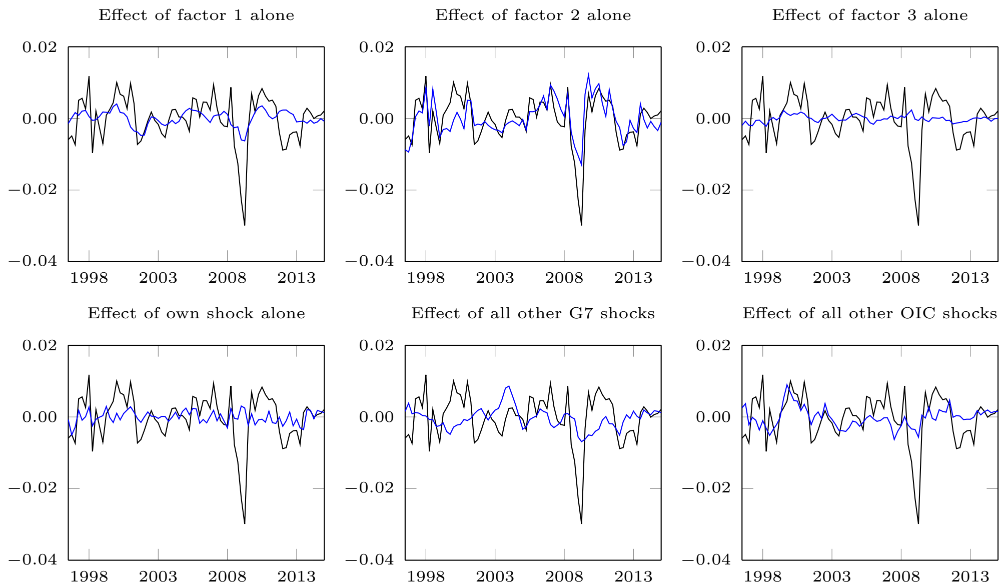
See figure 3 for a detailed description of the graphs.

Figure 5: Historical decompositions – Germany



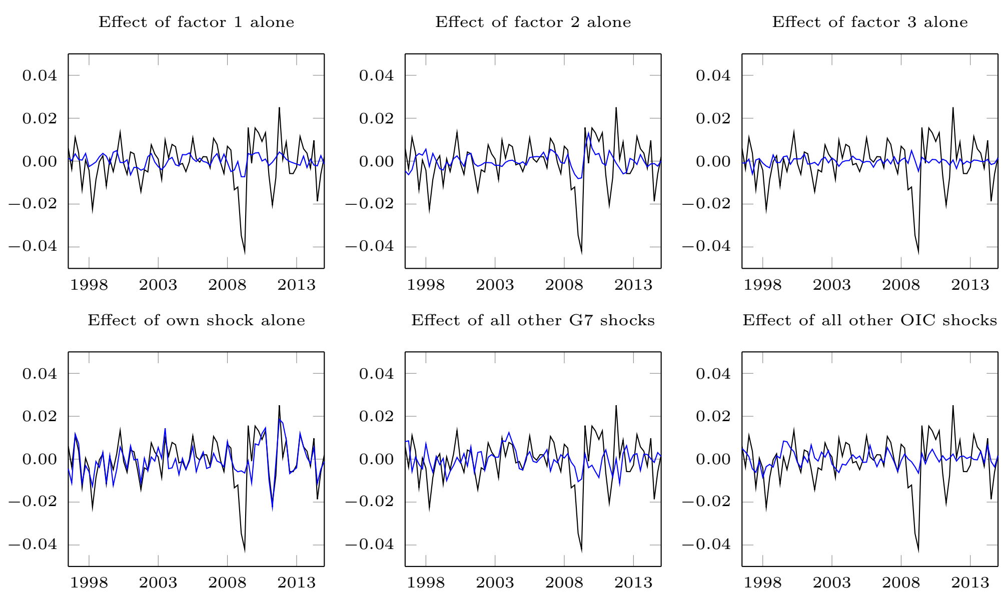
See figure 3 for a detailed description of the graphs.

