# The Transmission Dynamics of US Monetary Policy and the Global Economy* 

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#### Abstract

We propose a new class of Bayesian Global Vector Autoregressive (GVAR) models to track the dynamic transmission dynamics between US monetary policy and the other economies over the last three decades. In addition to assessing global linkages explicitly, the model specification accounts for Time-Varying Parameters (TVP) and Stochastic Volatility (SV). The TVP-SV-GVAR model allows to analyze the interaction between monetary policy in the United States (US) and the global economy in a very flexible manner. We use Bayesian shrinkage to achieve a simpler representation of the data. Our results suggest that US monetary policy responds to shocks to the global economy, in particular to shocks to global GDP growth and global inflation. On the other hand, changes to US monetary policy ( 50 basis points increase in short-term US interest rate) lead to a persistent global contraction and a drop in global inflation rates, together with a rise in global interest rates, and a real depreciation of currencies with respect to the US dollar. We find evidence for important heterogeneity of the spillovers across countries and for changes in the transmission of monetary policy shocks over time.


Keywords: Global Vector Autoregression, Time-varying parameters, Stochastic volatility, Monetary policy
JEL Codes: C30, E52, F41

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## 1 Introduction

A vast body of empirical literature assesses monetary policy and its transmission to the real economy. While several aspects of how monetary policy works remain empirically controversial, a broad consensus seem to have formed on some lines. First, monetary policy in the USA changed a great deal over the last three decades (Sims and Zha, 2006). Variation in the implementation of monetary policy and its effectiveness might be driven by several factors including regulatory changes and changes in domestic and global macroeconomic and financial market conditions. Second, US monetary policy can generate significant international spillovers. In the aftermath of the global financial crisis the US Fed began to lower interest rates and engaged in several "unconventional" policy measures to stimulate the economy. When in mid-2013 market participants started speculating about the timing of the Fed's exit from accommodative monetary policy, this triggered a surge in global volatility and an adverse shift of market sentiment towards emerging markets (Sahay et al., 2014). To assess the transmission dynamics between US monetary policy and the global economy, it seems to be essential to use a global framework and to allow for changes in the economic model (parameters) and in the volatility of shocks.

The empirical literature on the domestic effects of US monetary policy has long acknowledged the importance of modelling time variation in the transmission of monetary shocks. Sims and Zha (2006) use a regime-switching model that allows for parameter changes over time. Primiceri (2005) proposes a more flexible model that accommodates gradual drifts in parameters and the underlying volatility of shocks using time-varying stochastic volatility vector autoregressions (TVP-SV-VARs). The same framework is used in Cogley and Sargent (2005) to examine the evolution of monetary policy in the US during the post-WWII period. Boivin (2006), on the other hand, estimates a monetary policy rule in the spirit of Taylor (Taylor, 1993) with drifting coefficients and accounting for stochastic volatility. Most of these studies find evidence for gradual changes in both coefficients and disturbance variances. While TVP-SV-VAR specifications in the spirit of Primiceri (2005) are able to model salient features of the data, due to computational burden, applications are confined to small data sets only. These models are typically estimated using three to four variables (Primiceri, 2005; Cogley and Sargent, 2005; Canova and Gambetti, 2009). Given this limitation, Feldkircher and Huber (2015b) propose an extension of the standard VAR model using the Cholesky stochastic volatility structure advocated in Lopes et al. (2011). This approach relies on imposing a recursive ordering of the involved variables such that the variance-covariance matrix of the system is diagonal, thus allowing equation-by-equation estimation.

This paper focuses on spillovers between US monetary policy shocks and the global economy, rather than investigating their interaction within the domestic (US) economy. Monetary policy spillovers have been often investigated by either using stylized linear two-country VARs (see for example Kim, 2001; Peersman, 2005; Canova, 2005) or by estimating a system of country-specific models. This second approach has been advocated in Pesaran et al. (2004), who put forward Global VAR (GVAR) models as a
tool to quantify the global transmission of macroeconomic shocks. GVAR specifications take on board the dynamic interlinkages observed across countries in the world economy. As opposed to two-country VARs, the GVAR model incorporates third-country effects which have been proven to be of importance when it comes to the analysis of the effects of monetary and fiscal policy shocks. Several recent contributions use GVARs to investigate the propagation of different monetary and fiscal policy shocks across the world economy (see for instance Dees et al., 2007a; Des et al., 2010; Feldkircher and Huber, 2015b). Crespo Cuaresma et al. (2014) propose a Bayesian variant of the GVAR and Feldkircher et al. (2015) employ this framework to investigate the dynamic spillover effects of three US-based structural shocks. They find significant spillovers for all shocks considered, with persistent responses for aggregate supply and monetary policy shocks. Examining conditional forecasts of different future policy paths for the Federal Funds Rate (FFR), Feldkircher et al. (2015) find strong direct output effects for emerging economies, while second-round effects play a more prominent role for output in advanced economies.

