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DOI:
10.57938/217dd5e4-6b50-4823-9051-e19a0f86e97e

Published: 01/02/2017

Document Version:
Publisher's PDF, also known as Version of record

Department of Economics
Working Paper No. 239

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February 2017

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Abstract

This paper uses a global vector autoregressive (GVAR) model to analyze the relationship between FDI inflows and output dynamics in a multi-country context. The GVAR model enables us to make two important contributions: First, to model international linkages among a large number of countries, which is a key asset given the diversity of countries involved, and second, to model foreign direct investment and output dynamics jointly. The country-specific small-dimensional vector autoregressive submodels are estimated utilizing a Bayesian version of the model coupled with stochastic search variable selection priors to account for model uncertainty. Using a sample of 15 emerging and advanced economies over the period 1998:Q1 to 2012:Q4, we find that US outbound FDI exerts a positive long-term effect on output. Asian and Latin American economies tend to react faster and also stronger than Western European countries. Forecast error variance decompositions indicate that FDI plays a prominent role in explaining GDP fluctuations, especially in emerging market economies. Our findings provide evidence for policy makers to design macroeconomic policies to attract FDI inflows in the respective countries.

Keywords: FDI-output relationship, cross-country spillovers, transmission of external shocks, Bayesian global vector autoregressive model

JEL Codes: C30, E52, F41, E32

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1 Introduction

Foreign direct investment[1] (FDI) has expanded rapidly throughout the world economy in recent decades, supported by removing national barriers to capital transfer and increased efforts of many countries to attract more foreign capital, especially in developing and transition economies[2]. FDI differs from other types of international capital flows by representing a channel through which physical and intellectual capital are exchanged between countries. FDI flows allow transfers of firm-specific knowledge across countries, knowledge that would be immobile otherwise (Ramondo and Rappoport, 2010). The acquisition of firm-specific knowledge appears to be an important determinant behind the recent increase in FDI, indicating that FDI serves as a pivotal channel for knowledge and technology diffusion (Barrell and Pain, 1997). Hence, the rationale for policies to attract more FDI is grounded in the fact that FDI not only provides direct capital financing, but also creates positive externalities through transfers of technology and managerial expertise, and thus enhances productivity and stimulates output growth in the host countries.[3]

From a theoretical perspective, several reasons have been identified why FDI induces long-run positive effects on output growth, predominantly within the framework of the neoclassical growth model. For example, Thompson (2008), and Mallick and Moore (2008) separate foreign from domestic capital and derive conditions under which economic growth is positively impacted by foreign capital. In contrast, within a microfounded general equilibrium framework, Helpman and Krugman (1985) view FDI as a production factor movement that establishes a direct relation to capital rather than investment. While the theoretical underpinnings of FDI spillovers have been extensively studied (see, for instance, Liu, 2008), finding robust empirical evidence to support their existence within and across economies is more difficult.[4]

The relationship between FDI and output growth has motivated a voluminous empirical literature, but with a variety of apparently conflicting results. For a review, see Moran et al. (2005), and Kose et al. (2009). There is still little support for robust empirical evidence of the growth effects of FDI. Firm-level and industry-level studies of particular countries do not provide conclusive evidence that FDI induces substantial spillover effects for the entire economy. The influential study of Aitken and Harrison

[1] Following de Mello (1997) foreign direct investment may be defined as an international investment that is associated with a lasting managerial interest (typically exceeding ten percent of equity stake). In this study we use a flow rather than a stock definition of FDI, measuring foreign direct investment inflows in host countries over a quarter of a year.

[2] In the FDI literature one may distinguish two major research directions. The focus of the first is on the determinants of FDI location choice, or in other words, on the economic factors/conditions in the host countries that pull in FDI flows. The second directs attention to the economic effects of FDI inflows on economic growth, employment and wages in the recipient countries. The purpose of the current paper is to contribute to this latter research direction.

[3] It has also been argued that FDI is less prone to sudden stops or reversals, as, for example, portfolio equity flows (Kose et al., 2009).

[4] See Lipsey and Sjöholm (2005) for a survey of the evidence on FDI spillovers.

(1999), for instance, does not find any evidence of positive technology spillovers from foreign firms to domestically owned ones in Venezuela between 1979 and 1989. Other researchers have reported evidence of positive spillovers in some industries, but location-specific, industry-specific and firm-specific factors – as emphasized by Dunning (2001) in his OLI paradigm of international production[5] – appear to be so important that the results do not support the overall conclusion that FDI induces substantial spillover effects for the entire economy (Carkovic and Levine, 2005).

Macroeconomic studies – overwhelmingly in the form of growth regressions using cross-section or panel data – generally suggest a positive role for FDI in generating output growth. A positive impact of FDI on output growth is noted, for instance, by de Mello (1999). In OECD countries, the positive impact is largely due to higher efficiency (total factor productivity), while in non-OECD countries it is the effect of FDI on capital accumulation rather than on efficiency that drives the positive output response. Other studies indicate that FDI flows generate output growth but only in recipient countries with appropriate local conditions, such as high levels of human capital (see Borensztein et al., 1998), financial sector development (see Alfaro et al., 2004; Durham, 2004), and policies fostering openness (see Balasubramanyam et al., 1996).

These macroeconomic findings, however, must be viewed skeptically due to several reasons. First, existing studies do not fully control for simultaneity bias, country-specific effects, and the routine case of lagged dependent variables in the growth regressions. These weaknesses can bias the coefficient estimates and the coefficient standard errors. Second, if FDI has a positive effect on output in the recipient economy, FDI does not exert a robust, independent impact when other factors such as controls for trade and domestic financial credit are taken into account (see, for example, Carkovic and Levine, 2005; Barrell and Pain, 1997). Third, the multi-country dimension of the relationship is overlooked, as the existing papers treat the countries as independent units and ignore their interdependencies. Finally, nearly all of the studies do not go beyond observations in the 1990s, even though the world economy today is operating under sharply different global financial conditions.

In this paper, we use a global vector autoregressive (GVAR) model to reassess the relationship between FDI inflows and host country output dynamics in a world of interdependent economies. By taking cross-country linkages seriously, the approach adopted is capable of answering the question whether FDI inflows can trigger short-term output movements. The research interest lies on quarterly FDI flows from the US (commonly termed US outbound FDI flows) to a set of host countries that includes eight advanced economies (Australia, Austria, Canada, Germany, France, Finland, Japan and the UK) and six emerging countries (Brazil, China, India, Mexico, South Korea and Turkey).[6]

[5] The OLI paradigm of international production is an eclectic approach that stresses **o**rganization-specific, **l**ocation-specific and **i**nternationalization-specific variables.

[6] These flows represent about 20 percent of all the inflows 2012 in the considered host countries measured in terms of US dollars. Unfortunately, greenfield investments can not be distinguished from mergers and acquisitions.

Our GVAR model features fifteen country-specific VAR models representing the fourteen host countries and the US, the source country of the FDI flows. These national models are linked to each other by weighted cross-section averages of foreign variables. This makes the GVAR model particularly useful to account for the multilateral nature of FDI flows and to study the dynamics and spatial interrelations between US outbound flows and output in the host countries, alongside other important long-term macroeconomic relations which may influence the FDI-output nexus.

Compared to existing studies on the issue, the present paper makes three important contributions. First, the study suggests a novel methodology as the recent FDI literature is largely based on cross-section or panel regressions, neglecting the dynamic and spatial behavior of FDI flows. Second, we use a global macroeconomic framework that enables to account for various transmission channels, including not only the FDI-output relationship, but also financial linkages (most notably through interest and exchange rates) that may influence the FDI-output nexus. Our GVAR model, specifically designed for analyzing international linkages and explaining the time series dimension of the data, is especially well suited to account for the multilateral nature of FDI flows in general and cross-country FDI spillovers in particular. The third main contribution is that we estimate the FDI and output equations jointly. This proves to be important given the substantial co-movement between US outbound flows and real output observed in the data.

In doing so, the paper builds on previous contributions to the GVAR literature, especially Pesaran et al. (2004), Dees et al. (2007), Dovern and Huber (2015), and Dovern et al. (2016). GVAR modeling was applied in the past to a variety of questions (see Chudik and Pesaran, 2014), but to our knowledge this paper presents the first application of the GVAR methodology to assessing the relationship between FDI flows and output dynamics.

Following Crespo Cuaresma et al. (2016), and Feldkircher and Huber (2016) we use a Bayesian variant of the model approach coupled with a particular prior specification. Stochastic search variable selection priors suggested by George et al. (2008) enable us to account for model uncertainty. In the first step, the country-specific small-dimensional models are consistently estimated conditional on the rest of the world. These models contain seven domestic variables (inward foreign direct investment, real output, unit labor costs, real exchange rate, inflation, short-term and long-term interest rates) and weighted cross-sectional averages of foreign variables, which are commonly referred to as "star" variables and treated as weakly exogenous. In the second step, the individual country VARX* models are stacked and solved simultaneously as one global VAR model. The model is then used to generate impulse responses for all variables in the world economy simultaneously.

The rest of the paper is organized as follows. Section 2 outlines the GVAR model along with a Bayesian approach to estimation and inference as it applies to our work here. Section 3 describes the data set, outlines the model specification and provides some metric of model fit. Section 4 uses the GVAR model to simulate the effects that (positive) shocks to US outbound FDI may have on real output across space and time in the global economy. In addition we also present the results of generalized forecast error variance decompositions to shed some light on the relative importance FDI inflows in explaining variation in output dynamics across the countries. The final section summarizes and concludes.

2 The Bayesian global vector autoregressive model

The global VAR approach, originally proposed in Pesaran et al. (2004), provides a simple and flexible means to analyzing the relationship between FDI and output dynamics across economies. The approach can be viewed as a two-step approach. In the first step, small scale country-specific models are estimated conditional on the rest of the world. These models feature domestic (=endogenous) variables and weighted cross-sectional averages of foreign variables. In the second step, the country-specific vector autoregressive models are stacked and solved simultaneously as one large global VAR model.

2.1 The global VAR model

At the core of the GVAR approach are small-scale country-specific conditional models. These individual country models feature the domestic variables of the economy, collected in the $k_i \times 1$ vector $\boldsymbol{x}_{it}$, as well as the country-specific cross-sectional averages of foreign variables[7], collected in the $k_i^* \times 1$ vector

$$\boldsymbol{x}_{it}^* = \sum_{j=0}^{N} w_{ij} \boldsymbol{x}_{jt}.$$

The weights w_{ij} $(i, j = 0, \ldots, N)$ represent the importance of country j for country i. These connectivity terms are elements of a conventional $(N+1) \times (N+1)$ row-stochastic[8] connectivity matrix, commonly used in spatial econometrics to encode the connectivity relationships between countries. By convention, w_{ii} equals zero for all i. Note that the more country i is connected to country j (i.e. the larger w_{ij} is) the more country i benefits from externalities from country j.