Figure 6: Historical decompositions – Italy



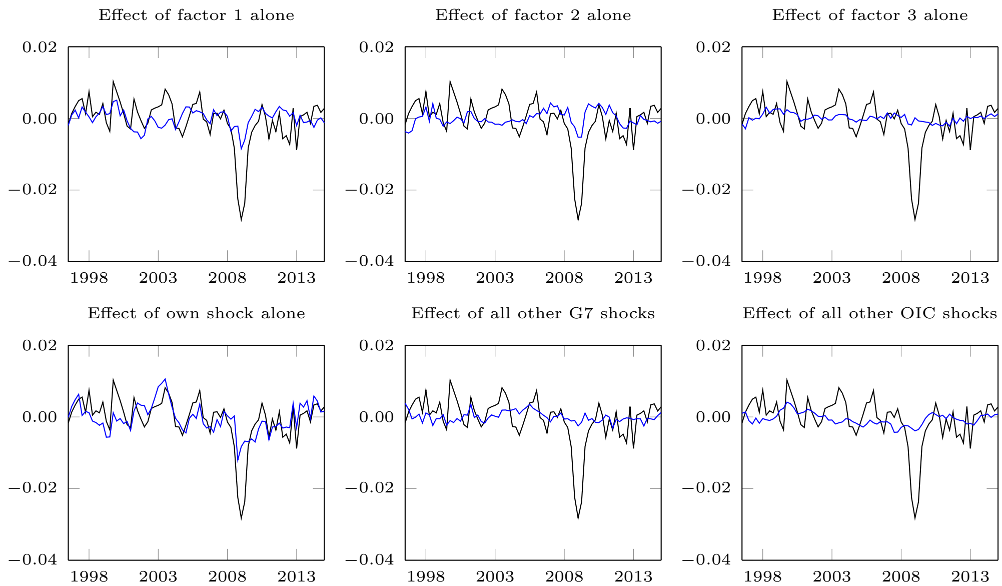
See figure 3 for a detailed description of the graphs.

Figure 7: Historical decompositions – Japan



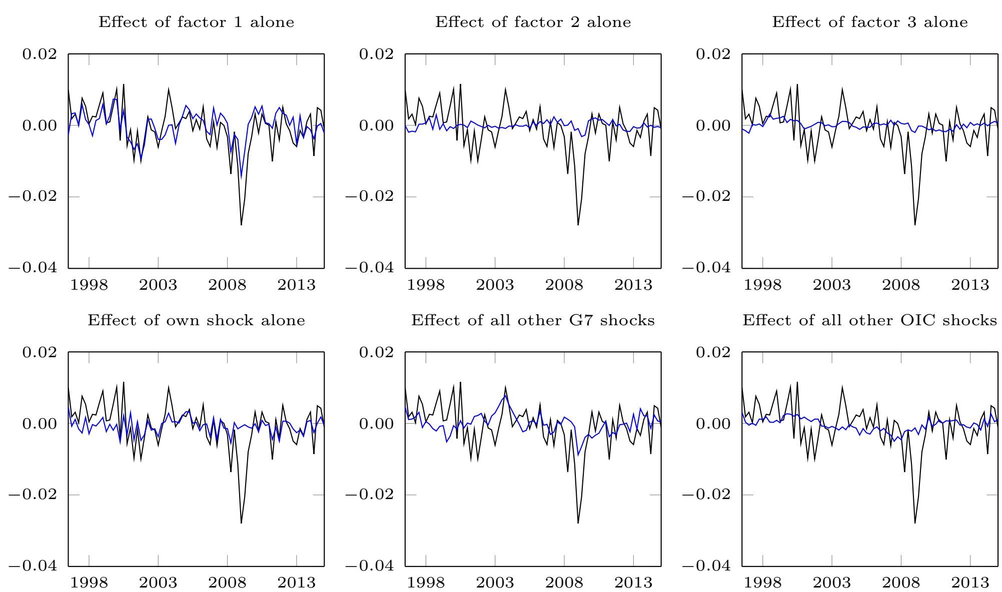
See figure 3 for a detailed description of the graphs.