The literature on global VARs has been hitherto largely confined to linear models, although recently ${ }^{1}$ In this paper, we propose combining the virtues of the literature on TVP-SV-VARs with the literature on Bayesian GVARs. We thus propose a GVAR model composed of individual TVP-SV-VARs for no less than 36 countries in a global system,corresponding to approximately $80 \%$ of the global economy. To cope with such a large dataset we combine the approach put forward in Feldkircher and Huber (2015a) in conjunction with the GVAR framework to exploit parallel computing. This permits us to estimate a large scale TVP-SV-GVAR with over 150 equations in a computationally efficient manner. Within this class of models, the curse of dimensionality is further intensified as compared to standard GVAR specifications. Thus, we make use of Bayesian methods to induce shrinkage into the model parameters. Using this model, we investigate the changing nature of the monetary policy transmission mechanism over the last three decades and draw conclusions on the existing differences across periods. Finally, the spatial dimension of the GVAR allows us to assess regional differences in the effectiveness of central bank actions. This gives us the possibility to answer questions such as whether monetary policy is more effective in developing economies as compared to developed countries in times of crisis or how its effectiveness has changed during the recent financial crisis across economies.

Our results can be summarized as follows.
First, the volatility of macroeconomic shocks to the global economy is changing over time. While many developed economies exhibit declining volatility until the mid 2000's (the so-called Great Moderation), we can observe a resurgence in volatility with the

[^1]start of the Great Recession in 2007. Many emerging economies in Latin America and Asia experienced sharp changes in volatility due economic crises.

Second, monetary policy in the US responds to global macroeconomic shocks. In particular, US short-term interest rates respond in a hump-shaped manner to global shocks to GDP growth with a peak response around 2-3 quarters. In contrast, the response of US interest rates to global inflation shocks appears stronger in the 1980s and 1990s, compared to recent periods.

Third, a contractionary shock to US monetary policy (a 50 basis points increase in short-term US interest rate) leads to (1) a persistent global contraction, (2) a drop in global inflation rates together with (3) a rise in global interest rates, and (4) a relative real depreciation with respect to the US dollar. The estimated effects are in line with the empirical literature on the effects of shocks to monetary policy originated in the US on other economies (see Eichenbaum and Evans (1995)). However, we find evidence for important heterogeneity of the spillovers on different countries and for a changing global transmission of monetary policy shocks over time. In particular, the global response to US monetary policy shocks becomes stronger in the mid-2000s, at the onset of the Great Recession. We also find it important to allow for stochastic volatility in macroeconomic variables during crises and turbulent episodes.

This paper is structured as follows. Section two presents the econometric framework including the necessary prior specifications and the Bayesian estimation strategy. Section three presents the results of the empirical study and section four concludes.

## 2 Econometric framework: The TVP-SV-GVAR specification

We assess the dynamic transmission mechanism between US monetary policy and the global economy, we estimate a global VAR model with time-varying parameters and stochastic volatility (TVP-SV-GVAR). This model is estimated using a broad panel of countries and macroeconomic aggregates, thus providing a truly global flexible representation of the world economy. In general, GVAR modelling can be thought of as consisting of two distinct stages. In the first stage, we estimate a set of $N+1$ countryspecific VAR models featuring exogenous regressors that aim to capture cross-country linkages. In a second stage, these models are combined using country weights to form a global model that is used to carry out impulse response analysis or forecasting.

### 2.1 The global vector autoregressive model with time-varying parameters

Let the endogenous variables for country $i=0, \ldots, N$ be contained in a $k_{i} \times 1$ vector $y_{i t}=\left(y_{i 1, t}, \ldots, y_{i k_{i}, t}\right)^{\prime}$. In addition, all country-specific models feature a set of $k_{i}^{*}$ weakly exogenous regressors $y_{i t}^{*}=\left(y_{i 1, t}^{*}, \ldots, y_{i k_{i}, t}^{*}\right)^{\prime}$ constructed as weighted averages of the endogenous variables in other economies,

$$
\begin{equation*}
y_{i j, t}^{*}=\sum_{s=0}^{N} w_{i s} y_{s j, t} \text { for } j=1, \ldots, k_{i}^{*} \tag{2.1}
\end{equation*}
$$

where $w_{i s}$ is the weight corresponding to the variable of country $s$ in country $i$ 's specification. These weights are typically assumed to be related to bilateral trade exposure or financial linkages. In line with the bulk of the literature on GVAR modelling, we assume that $\sum_{s=0}^{N} w_{i s}=1$ and $w_{i i}=0$.