Then $\boldsymbol{x}_{it}$ may be modeled as a VAR augmented by a vector of the star variables $\boldsymbol{x}_{it}^*$ and its lagged values.

$$\boldsymbol{x}_{it} = \boldsymbol{a}_{i0} + \boldsymbol{a}_{i1} t + \boldsymbol{\Phi}_{i1} \boldsymbol{x}_{it-1} + \boldsymbol{\Lambda}_{i0} \boldsymbol{x}_{it}^* + \boldsymbol{\Lambda}_{i1} \boldsymbol{x}_{it-1}^* + \boldsymbol{\varepsilon}_{it} \tag{1}$$

where $\boldsymbol{\Phi}_{i1}$ and $\boldsymbol{\Lambda}_{is}$ $(s = 0, 1)$ are $k_i \times k_i$ and $k_i \times k_i^*$ matrices of unknown parameters, respectively. $\boldsymbol{a}_{ir}$ $(r = 0, 1)$, and $\boldsymbol{\varepsilon}_{it}$ are $k_i \times 1$ coefficient vectors of the deterministics and error vectors, respectively. We assume that

$$\boldsymbol{\varepsilon}_{it} \sim \mathcal{N}(\mathbf{0}, \boldsymbol{\Sigma}_{\varepsilon i}).$$

[7] Hereby we implicitly assume that $k_i = k_j$ for all i, j.

[8] The term row-stochastic refers to a non-negative matrix having row sums normalized so they equal one.

$\boldsymbol{\Sigma}_{\varepsilon i}$ denotes a $k_i \times k_i$ variance-covariance matrix. In the case where $\boldsymbol{\Lambda}_{i0} = \boldsymbol{\Lambda}_{i1} = \mathbf{0}$ Eq. (1) reduces to a standard first-order VAR process, VAR(1). But in the presence of foreign variables Eq. (1) is an augmented VAR model that is commonly denoted by VARX*$(1, 1)$.

The separate estimation of the $N + 1$ country-specific VARX* models constitutes the first step of the GVAR approach as proposed by Pesaran et al. (2004), based on the assumption that foreign variables are weakly exogenous. Chudik and Pesaran (2014) emphasize that the assumption of weak-exogeneity is typically not rejected when the economy under consideration is small relative to the rest of the world and the weights used in the construction of the foreign variables are granular. The granularity conditions state that the weights w_{ij} between countries i and j are of order $1/N$ for all i, j, ruling out cases where w_{ij} becomes comparatively large for some countries (Forni and Lippi, 2001; Chudik and Pesaran, 2011).

It is easy to show how to combine the $N + 1$ country-specific models to obtain the global VAR model (see Appendix A for further details). After some straightforward algebraic manipulations, we arrive at the global VAR model given by

$$\boldsymbol{x}_t = \boldsymbol{b}_0 + \boldsymbol{b}_1 t + \boldsymbol{F}\boldsymbol{x}_{t-1} + \boldsymbol{e}_t \tag{2}$$

where $\boldsymbol{x}_t = (\boldsymbol{x}'_{0t}, \boldsymbol{x}'_{1t}, \ldots, \boldsymbol{x}'_{Nt})'$ denotes the global vector and the remaining elements of Eq. (2) are stacked vectors and matrices that consist of the country-specific coefficient estimates and the corresponding weights.[9] For global stability of the model, it is crucial that the eigenvalues of $\boldsymbol{F}$ lie within the unit circle.

Note that Eq. (2) resembles a standard VAR(1) with a deterministic trend. This implies that we can use this model to conduct (generalized) impulse response analysis for investigating the effects that shocks of US outbound FDI may have on output over time. Generalized forecast error variance decompositions enable us to shed some light on the relative importance of FDI inflows in explaining variation in output dynamics.

2.2 Bayesian estimation of the global VAR model

We use a Bayesian approach to estimating the country-specific models. To cope with the "curse of dimensionality" problem, we use a hierarchical prior structure on the coefficients and shrink the parameter space by using stochastic search variable selection (SSVS) priors introduced by George and McCulloch (1993) that enable to effectively account for the prevailing heterogeneity observed in the world economy and to select the appropriate model specification (Feldkircher and Huber, 2016).

For the subsequent discussion it is convenient to work with the stacked m_i-dimensional vector $\boldsymbol{\psi}_i$ ($m_i = 2k_i + k_i^2 + 2k_i k_i^*$) of coefficients for country i

$$\boldsymbol{\psi}_i = (\boldsymbol{a}'_{i0}, \boldsymbol{a}'_{i1}, \mathrm{vec}(\boldsymbol{\Phi}_{i1})', \mathrm{vec}(\boldsymbol{\Lambda}_{i0})', \mathrm{vec}(\boldsymbol{\Lambda}_{i1})')'.$$

The SSVS priors impose a mixture normal prior on each coefficient

$$\psi_{ij}|\delta_{ij} \sim \delta_{ij}\mathcal{N}(0, \tau_{i0}^2) + (1 - \delta_{ij})\mathcal{N}(0, \tau_{i1}^2) \text{ for } j = 1, \ldots, m_i. \tag{3}$$

[9]For precise definitions of the matrices $\boldsymbol{b}_0, \boldsymbol{b}_1, \boldsymbol{F}$ and $\boldsymbol{e}_t$, see Appendix A.

δ_{ij} is a binary random variable that controls the normal distribution to use for coefficient j in country i. The prior variances τ_{i0}^2 and τ_{i1}^2 are set such that $\tau_{i0}^2 \gg \tau_{i1}^2$ for all i. Thus, if $\delta_{ij} = 1$, the prior on coefficient j is effectively rendered non-influential. This captures the notion that no significant prior information for that parameter is available, centering the corresponding posterior distribution around the maximum likelihood estimate. If $\delta_{ij} = 0$ we impose a dogmatic prior, shrinking ψ_{ij} towards zero. This case would lead to a posterior which is strongly centered around zero, implying that we can safely regard that coefficient being equal to zero.

Let us define a scalar parameter h_{ij} given by

$$h_{ij} = \begin{cases} \tau_{i0} & \text{if } \delta_{ij} = 1 \\ \tau_{i1} & \text{if } \delta_{ij} = 0 \end{cases}$$

and collect the h_{ij}s in a matrix $\boldsymbol{H}_i = diag(h_{i1}, ..., h_{im_i})$ then

$$\boldsymbol{\psi}_i | \boldsymbol{H}_i \sim \mathcal{N}(\underline{\boldsymbol{\mu}}_{\psi_i}, \boldsymbol{H}_i \boldsymbol{R}_i \boldsymbol{H}_i). \tag{4}$$

$\underline{\boldsymbol{\mu}}_{\psi_i}$ denotes the m_i-dimensional prior mean vector, which is assumed to equal zero in this case. Moreover, $\boldsymbol{R}_i$ represents a $m_i \times m_i$ prior correlation matrix. For simplicity we assume $\boldsymbol{R}_i$ to equal the identity matrix. This prior shows several advantages which make it well suited for GVAR models. First, it allows for different model specifications across countries. This is important for impulse response analysis since it introduces a flexible way to apply shrinkage to coefficients where appropriate. Second, prior specification boils down to choosing appropriate scaling factors for the normal mixture prior.

For the country-specific variance-covariance matrix, we assume an inverted Wishart prior on $\boldsymbol{\Sigma}_{\varepsilon i}$

$$\boldsymbol{\Sigma}_{\varepsilon i} \sim \mathcal{IW}(\underline{v}_i, \underline{\boldsymbol{C}}_i) \tag{5}$$

where $\underline{\boldsymbol{C}}_i$ and $\underline{v}_i$ denote the $k_i \times k_i$ prior scale matrix and the prior degrees of freedom, respectively.

Finally, the discussion of the prior setup is completed with the prior on δ_{ij}. Following George et al. (2008) we use a Bernoulli prior, which implies

$$\delta_{ij} \sim Bernoulli\ (\underline{q}_j) \tag{6}$$

that can be interpreted as the prior probability to include the jth parameter in the model, implying that $P(\delta_{ij} = 1) = \underline{q}_j$ and $P(\delta_{ij} = 0) = 1 - \underline{q}_j$.

This prior specification allows us to unveil the structural differences between countries in a flexible fashion. Due to the fact that the number of parameters to be estimated exceeds the number of observations markedly, this prior setup serves as a regularization device that shrinks the parameter space. A typical caveat related to the reduced form of the model is that structural inferences should be made with some care. However, in the present application we utilize the SSVS prior solely to obtain more precise reduced form estimates of the parameters that are later mapped into quantities of interest like generalized impulse responses.

The improvements in terms of modeling flexibility and dimension reduction of the parameter space come at a cost. Namely, posterior solutions for the parameters of interest are not available in closed form. Hence, we have to adopt Markov Chain Monte Carlo (MCMC) methods to perform posterior inference. Fortunately, the conditional posteriors are of well known form, which allows to set up a simple Gibbs sampling scheme proposed by George et al. (2008). For more details see Appendix B.

3 Empirical implementation

Section 3.1 serves to briefly describe the variables and data, and outline the model specification adopted. Moreover, Section 3.2 shows some metric of the model fit for the variables in order to provide some evidence that our model is capable of replicating key features of the data.

3.1 Variables, data and model specification

We use quarterly data starting in 1998:Q1 and ending in 2012:Q4. Our country sample comprises fifteen countries listed in Table 1 including nine advanced and six emerging countries. These countries account for around 83 percent of world output, measured in terms of GDP, in 2012. The country-specific VARX* models generally include seven domestic variables.

Since the relationship between US outbound FDI and output dynamics is the subject of our interest, we include FDI and output, measured in terms of GDP, as our key variables. Note that output is also typically used as a proxy for market size. In addition, we consider macroeconomic variables that may be important in explaining the FDI-output nexus. More specifically, we include the real exchange rate, short-term and long-term interest rates, inflation and labor costs. The real exchange rate relative to the US is expected to affect US outbound FDI flows, in so far as it affects a firm's cash flow, expected profitability and the attractiveness of domestic assets to US investors. Labor costs and inflation are used to approximate important supply side dynamics that may determine the size of potential US based FDI inflows. These variables are typically used to measure the competitiveness of a given economy. Finally, short-term and long-term interest rates are taken to capture the potential effects of financial markets and the costs of capital on the FDI-output nexus (Barrell and Pain, 1996). The choice of these variables[10] is consistent with several macroeconomic models that are typically used to describe business cycle dynamics, the effects of monetary policy on the real economy

[10] The choice is also consistent with the literature on multinationality and exporting (see the meta-paper by Yang and Mallick, 2014).

or the transmission of aggregate demand shocks (Rabanal and Rubio-Ramírez, 2005; Chari et al., 2008).[11]

[Table 1 about here.]

We construct seven country-specific foreign series corresponding to cross-section averages of inward foreign direct investment, output, labor costs, exchange rates, inflation, short-term and long-term interest rates in foreign countries. Hence, the country-specific vector of domestic variables is

$$\boldsymbol{x}_{it} = (fdi_{it}, y_{it}, \pi_{it}, er_{it}, stir_{it}, ltir_{it}, ulc_{it})' \text{ for } i = 1, ..., N.$$

fdi is inward foreign direct investment from the US (in logarithms), y the log of real output measured in terms of seasonally adjusted GDP (average of 2005=100), π the rate of consumer price inflation, er the nominal real exchange rate relative to the US dollar, $stir$ the short-term interest rate, $ltir$ the long-term interest rate, and ulc the unit labor cost index in logarithms. In the case of Brazil, China, India, Mexico and Turkey, owing to data constraints, labor costs are excluded from the set of endogenous variables. A list of the variables used as well as the general specification of the individual country models is given in Table 2, while Appendix C shows the average posterior inclusion probabilities across countries providing evidence for the importance of the variables included in the GVAR model.