Figure 8: Historical decompositions – UK



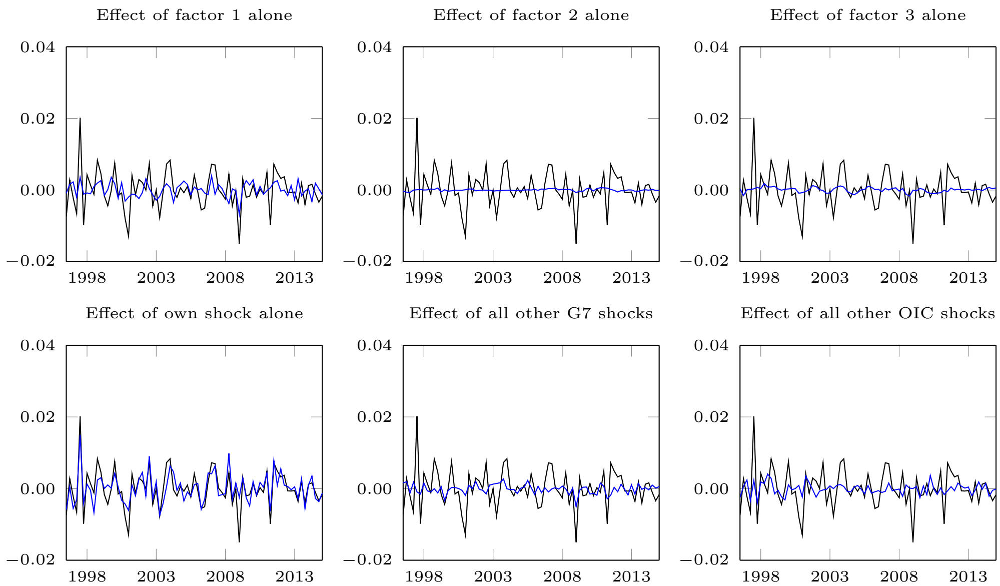
See figure 3 for a detailed description of the graphs.

Figure 9: Historical decompositions – US



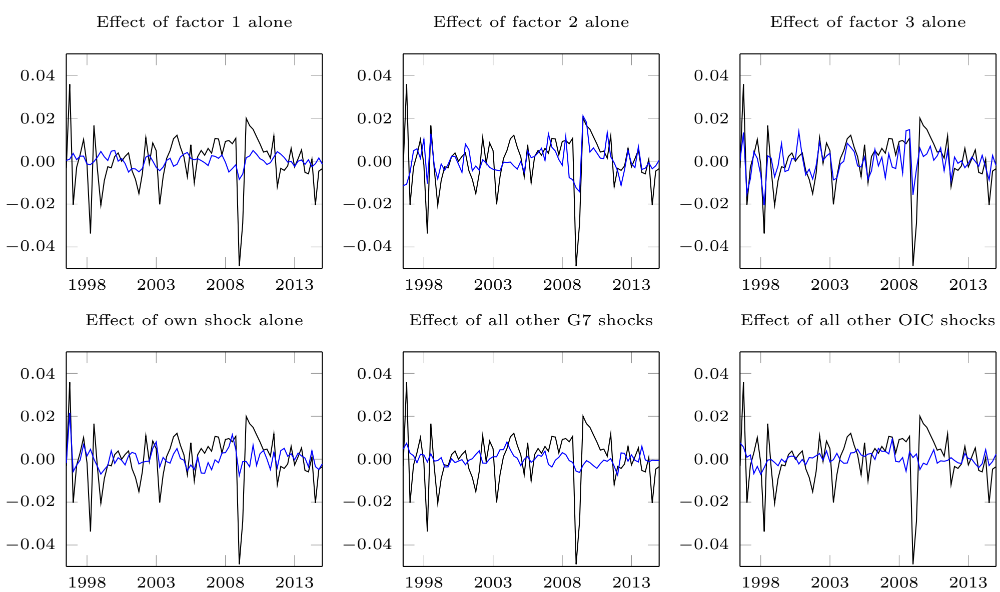
See figure 3 for a detailed description of the graphs.