We depart from the standard GVAR modelling efforts by specifying country-specific structural VAR models featuring exogenous regressors, time-varying parameters and stochastic volatility, so that

$$
\begin{equation*}
A_{i 0, t} y_{i t}=\sum_{p=1}^{P} B_{i p, t} y_{i t-p}+\sum_{q=0}^{Q} \Lambda_{i q, t} y_{i t-q}^{*}+\varepsilon_{i t} \tag{2.2}
\end{equation*}
$$

where

- $A_{i 0, t}$ is a $k_{i} \times k_{i}$ matrix of structural coefficients used to establish contemporaneous relationships between the variables in $y_{i t}$. We assume that $A_{i 0, t}$ is a lower triangular matrix with $\operatorname{diag}\left(A_{i 0, t}\right)=1$. This choice ensures that the errors of the model are orthogonal to each other by imposing a Cholesky structure on the specification,
- $B_{i p, t}(p=1, \ldots, P)$ is a $k_{i} \times k_{i}$ matrix of coefficients associated with the lagged endogenous variables,
- $\Lambda_{i q, t}(q=0, \ldots, Q)$ denotes a $k_{i} \times k_{i}^{*}$ dimensional coefficient matrix corresponding to the $k_{i}^{*}$ weakly exogenous variables in $y_{i t}^{*}$,
- $\varepsilon_{i t} \sim \mathcal{N}\left(0, D_{t}\right)$ is a heteroskedastic vector error term with $D_{t}=\operatorname{diag}\left(\lambda_{i 0, t}, \ldots, \lambda_{i k_{i}, t}\right) .{ }^{2}$

Stacking the lagged endogenous and weakly exogenous variables in an $m_{i}$-dimensional vector, with $m_{i}=k_{i} P+k_{i}^{*}(Q+1)$,

$$
\begin{equation*}
x_{i t}=\left(y_{i t-1}, \ldots, y_{i t-P}, y_{i t}^{*}, \ldots, y_{i t-Q}^{*}\right)^{\prime} \tag{2.3}
\end{equation*}
$$

and storing all coefficients in a $k_{i} \times\left(m_{i} k_{i}\right)$ matrix $\Psi_{i t}$,

$$
\begin{equation*}
\Psi_{i t}=\left(B_{i 1, t}, \ldots, B_{i P, t}, \Lambda_{i 0, t}, \ldots, \Lambda_{i Q, t}\right)^{\prime} \tag{2.4}
\end{equation*}
$$

allows us to rewrite Eq. (2.2) as

$$
\begin{equation*}
A_{i 0, t} y_{i t}=\left(I_{k_{i}} \otimes x_{i t}^{\prime}\right) \operatorname{vec}\left(\Psi_{i t}\right)+\varepsilon_{i t} \tag{2.5}
\end{equation*}
$$

Collecting the elements of $A_{i 0, t}$ which are not zero or unity in a $k_{i}\left(k_{i}-1\right) / 2$-dimensional vector $a_{i 0, t}$, the law of motion of $a_{i 0, t}$ is assumed to be given by

$$
\begin{equation*}
a_{i 0, t}=a_{i 1, t-1}+\epsilon_{i t}, \epsilon_{i t} \sim \mathcal{N}\left(0, V_{i}\right) \tag{2.6}
\end{equation*}
$$

[^2]where $V_{i}$ is a (block-diagonal) variance-covariance matrix with $V_{i}=\operatorname{diag}\left(V_{i 1}, \ldots, V_{i k_{i}}\right)$. The block-diagonal nature stems from the fact that we estimate the model on a equation-by-equation basis, thus effectively disregarding the contemporaneous relationships between parameters in different equations. Likewise, we assume that the autoregressive coefficients in $\Psi_{i t}$ evolve according to
\[

$$
\begin{equation*}
\operatorname{vec}\left(\Psi_{i t}\right)=\operatorname{vec}\left(\Psi_{i t-1}\right)+\eta_{i t}, \quad \eta_{i t} \sim \mathcal{N}\left(0, Q_{i}\right) \tag{2.7}
\end{equation*}
$$

\]

with $Q_{i}=\operatorname{diag}\left(Q_{i 1}, \ldots, Q_{i k_{i}}\right)$ being a $K_{i} \times K_{i}$ variance-covariance matrix. Finally, the the variances $\lambda_{i l, t}$ are assumed to follow a stationary stochastic process,

$$
\begin{equation*}
\log \left(\lambda_{i l, t}\right)=\mu_{i l}+\rho_{i l}\left(\log \left(\lambda_{i l, t}\right)-\mu_{i}\right)+v_{i t}, v_{i l, t} \sim \mathcal{N}\left(0, \varsigma_{i l}^{2}\right) \tag{2.8}
\end{equation*}
$$

where $\mu_{i l}$ denotes the unconditional expectation of the log-volatility, $\rho_{i l}$ the corresponding persistence parameter and $\varsigma_{i l}^{2}$ is the innovation variance of the process.