For the US model (country $i = 0$) we replace foreign direct investment by domestic investment, di, as endogenous variable[12]

$$\boldsymbol{x}_{0t} = (di_{0t}, y_{0t}, \pi_{0t}, stir_{0t}, ltir_{0t}, ulc_{0t})'.$$

The corresponding vector of country-specific foreign variables is symmetric across countries

$$\boldsymbol{x}^*_{it} = (fdi^*_{it}, y^*_{it}, \pi^*_{it}, er^*_{it}, stir^*_{it}, ltir^*_{it}, ulc^*_{it})' \text{ for } i = 0, ..., N.$$

To construct the foreign variables we use the row-standardized connectivity matrix between countries, based on (average) trade flows computed over the time period from 1998 to 2012 (see Appendix D). Note that the choice of the connectivity terms in constructing relative variables is an open question in the GVAR literature, but the preferred option in international macroeconomics is using trade weights.[13] Chudik and Pesaran (2014) did not show, but emphasize that weights are likely to be of secondary importance if the granularity conditions described above apply. For the present application, we rely on trade weights since the usage of FDI based weights would imply serious endogeneity issues.

[11] It is straightforward to show that Eq. (1) is a generalization of a simple macroeconomic backward looking model (Rudebusch and Svensson, 1999) that incorporates international linkages.

[12] Since the nominal exchange rate er is measured relative to the US dollar, the variable is excluded from the US country model.

[13] For a recent Bayesian treatment on the issue of choosing weights in a GVAR model, see Feldkircher and Huber (2016).

[Table 2 about here.]

Before we proceed to Section 3.2, a brief word on model specification issues. Typically, GVAR models are estimated by imposing long-run relations between the macroeconomic aggregates under scrutiny. In a Bayesian framework, however, we capture the low to medium frequency behavior of the included time series by assuming that most of them are integrated of order unity (Sims et al., 1990). For all variables except FDI flows, this assumption appears to be reasonable as indicated by traditional unit root tests. If the time series included display a common stochastic trend, using first differences (or equivalently transforming everything to be approximately stationary) would seriously distort inference, effectively implying underestimating long-run impacts of FDI movements on output (Naka and Tufte, 1997). Nonetheless, previous literature on the Bayesian estimation of large dimensional time series models suggests that including the variables in (log) levels appears to be a robust choice in the presence of long-run cointegrating relations (for a discussion within an univariate framework see Sims and Uhlig, 1991).

While the estimation of vector error correction models would allow for additional inferential possibilities, their Bayesian treatment introduces additional difficulties in terms of model specification like the appropriate choice of the number of cointegrating relationships and the specification of suitable priors on the cointegrating vectors (Strachan and Inder, 2004; Koop et al., 2009).

3.2 Some metric of model fit

Since output and FDI flows are at the core concern of the paper, it is important to analyze how well our model replicates features of the data. From a Bayesian perspective, a typical criterion to assess model fit is the marginal likelihood or (equivalently) the full sequence of one-step-ahead predictive likelihoods (Geweke and Amisano, 2010). However, given that we are not interested in discriminating between a set of competing models, we focus solely on how well the Bayesian GVAR fits the data.

For this purpose, Table 3 reports the correlation between the median of the one-step-ahead predictive density (computed using the first 30 quarters of observations as a training sample) and the actual time series. Note that for all variables, average correlations (shown in the last row of Table 3) exceed values of 0.65, implying that our model successfully captures major movements of the corresponding data. The rather strong performance of our model can be attributed to the fact that we closely match the trend and the medium frequency behavior for most quantities under consideration.

Moving to variable-specific results reveals that for FDI flows, our model tracks most time series properties successfully for almost all countries under scrutiny. Some exceptions, however, are worth emphasizing. First, FDI flows to most major emerging market economies appear to be much more persistent, featuring a steady upward trend. This implies that our model displays a better fit as compared to FDI flows into countries that feature somewhat less persistent FDI flows (most notably Finland). This finding carries over to the behavior of CPI inflation. Here we see that countries that exhibit a pronounced trend in inflation (i.e. steadily increasing trend inflation) are well modeled by means of the GVAR approach whereas for other cases the fit is less spectacular.

[Table 3 about here.]

For the remaining variables (y, er, $stir$, $ltir$, and ulc) our model yields correlations that exceed 0.8 for most variables and countries in the analysis. This stems from the fact that the bulk of the remaining variables display a clear trend over time which our model successfully replicates. Moreover, the inclusion of lagged endogenous variables on the right-hand side (see Appendix C) also improves the model fit significantly.

4 Empirical application

In this section we use the GVAR model to simulate the effects that (positive) shocks to US outbound FDI may have on the GDP variable over time. To this purpose, we utilize the generalized impulse response function (GIRF) approach that consists in tracing the response of the system associated with a unit shift to the observed variable (in our case one standard error to the US outbound FDI), and integrating out the effects of other shocks. We then present the results of generalized forecast error variance decompositions to shed some light on the relative importance of FDI inflows in explaining variation in output dynamics.

4.1 Dynamic effects of positive US outbound FDI shocks on GDP

We use the GVAR model to simulate the effects that shocks of US outbound FDI may have on economic growth. To this aim, given the absence of strong *a priori* information for identifying the dynamics of our system (in general, for the GVAR model discussed above, exact identification would require $k(k-1)/2$ restrictions) we use the generalized impulse response function (GIRF) approach. This approach, advanced in Koop et al. (1996), and Pesaran and Shin (1998), does not claim to structurally identify shocks according to economic theory or ad-hoc economic reasoning, but considers a counterfactual exercise where the historical correlation of the shocks is assumed to be given. In the context of the GVAR model in Eq. (2) the $k \times 1$ vector of g-step ahead GIRFs with respect to a one standard error global shock to the jth variable is given by

$$\begin{aligned} GIRF(g, \tilde{e}_{jt}, \mathcal{I}_T) &= E\left(\boldsymbol{x}_{T+g} | \mathcal{I}_T, \tilde{e}_{jt} = \sqrt{\mathfrak{a}_j' \boldsymbol{\Sigma}_\varepsilon \mathfrak{a}_j}\right) - E\left(\boldsymbol{x}_{T+g} | \mathcal{I}_T\right) \\ &= \frac{\boldsymbol{F}^g \boldsymbol{G}^{-1} \boldsymbol{\Sigma}_\varepsilon \mathfrak{a}_j}{\sqrt{\mathfrak{a}_j' \boldsymbol{\Sigma}_\varepsilon \mathfrak{a}_j}} \text{ for } g = 0, 1, \dots \ . \end{aligned} \tag{7}$$

The expectation operator E in Eq. (7) is taken assuming that the GVAR model (2) is the data generating process. The information set $\mathcal{I}_T = (\boldsymbol{x}_T, \boldsymbol{x}_{T-1}, ..., \boldsymbol{x}_0)$ is the information set of all available information at time T. $\boldsymbol{F}^g$ denotes the gth matrix power of $\boldsymbol{F}$, and $\tilde{e}_{jt}$ the standard deviation of the jth equation in Eq. (11) in Appendix

A. $\mathfrak{a}_j$ is a $k \times 1$ selection vector, $\mathfrak{a}_j = [\mathfrak{a}'_{0j}, \mathfrak{a}'_{1j}, ..., \mathfrak{a}'_{Nj}]'$. $\mathfrak{a}_{ij}$ is the $k_i \times 1$ vector with zero elements, except for its jth element that corresponds to the jth variable which is set equal to the purchasing power parity adjusted GDP weight of country i, the weight of the ith country in the world economy. By construction, the weights sum up to unity. Note that the GIRFs have also the nice property of being invariant to the ordering of both, countries and variables.

The shock that we consider is a positive global one standard error shock to US outbound FDI. Figure 1 presents the results of the GIRF approach, the country-specific GDP responses associated with one standard error shift to the observed US outbound variable. A one standard error shock corresponds in this case to an increase of US outbound FDI of around 4.5%.

In the discussion of the results, we focus on the first five years following the shock. This appears to be a reasonable time horizon. After five years, the GIRFs settle down reasonably quickly, suggesting that the model is stable. The figures display the posterior distribution of impulse responses, along with their 25th and 75th percentiles, based on 1,000 posterior draws.

For presentation purposes we group the countries used in this study into three regional aggregates (briefly termed regions): Western Europe (see Fig. 1 (a)) including the three largest economies (Germany, France, United Kingdom) and two smaller countries (Austria, Finland); Asia (see Fig. 1 (b)) including China, India, Japan and South Korea; Latin America (see Fig. 1 (c)) including Brazil and Mexico; and a category termed Rest of the World (see Fig. 1 (d)) including Australia, Canada and Turkey. Figure 1 not only shows the fourteen country-specific GDP responses, but also the effects of the same shock on these four aggregates of countries, which are constructed by grouping the corresponding countries together using GDP weights.

[Fig. 1 about here.]

There are some important results worth noting. *First*, a positive one standard error global shock to US outbound FDI has a significant positive long-term effect on GDP in all countries considered, with a maximum impact of more than 0.40% in Asia and the Rest of the World, five years after the shock. The impacts appear somewhat weaker in Western Europe and Latin America, but the differences are rather negligible. The findings for Europe might be caused by the fact that FDI from the US could be complementary to exports (i.e. the imports of the host countries) which, in turn, could have a dampening rather than boosting effect on GDP. For the case of Europe, the weaker responses of output dynamics hint to a more complementary rather than substituting relationship between FDI and exports.[14]

Second, short-term effects show a different pattern across the four categories of countries. In Asia, the transmission of the shock takes place rather quickly and the short-term effects are statistically significant, with magnitudes ranging from 0.20% to 0.40%. Additionally, most impulse response functions in this group share the same,

[14] We would like to thank an anonymous reviewer for pointing this out.

"hump-shaped" reaction with respect to FDI inflows. Quantitatively, this implies that output increases tend to rise within the first two quarters, reaching a peak after around three quarters, petering out afterwards. A similar pattern can be found for the countries in Latin America. In this country group the peak is reached after around five to ten quarters, implying that Latin American countries need some more time to fully profit from inward FDI. The reason why countries in Asia and Latin America tend to react faster and also stronger to US FDI shocks might be due to their relative capital scarcity. Indeed, all countries considered in Asia and Latin America are low to medium income economies (with the notable exception of Japan), profiting more from additional capital inflows than countries in Western Europe.[15]

Third, in this world region the short-term effects of US outbound FDI are barely significant. In the cases of Germany and France the GDP effect is not significantly different from zero during the first four quarters after the shock. With displaying significant impact magnitudes of around 0.3%, the UK presents an interesting exception to this pattern. This case can partly be explained by noting the stronger trade linkages to the US (see Appendix D). The almost instantaneous transmission of the shock might also be attributed to the comparatively more developed financial sector within the UK, leading to faster absorption rates of capital inflows.

The reason why responses of other Western European economies are more muted are at least twofold. In particular, all Western European countries considered are high income countries, which are relatively capital abundant. This implies that additional capital inflows do not lead to pronounced output increases within the first few quarters. Moreover, the real exchange rate against the US dollar tends to appreciate in the short-run. This result, known as the "Dutch disease" in the literature (Saborowski, 2009; Edwards, 1998), implies that adverse effects on the exchange rate leads to a deterioration of export competitiveness which appears to increase macroeconomic instability. As a reaction to FDI inflows, exchange rates in Latin America, Asia and the Rest of the World tend to appreciate vis-á-vis the US dollar in the short-run, diminishing the respective countries' terms of trade. However, prices adjust in the medium run and the effect on the real exchange rate becomes insignificant. This finding holds for all regions under consideration with an important exception, namely the exchange rate responses in Western Europe. Here it is worth noting that the Euro exchange rate market proves to be one of the most liquid markets in the world, where individual FDI transactions only play a minor role relative to total transactions.[16]

Finally, it is worth mentioning that Australia and Canada exhibit responses that are similar to the one obtained for the UK. This again corroborates our finding that trade linkages help to exploit FDI inflows faster.