Figure 10: Historical decompositions – Australia



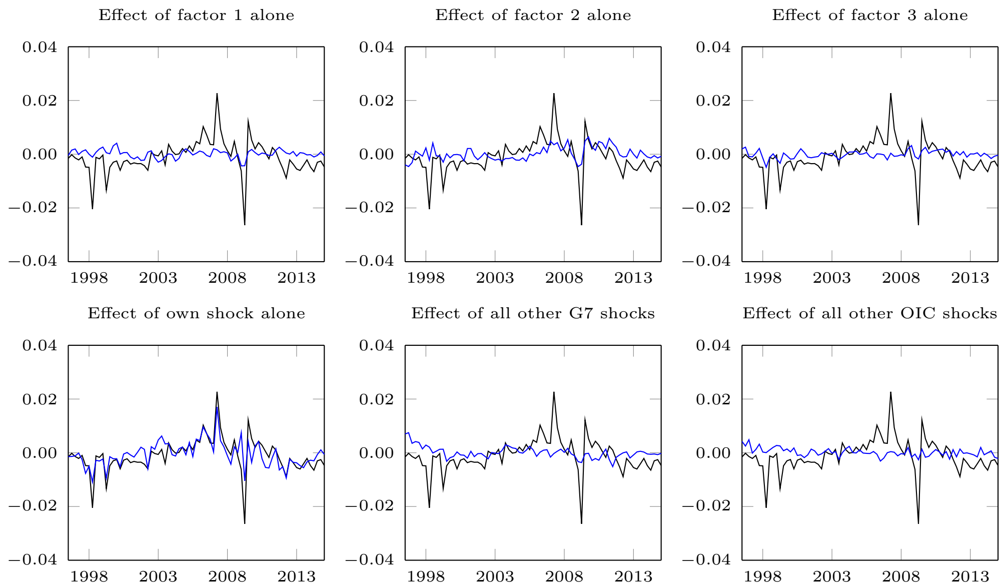
See figure 3 for a detailed description of the graphs.

Figure 11: Historical decompositions – Brazil



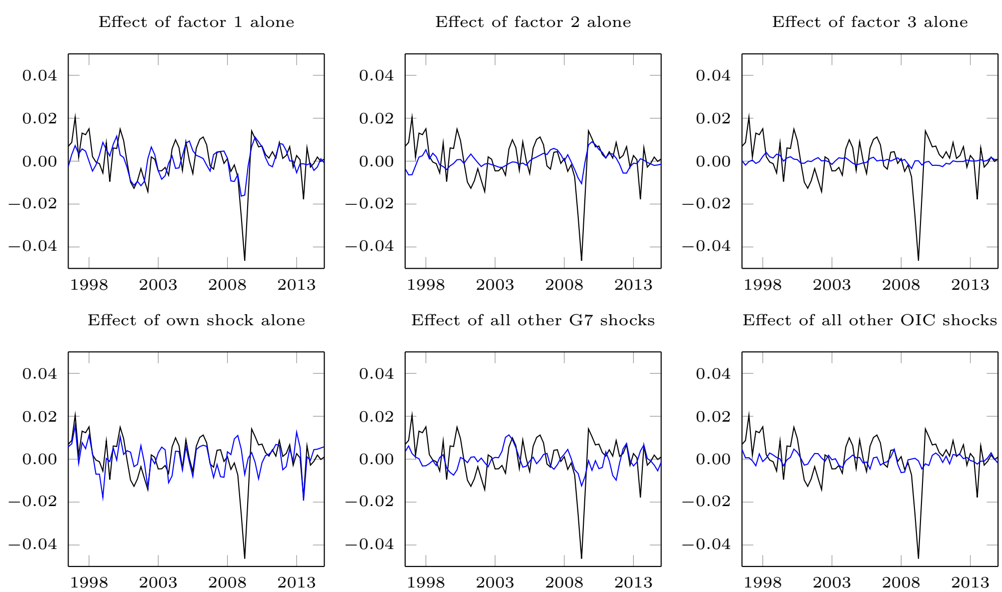
See figure 3 for a detailed description of the graphs.