[Fig. 2 about here.]

[15] This can easily be seen by looking at the relationship between initial income per capita and the corresponding maximum output response.

[16] Corresponding figures are available on request.

To shed some further light on the magnitude of cross-country spillovers from FDI, we also investigated the GDP effects of regionally concentrated US FDI activities. A regionally concentrated one standard error US outbound FDI shock is calculated by replacing the selection vector $\mathfrak{a}_j$ by a vector $\mathfrak{b}_j = [\mathfrak{b}'_{0j}, \mathfrak{b}'_{1j}, \ldots, \mathfrak{b}'_{Nj}]'$ in Eq.(7). $\mathfrak{b}_{ij}$ is set equal to a zero vector if the corresponding country is not located within a pre-specified regional aggregate, whereas in all other cases $\mathfrak{b}_{ij}$ is constructed analogously to $\mathfrak{a}_{ij}$. In the following discussion we simulate a regionally concentrated one standard error shock to US outbound FDI in Asia. Since Asia is the region that experienced the highest GDP growth rates in recent decades and has been one of the most prominent receiving regions of US FDI inflows, this proves to be a natural choice to gain a deeper understanding of the underlying transmission channels.

Figure 2 depicts the effects of US based FDI flows to Asia on real GDP in (a) Western Europe, (b) Asia, (c) Latin America and (d) the Rest of the World, over a time frame of five years. The time profiles of the GDP responses appear to be quite similar to those obtained from a global shock to US outbound FDI. Note, however, that the overall magnitudes are lower for all aggregates of the countries. Output reactions in Asia tend to be around one fourth of the reactions obtained by simulating a global FDI shock.[17] This suggests that, in addition to direct effects arising from FDI inflows, output responses in Asia seem to be strongly driven by international spillover effects of FDI. Note that output reactions in other regions closely follow the responses obtained from a global shock. This is mainly due to the fact that, given the strong co-movement of FDI flows in the data, regionally concentrated shocks lead to portfolio re-balancing of US companies that seek to diversify their regional exposure (Bohn and Tesar, 1996). This finding is corroborated by the reactions of FDI inflows in regions except Asia. While the short-run reactions of FDI are either negative or insignificant, FDI inflows tend to increase within three to five quarters for all regions under consideration. On the other hand, FDI inflows, after increasing by around five to eight percent on average within the first three quarters, tend to return to their initial value. This provides evidence that even under the assumption that US FDI activities are strongly concentrated in Asia, such effects are only transitory, leading to portfolio adjustments in the medium run.

4.2 The relative importance of FDI inflows in explaining variation in output

Clearly, when we shock US outbound FDI we will not be able to distinguish between possible causes of the shift, but forecast error variance decomposition, closely related to the impulse response analysis, shows the relative contribution of the shocks to reducing the mean square error of forecasts of the GDP variable at a given time horizon g. In a structural VAR framework, the forecast error variance decomposition is performed on a set of orthogonalized shocks (structural innovations) and can be interpreted as the jth innovation to the variance of the g-step ahead forecast of the model. In this case the

[17]Across all other regional aggregates, output reactions tend to be one fourth to one third.

sum of the individual innovation contributions add up to one. In reduced form VARs, the lack of identification of reduced form errors implies that the correlation between shocks is generally different from zero and this invalidates the traditional interpretation of the forecast error variance decomposition.

An alternative approach in the GVAR context is to compute the generalized forecast error variance decomposition (GFEVD) that identifies the proportion of the variance of the g-step ahead forecast errors of each variable that is explained by conditioning on contemporaneous and future values of non-orthogonalized (generalized) shocks of the system. The contribution of the jth innovation to the mean-square error to the g-step ahead forecast of $\boldsymbol{x}_t$ (Dees et al., 2007) is

$$GFEVD([\boldsymbol{x}_t]_l, [\boldsymbol{e}_t]_j, g) = \frac{\sigma_{\varepsilon,jj}^{-1} \sum_{l=0}^{g} (\mathfrak{e}_l' \boldsymbol{F}^g \boldsymbol{G}^{-1} \boldsymbol{\Sigma}_\varepsilon \mathfrak{e}_j)^2}{\sum_{l=0}^{n} \mathfrak{e}_l' \boldsymbol{F}^g \boldsymbol{G}^{-1} \boldsymbol{\Sigma}_\varepsilon (\boldsymbol{G}^{-1})' (\boldsymbol{F}^g)' \mathfrak{e}_l} \text{ for } g = 0, 1, 2, \ldots \,, \tag{8}$$

where $[\cdot]_l$ selects the lth element of a given vector, and $l = 1, \ldots, k$. $\mathfrak{e}_l$ is a $k \times 1$ selection vector that selects the lth variable. Furthermore $\sigma_{\varepsilon,jj}$ denotes the jth diagonal element of Σ_ε. Expression (8) measures the impact of the jth element of $[\boldsymbol{e}_t]$ on $[\boldsymbol{x}_{t+g}]$. To compute quantities of interest like the posterior mean of GFEVDs we just sample from the global posterior (see Eq. (21) in Appendix B) and use these draws together with expression (8). As a point estimate we use the mean of the posterior of the GFEVDs.

[Table 4 about here.]

Table 4 shows the average generalized forecast error variance decompositions of shocks to real GDP in Western Europe, Asia, Latin America and the Rest of the World, in terms of their top ten determinants at the 20-quarter horizon. This provides information on the domestic versus international determinants in explaining the forecast variance of each aggregate of countries. Domestic determinants are defined here as the sum of shares of variation in output explained exclusively by country-specific domestic variables, in each aggregate of countries. Likewise, international determinants are measured as the sum of shares of variation in output explained by other countries' endogenous variables. The last row in each decomposition shows the sum of the top ten determinants. Note that the individual shock contributions to the generalized forecast variance decompositions do not need to sum to unity, given the general non-zero correlation between countries.

Three observations are worth mentioning. *First*, the figures reveal that a large share of short-run output variation (short-run in the sense of up to three quarters ahead) can be explained by domestic determinants, most notably lagged output. US based FDI inflows tend to account for around five to ten percent of output variation between the first few quarters across all regions considered. Moreover labor costs, contributing around five to seven percent, prove to be important to explain output fluctuations in the short- and medium-run.

Second, the share of proportion explained by international determinants increases over time. Results for Asia and Latin America reveal that foreign FDI inflows are important drivers of long-run GDP variation. This holds true for both domestic and foreign FDI inflows.[18] The latter roughly explains one fourth of the forecast variance due to international determinants of real output after five years (see Table 4). Asian and Latin American economies, which are relatively capital scarce, tend to profit more from inward FDI as compared to the capital abundant counterparts in Western Europe and the Rest of the World.

Third and finally, the results for Western Europe show that FDI contributes much less than in Asia and Latin America, while variation in other countries' output plays the biggest role, explaining more than half of the total variance. This result does not carry over to other regional aggregates. One possible interpretation of this result is that the highly developed countries in Western Europe can be viewed as physical and human capital abundant, implying diminishing returns with respect to additional capital inflows.

4.3 Dynamic effects of a positive shock to the stock of US FDI

This study relies on defining movements in FDI as being investment inflows in host countries over a quarter of a year. Nevertheless it seems worthwhile to briefly assess the sensitivity of our findings with respect to shocking the stock of FDI in the host country. For this purpose we use yearly data on US FDI stocks in each country (obtained from the US Bureau of Economic Analysis) and take the information on quarterly FDI flows to interpolate the corresponding time series.

[Fig. 3 about here.]

For the sake of brevity, Fig. 3 reports only the average regional responses.[19] A one standard error shock to the FDI stock yields additional FDI inflows of about 2.7% on average, across countries. Consistent with the findings presented in Section 4.1, output reacts positively to FDI movements. The shape and pattern of the responses show a striking similarity with the ones presented in Fig. 1, with one notable exception. Average responses in the Rest of the World suggest different dynamics of the responses between FDI and output, yielding different time profiles of the corresponding impulse responses. This result is driven by markedly different reactions of the Turkish output (not shown), which shows no statistically significant reaction to FDI movements (as opposed to the finding presented in Section 4.1). For Asia, the initial increase in output is slightly more muted as compared to the case of FDI flows, peaking after around three quarters. This exercise lends further confidence in our results, suggesting that there seems to be a robust relationship between short-term output dynamics and FDI, irrespective of whether we choose to rely on a stock or flow definition of FDI.

[18] More detailed results, including individual domestic determinants, are available from the authors.

[19] Country-specific results are available upon request from the authors too.

5 Closing remarks

Dynamic stochastic general equilibrium models provide theoretical foundations on the importance of foreign direct investment on output dynamics in stylized two-country settings. While macroeconomic empirical studies increasingly focus attention on multi-country analysis, they generally fail to incorporate dynamics across space and time simultaneously in measuring the impact of FDI on output. This paper suggests a global macroeconometric framework to address both the spatial and dynamic aspects of the relationship. The co-movement between variations in inward foreign direct investment and local output fluctuations is modeled within a VAR approach that includes five additional variables (real exchange rate, unit labor costs, inflation, short-term and long-term interest rates).

The co-movement between inward FDI and output dynamics across countries is analyzed by combining local VARs featuring trade weighted averages of the corresponding foreign variables in a global vector autoregressive model. This global model includes a sample of fifteen countries and accounts for cross-country FDI spillovers among country-specific VAR blocks. A Bayesian approach coupled with stochastic search variable selection priors is utilized to estimate the country-specific submodels that constitute the GVAR model. This approach appears reasonable given the high dimensionality of the parameter space and the prevailing heterogeneity in the world economy.

The approach can be used to gauge the effect of FDI on output in various scenarios, such as a positive one standard error global shock to US outbound FDI. The main results of the analysis may be summarized as follows. *First*, US outbound FDI has a positive long-term effect on GDP that is statistically significant in all countries considered. *Second*, the transmission of the shock takes place rather quickly in Asia and Latin America, and the short-term effects are statistically significant in these countries, in contrast to Western European economies. *Third*, FDI is an important driver of long-run GDP variation in Asian and Latin American economies, which are relatively capital scarce, profiting more from inward FDI than capital abundant countries in Western Europe. *Finally*, the simulation of a regionally based FDI shock suggests that indirect spillover effects tend to play an important role, with output reactions being about one fourth to one third of a global FDI shock.

The study provides a rich picture on how inward FDI affects output across space and time in a global macroeconomic framework, yielding useful insights to motivate the adoption of macroeconomic policies that aim to foster FDI inflows. But it should be noted that our analysis is confined to a linear setting, implying that the underlying transmission mechanism is assumed to be constant over time. This assumption simplifies the analysis considerably, but may be overly simplistic in turbulent economic times such as the 2007-2009 financial crisis. Hence, extension of the linear setting to allow for non-linearities might be a promising avenue for future research. Moreover, our approach adopts a rather aggregated view on how FDI impacts output dynamics. Discriminating between different sectors of outward FDI could provide further insights on whether different types of FDI lead to distinct reactions of output in the receiving economies. For example, if FDI flows are strongly driven by non-tradable goods through outsourcing, the impact on macroeconomic activity in the receiving country might have a different effect.[20]

Acknowledgements: *The authors gratefully acknowledge financial support from the Austrian National Bank, Jubiläumsfond grant no. 16249.*

Appendix A Derivation of the GVAR model

To construct the global VAR from these country-specific models, we define a $(k_i + k_i^*) \times 1$ vector $\boldsymbol{z}_{it} = (\boldsymbol{x}_{it}', \ \boldsymbol{x}_{it}^{*\prime})'$ and then rewrite Eq. (1) as

$$\boldsymbol{A}_i \boldsymbol{z}_{it} = \boldsymbol{a}_{i0} + \boldsymbol{a}_{i1} t + \boldsymbol{B}_i \boldsymbol{z}_{it-1} + \boldsymbol{\varepsilon}_{it} \tag{9}$$

with

$$\begin{aligned} \boldsymbol{A}_i &= (\boldsymbol{I}_{k_i}, \boldsymbol{\Lambda}_{i0}) \\ \boldsymbol{B}_i &= (\boldsymbol{\Phi}_{i1}, \boldsymbol{\Lambda}_{i1}). \end{aligned}$$

The dimensions of $\boldsymbol{A}_i$ and $\boldsymbol{B}_i$ are $k_i \times (k_i + k_i^*)$ for $i = 0, \ldots, N$. $\boldsymbol{I}_{k_i}$ denotes the identity matrix of order k_i. Let us collect all the country-specific variables in the $k \times 1$ global vector

$$\boldsymbol{x}_t = (\boldsymbol{x}_{0t}', \boldsymbol{x}_{1t}', ..., \boldsymbol{x}_{Nt}')'$$

where $k = \sum_{i=0}^{N} k_i$ is the total number of endogenous variables in the model. Then the global vector $\boldsymbol{x}_t$ stores all endogenous variables in the system. Thus, it is easily seen that the country-specific variables can be written in terms of $\boldsymbol{x}_t$,

$$\boldsymbol{z}_{it} = \boldsymbol{W}_i \boldsymbol{x}_t. \tag{10}$$

$\boldsymbol{W}_i$ is a country-specific $(k_i + k_i^*) \times k$ matrix of fixed constants defined in terms of the weights w_{ij} that can be viewed as a linking matrix that allows the country-specific models to be written in terms of the global variable vector $\boldsymbol{x}_t$. Inserting Eq. (10) into Eq. (9) we get

$$\boldsymbol{A}_i \boldsymbol{W}_i \boldsymbol{x}_t = \boldsymbol{a}_{i0} + \boldsymbol{a}_{i1} t + \boldsymbol{B}_i \boldsymbol{W}_i \boldsymbol{x}_{t-i} + \boldsymbol{\varepsilon}_{it}.$$

$\boldsymbol{A}_i \boldsymbol{W}_i$ and $\boldsymbol{B}_i \boldsymbol{W}_i$ are both $k_i \times k$ -dimensional matrices. Stacking the $\boldsymbol{A}_i \boldsymbol{W}_i$ and $\boldsymbol{B}_i \boldsymbol{W}_i$ for all i yields

$$\boldsymbol{G} \boldsymbol{x}_t = \boldsymbol{a}_0 + \boldsymbol{a}_1 t + \boldsymbol{L} \boldsymbol{x}_{t-1} + \boldsymbol{\varepsilon}_t \tag{11}$$

[20]See Yang and Mallick (2014) for a recent meta-study on this issue.

with

$$\begin{aligned}
\boldsymbol{G} &= ((\boldsymbol{A}_0\boldsymbol{W}_0)', ..., (\boldsymbol{A}_N\boldsymbol{W}_N)')' \\
\boldsymbol{L} &= ((\boldsymbol{B}_0\boldsymbol{W}_0)', ..., (\boldsymbol{B}_N\boldsymbol{W}_N)')' \\
\boldsymbol{a}_0 &= (\boldsymbol{a}'_{00}, ..., \boldsymbol{a}'_{N0})' \\
\boldsymbol{a}_1 &= (\boldsymbol{a}'_{01}, ..., \boldsymbol{a}'_{N1})' \\
\boldsymbol{\varepsilon}_t &= (\boldsymbol{\varepsilon}'_{0t}, ..., \boldsymbol{\varepsilon}'_{Nt})'.
\end{aligned}$$

The variance-covariance structure of $\boldsymbol{\varepsilon}_t$ is given by $\boldsymbol{\Sigma}_\varepsilon$, which is a $k \times k$ block-diagonal matrix constructed by using the individual country variance-covariance matrices $\boldsymbol{\Sigma}_{\varepsilon i}$ $(i = 0, \dots, N)$. More specifically, $\boldsymbol{\Sigma}_\varepsilon$ is given by

$$\boldsymbol{\Sigma}_\varepsilon = \begin{pmatrix} \boldsymbol{\Sigma}_{\varepsilon 1} & \mathbf{0} & \cdots & \mathbf{0} \\ \mathbf{0} & \boldsymbol{\Sigma}_{\varepsilon 2} & \cdots & \mathbf{0} \\ \vdots & \vdots & \ddots & \vdots \\ \mathbf{0} & \mathbf{0} & \cdots & \boldsymbol{\Sigma}_{\varepsilon N} \end{pmatrix}.$$

If the $k \times k$ matrix $\boldsymbol{G}$ is invertible[21], then we obtain the GVAR model by multiplying Eq. (11) by $\boldsymbol{G}^{-1}$ from the left

$$\boldsymbol{x}_t = \boldsymbol{b}_0 + \boldsymbol{b}_1 t + \boldsymbol{F}\boldsymbol{x}_{t-1} + \boldsymbol{e}_t \tag{12}$$

with

$$\begin{aligned}
\boldsymbol{F} &= \boldsymbol{G}^{-1}\boldsymbol{L} \\
\boldsymbol{b}_0 &= \boldsymbol{G}^{-1}\boldsymbol{a}_0 \\
\boldsymbol{b}_1 &= \boldsymbol{G}^{-1}\boldsymbol{a}_1 \\
\boldsymbol{e}_t &= \boldsymbol{G}^{-1}\boldsymbol{\varepsilon}_t.
\end{aligned}$$

We assume that $\boldsymbol{e}_t \sim \mathcal{N}(\mathbf{0}, \boldsymbol{\Sigma}_e)$ with variance-covariance matrix

$$\boldsymbol{\Sigma}_e = \boldsymbol{G}^{-1}\boldsymbol{\Sigma}_\varepsilon(\boldsymbol{G}^{-1})'.$$

[21] $\boldsymbol{G}$ is usually of full rank and hence invertible.

Appendix B Local posterior distributions and prior implementation

Bayesian estimation of the country-specific models requires MCMC methods. To simplify notation, we rewrite the country models given by Eq. (1) as

$$\boldsymbol{x}_{it} = \boldsymbol{P}_{it}\boldsymbol{\psi}_i + \boldsymbol{\varepsilon}_{it}$$

with

$$\begin{aligned}\boldsymbol{P}_{it} &= \boldsymbol{I}_{k_i} \otimes \boldsymbol{d}'_{it}\\ \boldsymbol{d}_{it} &= (1, t, \boldsymbol{x}'_{it-1}, \boldsymbol{x}^{*'}_{it}, \boldsymbol{x}^{*'}_{it-1})'.\end{aligned}$$

$\boldsymbol{d}_{it}$ is a K_i- dimensional vector of stacked data, where $K_i = m_i/k_i$.

The conditional posteriors for the parameters of the model associated with country i take the form

$$\delta_{ij}|\delta_{i\boldsymbol{\cdot}}, \boldsymbol{\psi}_i, \boldsymbol{\Sigma}_{\varepsilon i}, \mathcal{D} \sim \textit{Bernoulli}\ (\overline{p}_{ij}) \tag{13}$$

$$\boldsymbol{\psi}_i|\boldsymbol{H}_i, \boldsymbol{\Sigma}_{\varepsilon i}, \mathcal{D} \sim \mathcal{N}(\overline{\boldsymbol{\mu}}_{\psi_i}, \overline{\boldsymbol{V}}_{\psi_i}) \tag{14}$$

$$\boldsymbol{\Sigma}_{\varepsilon i}|\boldsymbol{H}_i, \boldsymbol{\psi}_i, \mathcal{D} \sim \mathcal{IW}(\overline{v}_i, \overline{\boldsymbol{C}}_i) \tag{15}$$

where $\mathcal{D}$ denotes all data available, and $\delta_{i\boldsymbol{\cdot}}$ conditioning on all δ_{il} for all $l \neq j$.

The posterior moments for the conditional posterior of δ_{ij}, the probability that $\delta_{ij} = 1$, is given by

$$\overline{p}_{ij} = \frac{\frac{1}{\tau_{i0}} \exp\left(-\frac{1}{2}(\frac{\psi_{ij}}{\tau_{i0}})^2\right) \underline{q}_j}{\frac{1}{\tau_{i0}} \exp\left(-\frac{1}{2}(\frac{\psi_{ij}}{\tau_{i0}})^2\right) \underline{q}_j + \frac{1}{\tau_{i1}} \exp\left(-\frac{1}{2}(\frac{\psi_{ij}}{\tau_{i1}})^2\right)(1 - \underline{q}_j)} \tag{16}$$

and the posterior moments of $\boldsymbol{\psi_i}$ by

$$\overline{\boldsymbol{V}}_{\boldsymbol{\psi_i}} = \left[\boldsymbol{\Sigma}_{\varepsilon i}^{-1} \otimes (\boldsymbol{D}'_i\boldsymbol{D}_i)^{-1} + (\boldsymbol{H}_i\boldsymbol{H}_i)^{-1}\right]^{-1} \tag{17}$$

$$\overline{\boldsymbol{\mu}}_{\boldsymbol{\psi_i}} = \overline{\boldsymbol{V}}_{\boldsymbol{\psi_i}}\left[(\boldsymbol{I}_{k_i} \otimes (\boldsymbol{D}'_i\boldsymbol{X}_i))vec(\boldsymbol{\Sigma}_{\varepsilon i}^{-1}) + (\boldsymbol{H}_i\boldsymbol{H}_i)^{-1}\underline{\boldsymbol{\mu}}_{\boldsymbol{\psi_i}}\right] \tag{18}$$

with $\boldsymbol{X}_i = (\boldsymbol{x}_{i1}, ..., \boldsymbol{x}_{iT})'$ and $\boldsymbol{D}_i = (\boldsymbol{d}_{i1}, ..., \boldsymbol{d}_{iT})'$ representing the full-data matrices.

Finally, for the posterior of $\boldsymbol{\Sigma}_i$, posterior degrees of freedom and scale matrix are given by

$$\overline{v}_i = T + \underline{v}_i \tag{19}$$

$$\overline{\boldsymbol{C}}_i = \left(\underline{\boldsymbol{C}}_{\boldsymbol{i}}^{-1} + \sum_{t=1}^{T}(\boldsymbol{x}_{it} - \boldsymbol{P}_{it}\boldsymbol{\psi}_i)'(\boldsymbol{x}_{it} - \boldsymbol{P}_{it}\boldsymbol{\psi}_i)\right). \tag{20}$$

All conditional posterior quantities described above have well known distributional forms, hence we can easily set up a simple Gibbs sampling scheme to simulate the joint posterior density.

Prior implementation requires specific settings of the hyperparameters of the prior distributions. In the empirical application we use the following hyperparameters:

- For the prior on δ_{ij} we set the prior inclusion probability $\underline{q}_j$ equal to 0.5 for all j, implying that *a priori* every variable is equally likely to enter the model.

- Given δ_{ij}, the prior on the coefficients $\boldsymbol{\psi}_i$ is constructed using the semi-automatic approach put forward by George et al. (2008). This implies that the variances of the mixture normal distributions are scaled using the least squares standard deviations from the estimation of the unconstrained model. Furthermore, the hyperparameters τ_{i0} and τ_{i1} are set equal to 3.0 and 0.1, respectively.