Figure 12: Historical decompositions – China



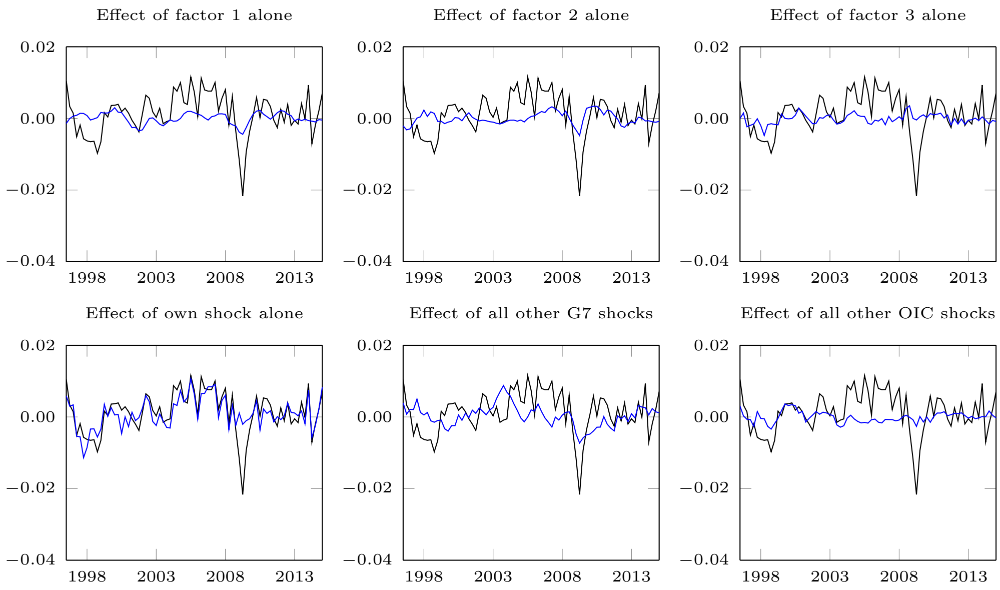
See figure 3 for a detailed description of the graphs.

Figure 13: Historical decompositions – Mexico



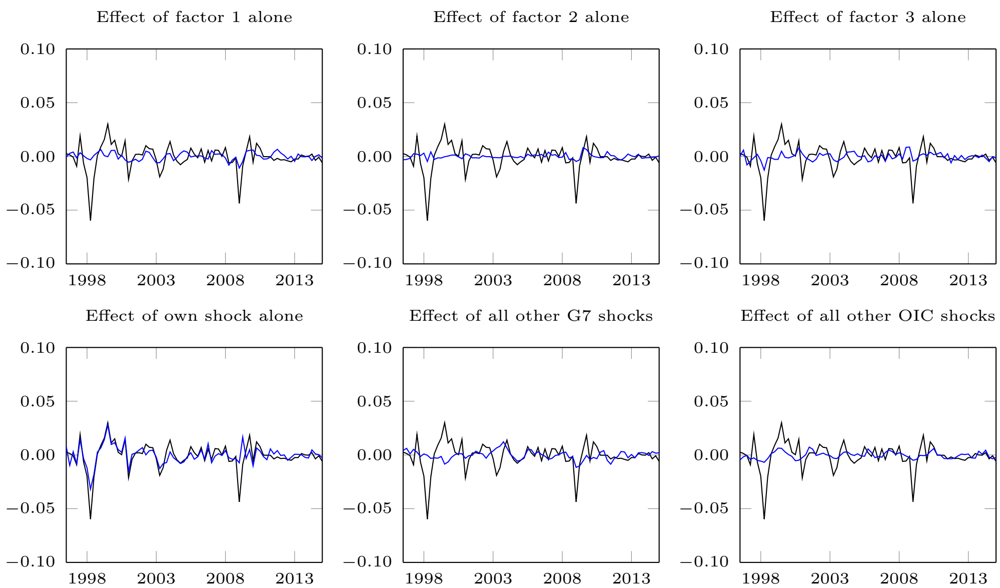
See figure 3 for a detailed description of the graphs.