- Finally, we set $\underline{\boldsymbol{C}}_i = \frac{1}{1000}\boldsymbol{I}_{k_i}$ and the prior degrees of freedom $\underline{v}_i$ equal to zero, rendering the prior on $\boldsymbol{\Sigma}_{\varepsilon i}$ effectively non-influential.

To sample from the joint posterior density a simple Gibbs sampling algorithm can be set up, where we sample iteratively from the conditional posteriors given by Eqs. (13) to (15). Repeating this procedure n_{rep} times yields valid draws from the joint posterior density. The Gibbs output can then be used to calculate any quantity of interest like impulse response functions, forecasts or forecast error variance decompositions. Specifically, following George et al. (2008), we use the algorithm described below to sample from the corresponding posterior distributions:

Step 1 Initialize $\boldsymbol{\Sigma}_{\varepsilon i}$ and $\boldsymbol{\psi}_i$ using the maximum likelihood estimates. Furthermore, $\delta_{ij} = 1 \; \forall \; j$.

Step 2 Draw $\boldsymbol{\Sigma}_{\varepsilon i}$ from $\mathcal{IW}(\overline{v}_i, \overline{\boldsymbol{C}}_i)$.

Step 3 Draw $\boldsymbol{\psi}_i$ from $\mathcal{N}(\overline{\boldsymbol{\mu}}_{\boldsymbol{\psi}_i}, \overline{\boldsymbol{V}}_{\boldsymbol{\psi}_i})$.

Step 4 Draw δ_{ij} from *Bernoulli* $(\overline{p}_{ij})$ for $j = 1, ..., m_i$.

Step 5 If $i_{rep} > n_{burn}$, store current draw of $\boldsymbol{\Sigma}_{\varepsilon i}$, $\boldsymbol{\psi}_i$ and δ_{ij}, where i_{rep} denotes the current iteration of the MCMC loop and n_{burn} the number of discarded draws.

Due to the fact that the MCMC scheme described above yields posterior draws for the local models, which are of no direct interest, we have to transform the draws to obtain the so-called global posterior distribution. Thus the final step of our MCMC algorithm involves utilizing Monte Carlo integration to draw from

$$\Xi, \boldsymbol{\Sigma}_{\boldsymbol{\varepsilon}} | \mathcal{D} \sim p(\Xi, \boldsymbol{\Sigma}_{\boldsymbol{\varepsilon}} | \mathcal{D}) \tag{21}$$

where Ξ is the set of coefficient matrices $\boldsymbol{G}, \boldsymbol{L}, \boldsymbol{a}_0, \boldsymbol{a}_1$ in Eq. (11) and $p(\Xi, \boldsymbol{\Sigma}_{\boldsymbol{\varepsilon}} | \mathcal{D})$ reflects the unknown joint posterior distribution.

This implies sampling from Eqs. (13)-(15) and transforming the draws using the algebra outlined above. Furthermore, running this MCMC scheme $N + 1$ times is computationally demanding. However, due to the blocked structure of the GVAR model we can use parallel computing and exploit all available CPU cores, decreasing the execution time considerably.

The output of our MCMC algorithm can be used to shed some light on the importance of the different variables across countries. This can be seen by noting that the posterior mean of δ_{ij} can be interpreted as the posterior inclusion probability of variable j in country i.

Appendix C Country-specific posterior inclusion probabilities

The table shows the average posterior inclusion probabilities across countries providing evidence for the importance of the variables included in the GVAR model.

Table C.1: Average posterior inclusion probabilities across countries

	fdi	y	π	er	$stir$	$ltir$	ulc
Constant	0.493	0.784	0.814	0.601	0.696	0.822	0.650
Trend	0.576	0.941	0.877	0.852	0.900	0.949	0.933
fdi_t^*	0.485	0.754	0.798	0.444	0.670	0.831	0.587
y_t^*	0.435	0.810	0.501	0.559	0.466	0.478	0.485
π_t^*	0.461	0.565	0.717	0.556	0.633	0.729	0.609
er_t^*	0.268	0.401	0.454	0.820	0.489	0.448	0.448
$stir_t^*$	0.455	0.444	0.458	0.474	0.566	0.507	0.420
$ltir_t^*$	0.474	0.685	0.672	0.487	0.663	0.751	0.575
ulc_t^*	0.557	0.590	0.522	0.420	0.575	0.544	0.664
fdi_{t-1}^*	0.377	0.762	0.815	0.505	0.679	0.862	0.642
y_{t-1}^*	0.469	0.622	0.650	0.489	0.582	0.611	0.548
π_{t-1}^*	0.478	0.717	0.761	0.551	0.702	0.746	0.594
er_{t-1}^*	0.294	0.340	0.458	0.505	0.449	0.472	0.387
$stir_{t-1}^*$	0.363	0.479	0.513	0.445	0.461	0.404	0.421
$ltir_{t-1}^*$	0.476	0.708	0.691	0.505	0.595	0.749	0.572
ulc_{t-1}^*	0.519	0.555	0.570	0.505	0.547	0.542	0.642
fdi_{t-1}	0.504	0.645	0.663	0.473	0.660	0.681	0.586
y_{t-1}	0.415	0.977	0.431	0.452	0.446	0.469	0.540
π_{t-1}	0.532	0.649	0.751	0.460	0.688	0.756	0.641
er_{t-1}	0.480	0.667	0.548	0.511	0.506	0.461	0.994
$stir_{t-1}$	0.366	0.412	0.607	1.000	0.463	0.513	0.476
$ltir_{t-1}$	0.414	0.503	0.555	0.438	0.765	0.705	0.579
ulc_{t-1}	0.508	0.784	0.800	0.390	0.802	0.822	0.785

Notes: fdi denotes foreign direct investment from the US, y real output, π rate of consumer price inflation, er real exchange rate relative to the US dollar, $stir$ short-term interest rate, $ltir$ long-term interest rate, and ulc unit labor costs; $fdi^*, y^*, \pi^*, er^*, stir^*, ltir^*$ and ulc^* represent the corresponding foreign variables.

Appendix D Specification of the row-standardized connectivity matrix between countries

The table shows the row-standardized connectivity matrix between the fifteen countries based on average trade volumes (imports and exports) over the time period from 1998 to 2012, used to construct the foreign variables.

Table D.1: The row-standardized connectivity matrix between countries based on trade relationships

	US	UK	AT	FR	DE	CA	JP	CN	FI	TR	AU	BR	MX	ID	KR
US	0.000	0.079	0.007	0.050	0.098	0.406	0.190	0.005	0.015	0.023	0.005	0.012	0.008	0.071	0.034
UK	0.232	0.000	0.016	0.184	0.309	0.033	0.061	0.020	0.078	0.020	0.006	0.004	0.001	0.017	0.019
AT	0.054	0.047	0.000	0.072	0.737	0.007	0.021	0.009	0.029	0.004	0.001	0.002	0.001	0.011	0.004
FR	0.119	0.159	0.023	0.000	0.422	0.014	0.041	0.012	0.166	0.011	0.001	0.004	0.001	0.015	0.011
DE	0.153	0.172	0.140	0.272	0.000	0.014	0.064	0.024	0.092	0.013	0.002	0.005	0.002	0.031	0.015
CA	0.838	0.037	0.002	0.013	0.024	0.000	0.045	0.002	0.004	0.006	0.001	0.003	0.005	0.016	0.005
JP	0.427	0.046	0.005	0.033	0.081	0.041	0.000	0.006	0.011	0.092	0.010	0.016	0.004	0.154	0.075
CN	0.143	0.160	0.029	0.104	0.356	0.023	0.058	0.000	0.048	0.022	0.002	0.007	0.006	0.026	0.013
FI	0.087	0.142	0.019	0.362	0.293	0.010	0.032	0.010	0.000	0.008	0.002	0.010	0.007	0.013	0.005
TR	0.193	0.075	0.005	0.028	0.068	0.020	0.315	0.007	0.012	0.000	0.084	0.005	0.001	0.127	0.060
AU	0.189	0.066	0.004	0.024	0.052	0.023	0.169	0.004	0.009	0.356	0.000	0.003	0.003	0.058	0.041
BR	0.332	0.042	0.004	0.043	0.065	0.036	0.214	0.009	0.044	0.019	0.002	0.000	0.052	0.129	0.007
MX	0.411	0.026	0.003	0.018	0.075	0.115	0.106	0.011	0.056	0.007	0.003	0.102	0.000	0.062	0.005
ID	0.330	0.032	0.006	0.024	0.085	0.029	0.322	0.005	0.010	0.076	0.007	0.020	0.005	0.000	0.048
KR	0.300	0.043	0.003	0.033	0.083	0.013	0.334	0.005	0.007	0.065	0.009	0.003	0.001	0.101	0.000

Notes: US= United States of America, UK = United Kingdom, AT= Austria,FR = France, DE= Germany, CA=Canada, JP=Japan, CN=China, FI=Finland, TR=Turkey, AU=Australia, BR=Brazil, MX=Mexico, ID=India, KR= South Korea.

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Table 1: Countries in the GVAR model

Country	ISO country code
Australia	AU
Austria	AT
Brazil	BR
Canada	CA
China	CN
Germany	DE
Finland	FI
France	FR
India	ID
Japan	JP
Mexico	MX
South Korea	KR
Turkey	TR
United Kingdom	UK
United States of America	US

Table 1: General specification and description of the variables in the GVAR model

Country	Domestic variables	Foreign variables
Australia	fdi, y, π, er, $stir$, $ltir$, ulc	fdi^*, y^*, er^*, π^*, $stir^*$, $ltir^*$, ulc^*
Austria	fdi, y, π, er, $stir$, $ltir$, ulc	fdi^*, y^*, er^*, π^*, $stir^*$, $ltir^*$, ulc^*
Brazil	fdi, y, π, er, $stir$, $ltir$	fdi^*, y^*, er^*, π^*, $stir^*$, $ltir^*$, ulc^*
Canada	fdi, y, π, er, $stir$, $ltir$, ulc	fdi^*, y^*, er^*, π^*, $stir^*$, $ltir^*$, ulc^*
China	fdi, y, π, er, $stir$, $ltir$	fdi^*, y^*, er^*, π^*, $stir^*$, $ltir^*$, ulc^*
Germany	fdi, y, π, er, $stir$, $ltir$, ulc	fdi^*, y^*, er^*, π^*, $stir^*$, $ltir^*$, ulc^*
France	fdi, y, π, er, $stir$, $ltir$, ulc	fdi^*, y^*, er^*, π^*, $stir^*$, $ltir^*$, ulc^*
Finland	fdi, y, π, er, $stir$, $ltir$, ulc	fdi^*, y^*, er^*, π^*, $stir^*$, $ltir^*$, ulc^*
India	fdi, y, π, er, $stir$, $ltir$	fdi^*, y^*, er^*, π^*, $stir^*$, $ltir^*$, ulc^*
Japan	fdi, y, π, er, $stir$, $ltir$, ulc	fdi^*, y^*, er^*, π^*, $stir^*$, $ltir^*$, ulc^*
Mexico	fdi, y, π, er, $stir$, $ltir$	fdi^*, y^*, er^*, π^*, $stir^*$, $ltir^*$, ulc^*
South Korea	fdi, y, π, er, $stir$, $ltir$, ulc	fdi^*, y^*, er^*, π^*, $stir^*$, $ltir^*$, ulc^*
Turkey	fdi, y, π, er, $stir$, $ltir$	fdi^*, y^*, er^*, π^*, $stir^*$, $ltir^*$, ulc^*
United Kingdom	fdi, y, π, er, $stir$, $ltir$, ulc	fdi^*, y^*, er^*, π^*, $stir^*$, $ltir^*$, ulc^*
United States of America	di, y, π, $stir$, $ltir$, ulc	fdi^*, y^*, er^*, π^*, $stir^*$, $ltir^*$, ulc^*