Figure 14: Historical decompositions – South Africa



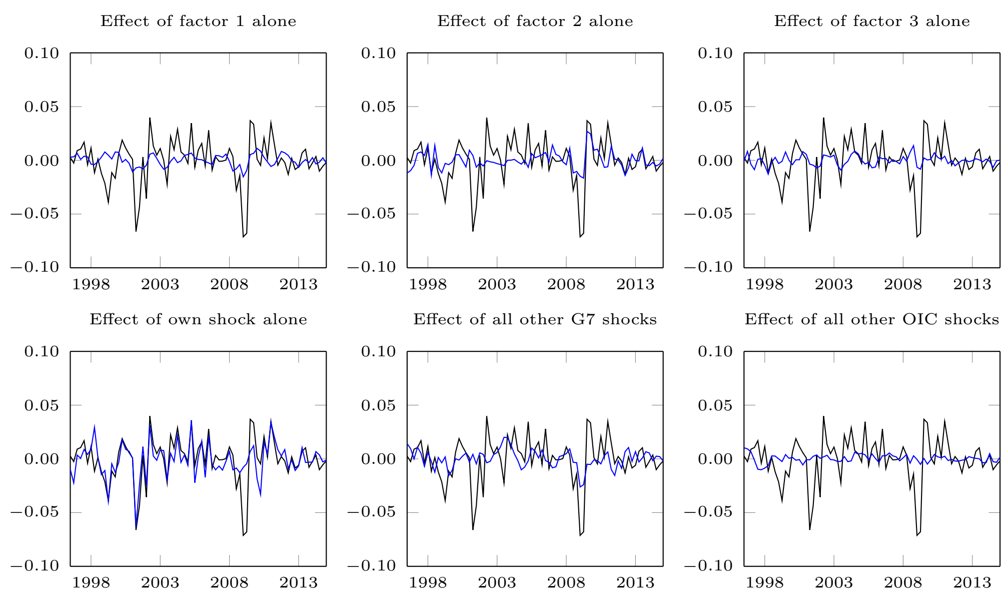
See figure 3 for a detailed description of the graphs.

Figure 15: Historical decompositions – South Korea



See figure 3 for a detailed description of the graphs.

Figure 16: Historical decompositions – Turkey



See figure 3 for a detailed description of the graphs.

Table 5: Forecast error variance shares of global business cycle indicators accounted for by G7 and OIC shocks

	All shocks		OIC shocks	
Indicator	$h = 1$	$h = 2$	$h = 1$	$h = 2$
OECD GDP	0.39	0.71	0.04	0.08
World industrial production	0.33	0.69	0.09	0.10
CPB world trade	0.27	0.56	0.08	0.10
CPB manufacturing prices	0.13	0.39	0.54	0.29
Brent oil price	0.80	0.63	0.20	0.37
World fuel prices	0.38	0.67	0.18	0.38
World commodity prices	0.36	0.51	0.08	0.13
MSCI World	0.34	0.55	0.18	0.26
Inflation volatility	0.82	0.65	0.18	0.35
Stock market volatility	0.91	0.84	0.09	0.16
Exchange rate volatility	0.72	0.61	0.28	0.39

Note: h denotes the forecast horizon. The columns "All shocks" report the variance share accounted for by all factors and shocks extracted from the FSVAR, $R^2_{\mathrm{G7}} + R^2_{\mathrm{OIC}}$. The columns "OIC shocks" report the variance share of all shocks accounted for by OIC factors and shocks, $R^2_{\mathrm{OIC}}/(R^2_{\mathrm{G7}} + R^2_{\mathrm{OIC}})$. The variables are described in Appendix B.