Variable	Description	Source
fdi	foreign direct investment inflows from the US, in logarithm (US: di=direct investment)	OECD
y	real output, measured in terms of seasonally adjusted GDP, average of 2005=100, in logarithm	IMF
π	rate of consumer price inflation (CPI), seasonally adjusted	IMF
er	nominal exchange rate relative to the US dollar, deflated by national CPI	IMF
stir	short-term interest rate, measured in terms of the 3-months-market rate, rate per annum	IMF
ltir	long-term interest rate, measured in terms of government bond yield, rate per annum	IMF
ulc	unit labor cost index, average of 2005=100, in logarithm	OECD
w_{ij}	bilateral trade flows from countries i to j, measured in terms of exports plus imports of goods and services, averaged over 1998 to 2012	OECD

Table 2: Correlations between the posterior median of the one-step-ahead predictive density and the actual data

	fdi	y	π	er	$stir$	$ltir$	ulc
AU	0.765	0.999	0.496	0.995	0.826	0.758	0.999
AT	0.551	0.999	0.708	0.973	0.812	0.820	0.995
BR	0.840	0.998	0.682	0.981	0.911	–	–
CA	0.683	0.998	0.351	0.995	0.918	0.958	0.997
CN	0.921	1.000	0.702	0.999	0.854	–	–
DE	0.874	0.999	0.702	0.995	0.799	0.806	0.831
FI	0.290	0.999	0.738	0.998	0.852	0.829	0.994
FR	0.840	0.999	0.778	0.995	0.793	0.793	0.921
ID	0.944	1.000	0.876	0.985	0.978	–	–
JP	0.654	0.973	0.508	0.967	0.765	0.614	0.992
MX	0.683	0.996	0.897	0.945	0.972	0.985	–
KR	0.637	0.999	0.446	0.988	0.886	0.920	0.968
TR	0.922	0.996	0.962	0.992	0.921	–	–
UK	0.591	0.996	0.685	0.983	0.959	0.903	0.998
US	0.609	0.991	0.581	–	0.956	0.932	0.994
KR	0.637	0.999	0.446	0.988	0.886	0.920	0.968
∅	0.720	0.996	0.674	0.985	0.880	0.847	0.969

Notes: The table depicts the correlation between the median of the one-step-ahead predictive density and the actual realization of the data used in the study. The final row displays the average correlation across countries.

Table 3: Generalized forecast error variance decompositions for four aggregates of countries: (a) Western Europe, (b) Asia, (c) Latin America, and (d) Rest of the World

(a) Western Europe

	Quarters																				
	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
Domestic	83.3	67.8	58.7	52.7	48.2	44.7	41.8	39.4	37.3	35.5	33.9	32.4	31.2	30.0	29.0	28.0	27.2	26.4	25.7	25.0	24.4
DE *y*	18.6	23.5	24.9	24.9	24.3	23.5	22.6	21.7	20.8	20.0	19.3	18.6	17.9	17.3	16.8	16.3	15.8	15.4	15.0	14.7	14.3
US *y*	4.7	7.2	8.9	10.0	10.8	11.2	11.5	11.6	11.6	11.9	12.3	12.6	12.8	12.9	13.0	13.1	13.1	13.1	13.1	13.0	13.0
UK *y*	3.8	5.2	5.7	5.8	7.3	8.6	9.8	10.7	11.4	11.5	11.4	11.3	11.1	11.0	10.8	10.6	10.5	10.3	10.6	11.1	11.6
FR *y*	3.6	4.3	4.2	5.6	5.7	5.5	5.3	5.1	4.9	4.7	5.3	6.0	6.7	7.5	8.1	8.8	9.4	10.0	10.1	10.0	9.9
FR *ulc*	1.1	2.1	3.8	4.1	3.9	3.8	3.7	3.6	3.9	4.5	4.6	4.4	4.7	5.0	5.3	5.5	5.7	5.9	6.1	6.2	6.4
DE *ltir*	0.9	1.9	2.6	2.8	2.9	2.9	3.3	3.6	3.8	4.1	4.2	4.4	4.4	4.5	4.6	4.7	4.8	4.9	4.9	4.9	5.1
US *di*	0.8	1.6	2.0	2.1	2.4	2.8	2.9	3.3	3.6	3.9	4.1	4.3	4.4	4.5	4.6	4.6	4.6	4.6	4.6	4.9	5.0
DE *fdi*	0.7	1.3	1.5	1.9	2.1	2.5	2.8	3.1	3.5	3.8	4.1	4.3	4.3	4.1	4.0	3.9	4.0	4.3	4.6	4.6	4.7
FI *y*	0.7	1.0	1.3	1.6	2.1	2.1	2.5	2.9	3.4	3.4	3.3	3.2	3.1	3.1	3.4	3.7	3.8	3.7	3.6	3.5	3.4
Σ Top 10	118.3	115.9	113.7	111.5	109.7	107.7	106.1	104.9	104.1	103.2	102.4	101.5	100.7	99.9	99.5	99.2	98.9	98.5	98.2	98.0	97.7

(b) Asia

	Quarters																				
	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
Domestic	110.4	102.8	94.1	85.6	78.1	71.8	66.5	62.0	58.2	54.9	52.1	49.6	47.5	45.6	43.9	42.4	41.0	39.8	38.7	37.7	36.8
US *y*	1.0	2.1	2.5	3.1	4.3	5.4	6.3	7.1	7.7	8.2	8.7	9.0	9.3	9.5	9.7	9.8	10.0	10.3	10.7	11.1	11.5
US *di*	1.0	1.7	2.2	2.8	3.5	4.1	4.6	5.0	5.4	6.0	6.7	7.3	7.9	8.4	9.0	9.5	9.9	10.0	10.1	10.2	10.2
DE *fdi*	0.9	1.6	2.0	2.7	3.0	3.3	3.9	4.6	5.3	5.7	6.0	6.2	6.5	6.7	6.9	7.0	7.2	7.3	7.5	7.6	7.7
UK *fdi*	0.7	1.2	2.0	2.7	2.8	3.2	3.5	3.7	4.1	4.3	4.5	4.8	5.0	5.2	5.5	5.7	5.8	6.0	6.2	6.3	6.5
FR *fdi*	0.6	1.1	1.9	2.2	2.5	2.9	3.3	3.7	4.0	4.3	4.5	4.7	4.8	5.0	5.1	5.1	5.2	5.2	5.3	5.3	5.4
TR *stir*	0.3	0.8	1.5	1.9	2.4	2.9	3.3	3.7	3.9	4.0	4.1	4.2	4.3	4.4	4.4	4.6	4.8	5.0	5.1	5.3	5.3
US *ulc*	0.2	0.8	1.3	1.7	2.3	2.8	2.7	2.8	3.0	3.2	3.4	3.6	3.9	4.2	4.4	4.5	4.5	4.5	4.5	4.6	4.6
JP *ulc*	0.2	0.7	1.1	1.7	2.3	2.3	2.5	2.7	2.6	3.0	3.3	3.6	3.7	3.8	3.8	3.9	3.9	4.0	4.0	4.0	4.1
US *stir*	0.1	0.5	1.0	1.7	1.8	2.1	2.3	2.2	2.6	2.5	2.4	2.3	2.3	2.4	2.4	2.4	2.5	2.6	2.7	2.7	2.8
Σ Top 10	115.4	113.2	109.6	106.2	103.1	100.8	99.0	97.5	96.8	96.2	95.8	95.4	95.2	95.0	94.9	94.8	94.8	94.8	94.8	94.8	94.8

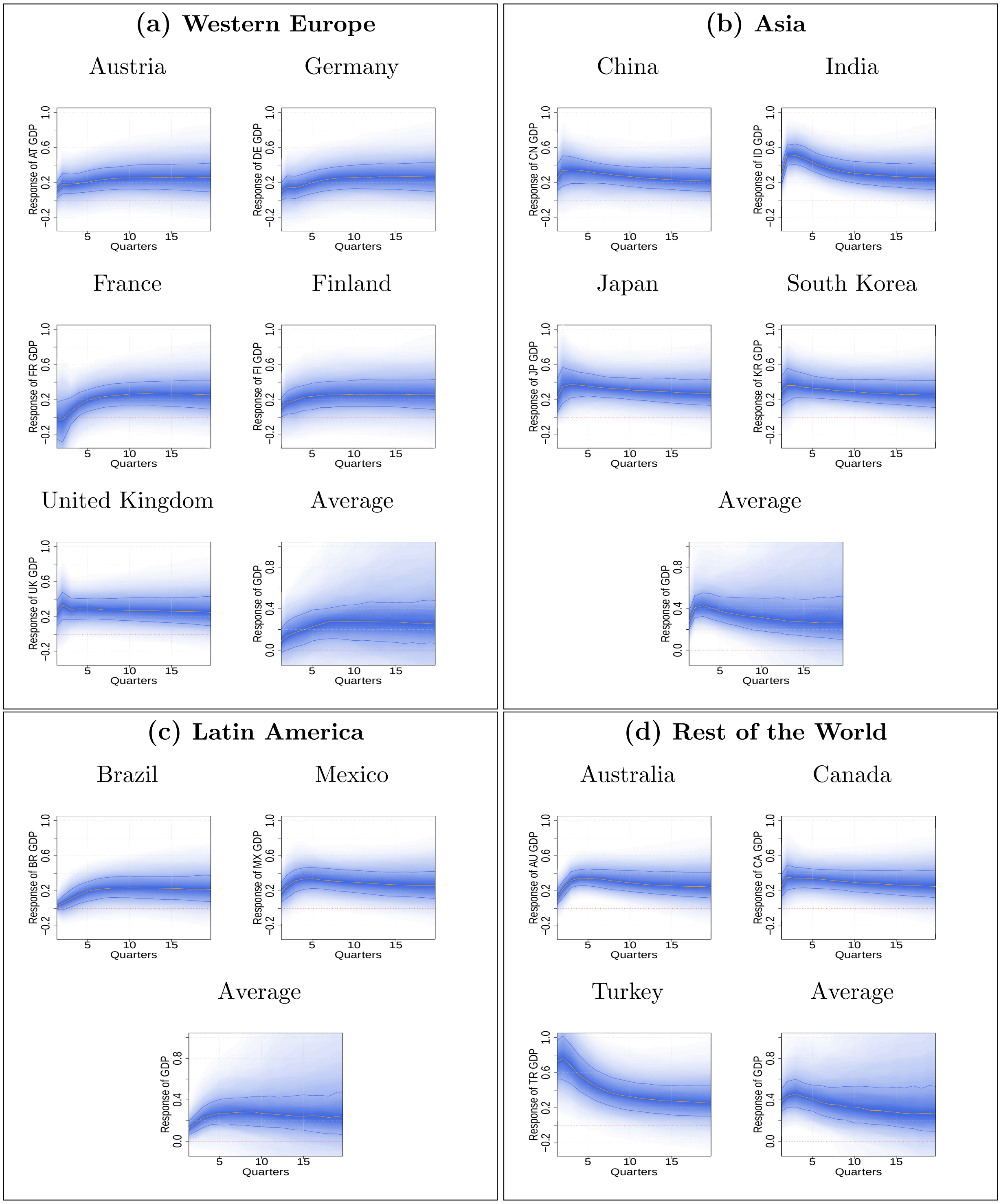
(c) Latin America

	Quarters																				
	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
Domestic	123.7	124.0	120.9	115.8	109.6	103.2	97.0	91.2	85.9	81.1	76.9	73.1	69.6	66.6	63.8	61.3	59.1	57.0	55.1	53.4	51.9
US *di*	1.5	2.3	2.8	3.2	4.6	6.0	7.3	8.6	9.8	10.8	11.8	12.6	13.4	14.1	14.7	15.3	15.8	16.3	16.7	17.2	17.5
CA *fdi*	0.3	0.9	1.9	3.0	3.0	3.1	3.6	4.2	4.6	5.0	5.4	5.6	6.0	6.3	6.6	6.9	7.2	7.4	7.6	7.8	8.0
US *stir*	0.2	0.8	1.3	1.9	2.4	3.0	3.2	3.8	4.3	4.8	5.2	5.6	5.9	6.1	6.3	6.5	6.6	6.7	6.9	7.0	7.1
JP *er*	0.2	0.5	0.9	1.6	2.3	2.8	3.2	3.5	3.7	3.9	4.0	4.1	4.2	4.3	4.4	4.5	4.7	4.9	5.0	5.2	5.3
ID *er*	0.1	0.4	0.9	1.4	2.0	2.6	3.0	3.0	2.9	2.8	3.2	3.5	3.8	4.1	4.3	4.4	4.5	4.8	5.0	5.2	5.3
JP *ulc*	0.1	0.3	0.8	1.2	1.5	1.7	1.9	2.0	2.4	2.8	2.8	3.1	3.4	3.7	4.0	4.3	4.5	4.5	4.6	4.6	4.6
BR *fdi*	0.1	0.3	0.6	0.8	1.2	1.5	1.8	2.0	2.2	2.4	2.8	2.7	2.7	2.7	2.8	2.9	2.9	3.0	3.0	3.0	3.1
US π	0.1	0.2	0.5	0.8	1.0	1.1	1.6	2.0	2.1	2.3	2.5	2.6	2.6	2.6	2.5	2.5	2.5	2.6	2.7	2.7	2.8
US *ulc*	0.1	0.2	0.4	0.6	0.8	1.0	1.3	1.7	2.1	2.2	2.2	2.3	2.3	2.3	2.4	2.5	2.4	2.4	2.3	2.3	2.3
Σ Top 10	126.3	129.9	131.0	130.2	128.4	126.1	123.9	121.9	120.0	118.2	116.7	115.2	114.0	112.8	111.9	111.1	110.3	109.6	109.0	108.4	107.9

(d) Rest of the World

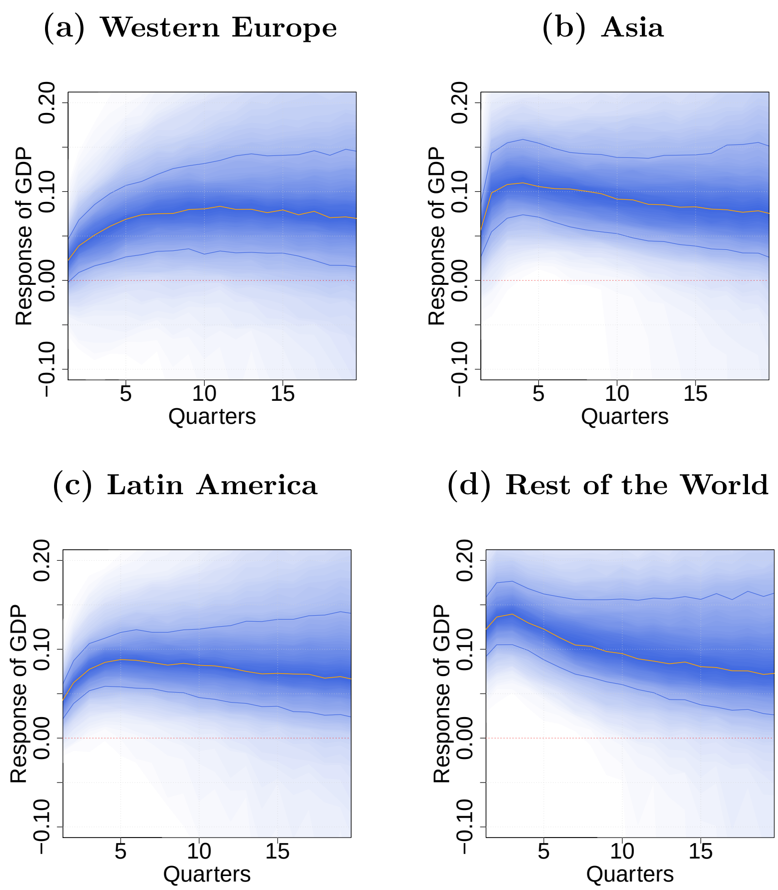
	Quarters																				
	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
Domestic	127.4	113.9	102.6	93.9	86.9	80.9	75.8	71.3	67.3	63.9	60.9	58.2	55.8	53.7	51.8	50.1	48.5	47.2	45.9	44.7	43.7
US *y*	7.3	8.9	8.8	10.1	11.2	11.8	12.2	12.5	12.6	12.6	12.6	12.6	12.6	12.6	13.3	13.9	14.4	15.0	15.4	15.9	16.3
US *ulc*	1.8	5.5	8.4	8.5	8.2	8.0	7.8	7.6	8.4	9.4	10.3	11.1	11.9	12.5	12.4	12.3	12.2	12.2	12.1	12.0	11.9
US *di*	1.3	1.9	2.9	3.6	4.0	5.1	6.3	7.4	7.4	7.3	7.2	7.0	6.9	6.8	6.7	6.6	6.5	6.8	7.0	7.2	7.4
US *ltir*	0.7	1.3	2.2	2.9	4.0	4.2	4.4	4.5	4.6	4.7	4.7	4.9	5.3	5.6	6.0	6.2	6.5	6.4	6.3	6.2	6.2
TR *y*	0.6	1.3	1.9	2.7	3.1	3.4	3.6	3.7	3.9	4.1	4.5	4.7	4.7	4.7	4.7	4.8	4.9	5.0	5.1	5.1	5.2
JP *er*	0.5	1.1	1.9	2.3	2.5	2.7	2.7	3.1	3.6	4.0	4.2	4.3	4.5	4.6	4.7	4.6	4.6	4.6	4.7	4.8	4.9
TR *stir*	0.4	1.1	1.0	1.0	1.4	2.0	2.5	2.7	2.7	2.7	3.0	3.3	3.5	3.8	4.0	4.2	4.4	4.5	4.6	4.6	4.5
UK *fdi*	0.3	0.4	0.7	0.9	1.3	1.5	1.7	2.0	2.4	2.7	2.6	2.6	2.5	2.5	2.4	2.4	2.4	2.4	2.4	2.5	2.5
JP *fdi*	0.2	0.3	0.5	0.9	1.0	1.3	1.6	1.7	1.8	1.9	1.9	2.0	2.0	2.1	2.2	2.3	2.3	2.3	2.3	2.3	2.4
Σ Top 10	140.5	135.7	130.9	126.9	123.6	120.9	118.5	116.5	114.7	113.2	111.9	110.7	109.6	108.8	108.1	107.4	106.8	106.3	105.8	105.4	105.1

Notes: Average forecast error variance decompositions across countries in each respective aggregate. Results based on the mean for 1,000 draws from the global posterior. The figures represent percentage contributions to a one standard error shock to real GDP. Top ten determinants reported. *Domestic* determinants are defined as the sum of shares of variation in output explained exclusively by country-specific domestic variables, in each aggregate of countries. *International* determinants are measured as the sum of shares of variation in output explained by other countries' endogenous variables. The sum of the top ten determinants may exceed 100 due to cross-country correlations. For the definition of the determinants see Table **??** and Table 1.



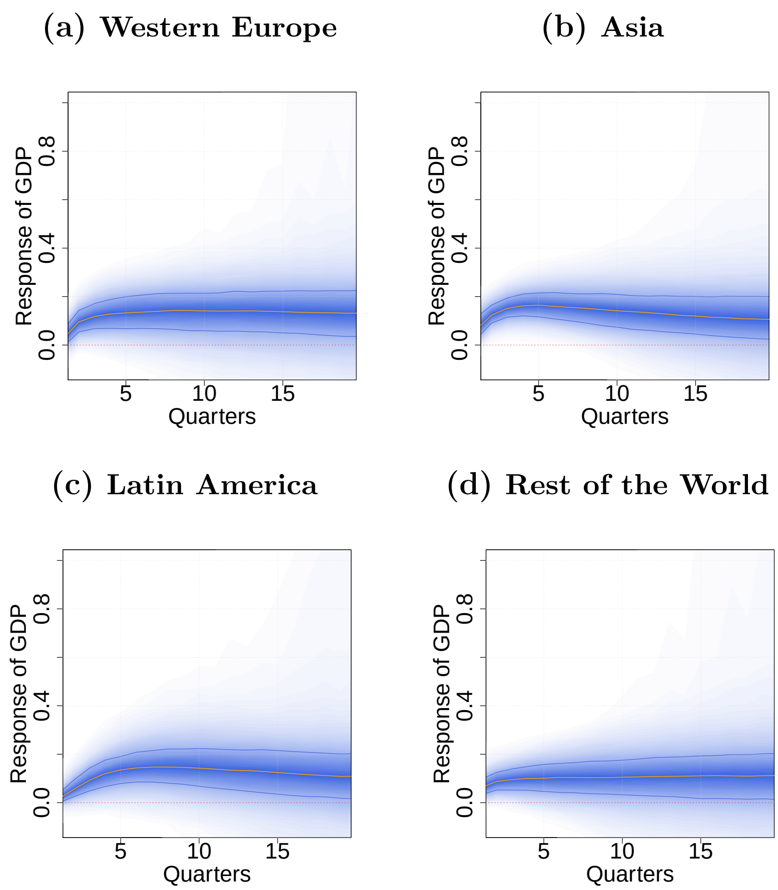
Notes: Posterior distribution of impulse responses. Median in orange along with 25th and 75th percentiles in dark blue. Results based on 1,000 posterior draws. Unweighted responses per aggregate of countries reported.

Fig. 1: Generalized impulse responses of a positive one standard error shock to US outbound foreign direct investment on real GDP in (a) Western Europe, (b) Asia, (c) Latin America, and (d) Rest of the World, over a time frame of five years



Notes: Posterior distribution of impulse responses. Median in orange along with 25th and 75th percentiles in dark blue. Results based on 1,000 posterior draws. Unweighted responses per aggregate of countries reported.

Fig. 2: Responses to a regionally concentrated one standard error shock to US outbound FDI in Asia on real GDP in (a) Western Europe, (b) Asia, (c) Latin America, and (d) Rest of the World, over a time frame of five years



Notes: Posterior distribution of impulse responses. Median in orange along with 25th and 75th percentiles in dark blue. Results based on 1,000 posterior draws. Unweighted responses per aggregate of countries reported.

Fig. 3: Responses to a global positive one standard error shock to the stock of US outbound FDI on real GDP in (a) Western Europe, (b) Asia, (c) Latin America, and (d) Rest of the World, over a time frame of five years