Table 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	0.00	0.00
	2	0.02	0.06	0.06	0.13	0.10	0.03	0.03
Investment	1	0.41	0.04	0.01	0.22	0.11	0.20	0.03
	2	0.23	0.12	0.12	0.33	0.35	0.12	0.07
Private consumption	1	0.23	0.09	0.57	0.15	0.05	0.31	0.23
	2	0.24	0.11	0.40	0.15	0.24	0.40	0.22
Imports	1	0.17	0.36	0.10	0.04	0.23	0.21	0.16
	2	0.11	0.30	0.08	0.06	0.08	0.28	0.14
Exports	1	0.06	0.05	0.04	0.13	0.17	0.11	0.09
	2	0.03	0.17	0.14	0.12	0.12	0.08	0.09
Employment	1	0.40	0.37	0.38	0.19	0.29	0.37	0.20
	2	0.16	0.32	0.47	0.32	0.49	0.31	0.20
Unemployment rate	1	0.23	0.19	0.29	0.48	0.36	0.26	0.28
	2	0.28	0.24	0.34	0.54	0.50	0.26	0.30
Current account balance	1	0.31	0.52	0.34	0.30	0.14	0.29	0.66
	2	0.34	0.46	0.29	0.16	0.21	0.37	0.50
Real effective exchange rate	1	0.37	0.42	0.29	0.42	0.43	0.36	0.06
	2	0.38	0.20	0.22	0.34	0.51	0.28	0.22
Nominal eff. exchange rate	1	0.33	0.40	0.37	0.45	0.47	0.43	0.02
	2	0.35	0.22	0.26	0.37	0.50	0.28	0.17
CPI inflation	1	0.45	0.07	0.08	0.28	0.18	0.15	0.33
	2	0.39	0.30	0.26	0.38	0.19	0.33	0.27
10-year government bond rate	1	0.03	0.30	0.32	0.27	0.17	0.31	0.15
	2	0.06	0.30	0.27	0.25	0.19	0.28	0.13
Stock market returns	1	0.41	0.25	0.18	0.21	0.22	0.21	0.25
	2	0.49	0.36	0.26	0.34	0.28	0.25	0.29
Inflation volatility	1	0.54	0.27	0.33	0.13	0.51	0.28	0.25
	2	0.39	0.24	0.19	0.21	0.46	0.22	0.20
Stock market volatility	1	0.12	0.13	0.10	0.21	0.11	0.11	0.06
	2	0.16	0.22	0.23	0.24	0.18	0.20	0.15
Exchange rate volatility	1	0.06	0.17	0.24	0.26	0.27	0.16	0.19
	2	0.09	0.25	0.29	0.35	0.23	0.28	0.23

Note: h denotes the forecast horizon. Reported is the variance share of all shocks accounted for by OIC factors and shocks, $R^2_{\mathrm{OIC}}/(R^2_{\mathrm{G7}} + R^2_{\mathrm{OIC}})$. The variables are described in Appendix B.

Table 7: Forecast error variance decompositions: Robustness checks

Country	Restriction	Forecast error standard deviation	Factor 1+ Factor 2+ Spillovers from G7	Factor 3	Spill-overs from OIC	Own shock
Canada	**Baseline**	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
	Alt. lag order	1.26	0.70	0.00	0.05	0.24
	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	**Baseline**	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
	Alt. lag order	1.11	0.67	0.00	0.08	0.24
	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	**Baseline**	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
	Alt. lag order	1.78	0.71	0.00	0.12	0.17
	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 7 continued

Country	Restriction	Forecast error standard deviation	Factor 1+ Factor 2+ Spillovers from G7	Factor 3	Spill-overs from OIC	Own shock
	Baseline	1.54	0.68	0.01	0.17	0.13
Italy	Clustered loadings	1.43	0.50	0.00	0.21	0.29
	Incl. outliers	1.54	0.70	0.02	0.13	0.15
	Alt. lag order	1.54	0.68	0.00	0.17	0.15
	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
	Baseline	2.06	0.35	0.01	0.13	0.51
Japan	Clustered loadings	1.97	0.21	0.01	0.14	0.65
	Incl. outliers	2.07	0.34	0.03	0.12	0.50
	Alt. lag order	2.13	0.34	0.01	0.10	0.55
	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
	Baseline	1.57	0.29	0.05	0.05	0.61
UK	Clustered loadings	1.72	0.28	0.01	0.05	0.66
	Incl. outliers	1.57	0.28	0.01	0.04	0.67
	Alt. lag order	1.60	0.27	0.04	0.04	0.64
	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 7 continued

Country	Restriction	Forecast error standard deviation	Factor 1+ Factor 2+ Spillovers from G7	Factor 3	Spill-overs from OIC	Own shock
	Baseline	1.40	0.68	0.04	0.05	0.23
US	Clustered loadings	1.43	0.70	0.02	0.05	0.23
	Incl. outliers	1.40	0.70	0.02	0.05	0.24
	Alt. lag order	1.39	0.67	0.04	0.06	0.23
	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 its 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 4. The subsequent rows report results from ceteris-paribus changes to that estimation setup.

Appendix

A 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:

$$\begin{aligned} v_t &= \Gamma f_t^{\mathrm{G14}} + \xi_t = \Gamma R' R f_t^{\mathrm{G14}} + \xi_t = \tilde{\Gamma} \tilde{f}_t^{\mathrm{G14}} + \xi_t & (6) \\ \mathrm{E}\left[\tilde{f}_t^{\mathrm{G14}} (\tilde{f}_t^{\mathrm{G14}})'\right] &= R\,\mathrm{E}\left[f_t^{\mathrm{G14}} (f_t^{\mathrm{G14}})'\right] R' = RR' = I_k & (7) \end{aligned}$$

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

We choose R to maximize the correlation between the first two factors from the second stage (based on the full country sample) with those from the first stage, f_t^{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:

$$\begin{aligned} h_1 &= \mathrm{corr}(\tilde{f}_{1t}^{\mathrm{G14}}, f_{1t}^{\mathrm{G7}}) = \frac{\sum \tilde{f}_{1t}^{\mathrm{G14}} f_{1t}^{\mathrm{G7}}}{T-1} = r_1 \frac{\sum f_t^{\mathrm{G14}} f_{1t}^{\mathrm{G7}}}{T-1} = r_1 \begin{pmatrix} c_{11} \\ c_{21} \\ c_{31} \end{pmatrix} & (8) \\ h_2 &= \mathrm{corr}(\tilde{f}_{2t}^{\mathrm{G14}}, f_{2t}^{\mathrm{G7}}) = \frac{\sum \tilde{f}_{2t}^{\mathrm{G14}} f_{2t}^{\mathrm{G7}}}{T-1} = r_2 \frac{\sum f_t^{\mathrm{G14}} f_{2t}^{\mathrm{G7}}}{T-1} = r_2 \begin{pmatrix} c_{12} \\ c_{22} \\ c_{32} \end{pmatrix} & (9) \end{aligned}$$

where c_{ij} denotes as the correlation between the ith unrotated second-stage factor and the jth 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 α, β and γ such that these correlations are maximized. A closed-form solution is available upon request.

B 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 8. 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..%c) for the period 1991-2014 from which we constructed an index that equals nominal GDP in 2005 (DS code chgdpcuma). 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 9."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 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 8: Data sources for real GDP and population

Series	Datastream code	Source	Period
A. Real GDP			
Australia	auoexo03d	OECD	1991-2014
Brazil	broexp03H	OECD	1991-1995
	broexo03d	OECD	1996-2014
Canada	cnoexo03d	OECD	1991-2014
China	chgdp..%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
B. Population			
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 9: 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