Some features of the model in Eq. (2.2) deserve explanation. All parameters are allowed to vary over time, which implies that we can explicitly account for changes in domestic and international transmission mechanisms with our specification. Moreover, we also account for heteroskedasticity by making the variance-covariance matrix of $\varepsilon_{i t}$ time-varying. Our model can thus simultaneously accommodate many features which are commonly observed in macroeconomic and financial time series data. On the other hand, the inclusion of weakly exogenous foreign variables accounts for cross-country linkages and enables us to investigate the stability properties of the model across both space and time. Given the marked increase in globalization and the stronger degree of business cycle synchronization experienced globally over the last decades, this is an essential ingredient in modelling the global transmission of shocks.

The set of $N+1$ country specific models can be linked together to yield a global VAR model (Pesaran et al., 2004). Collecting all contemporaneous terms of Eq. (2.2) and defining a $\left(k_{i}+k_{i}^{*}\right)$-dimensional vector $z_{i t}=\left(y_{i t}^{\prime}, y_{i t}^{*^{\prime}}\right)^{\prime}$, we obtain

$$
\begin{equation*}
C_{i t} z_{i t}=\sum_{s=1}^{S} L_{i s, t} z_{i t-s}+\varepsilon_{i t} \tag{2.9}
\end{equation*}
$$

with $C_{i t}=\left(A_{i 0, t},-\Lambda_{i 0, t}\right), L_{i s, t}=\left(B_{i p, t}, \Lambda_{i q, t}\right)$ and $S=\max (P, Q)$. A global vector $y_{t}=\left(y_{0 t}^{\prime}, \ldots, y_{N t}^{\prime}\right)^{\prime}$ of dimension $k=\sum_{i=0}^{N} k_{i}$ and a corresponding country-specific linkage matrix $W_{i}(i=1, \ldots, N)$ of dimension $\left(k_{i}+k_{i}^{*}\right) \times k$ can be defined so as to rewrite Eq. (2.9) exclusively in terms of the global vector,

$$
\begin{equation*}
C_{i t} W_{i} y_{t}=\sum_{s=1}^{S} L_{i s, t} W_{i} y_{t-s}+\varepsilon_{i t} \tag{2.10}
\end{equation*}
$$

Stacking the $N+1$ equations times yields

$$
\begin{equation*}
G_{t} y_{t}=\sum_{s=1}^{S} F_{s t} y_{t-s}+e_{t} \tag{2.11}
\end{equation*}
$$

where $G_{t}=\left(\left(C_{0 s, t} W_{0}\right)^{\prime}, \ldots,\left(C_{N s, t} W_{N}\right)^{\prime}\right), F_{s t}=\left(\left(L_{0 s, t} W_{0}\right)^{\prime}, \ldots,\left(L_{N s, t} W_{N}\right)^{\prime}\right)^{\prime}$ and $e_{t}=$ $\left(\varepsilon_{0 t}^{\prime}, \ldots, \varepsilon_{N t}^{\prime}\right)^{\prime}$. The error term $e_{t}$ is normally distributed with variance-covariance matrix $H_{t}=\operatorname{diag}\left(D_{0 l, t}, \ldots, D_{N l, t}\right)$. Equation (2.11) resembles thus a (very) large VAR model with drifting coefficients.

### 2.2 Bayesian estimation of the TVP-SV-GVAR model

We use Bayesian methods to carry out inference in the TVP-SV-GVAR model proposed. Given the risk of overparametrization that is inherent to the specifications used, we rely on Bayesian shrinkage methods to achieve simpler representation of the data. The timevarying nature of the parameters in the model and the presence of the weakly exogenous variables in Eq. (2.2) present further complications that will be tackled in the estimation procedure.

In a Bayesian framework we need to elicit priors on the coefficients in Eq. (2.5). We impose a normally distributed prior on the initial state of $\Psi_{i t}$, labeled as $\Psi_{i 0}$,

$$
\begin{equation*}
\operatorname{vec}\left(\Psi_{i 0}\right) \sim \mathcal{N}\left(\operatorname{vec}\left(\underline{\Psi}_{i}\right), \underline{V}_{\Psi_{i}}\right) \tag{2.12}
\end{equation*}
$$

with $\underline{\Psi}_{i}$ a $k_{i} \times m_{i}$ prior mean matrix and $\underline{V}_{\Psi_{i}}$ a $k_{i} m_{i} \times k_{i} m_{i}$ prior variance-covariance matrix. In addition, we specify a prior for the free parameters of the state equation. We impose an inverted Wishart prior on the variance-covariance matrix $Q_{i}$ in Eq. (2.7), in line with the literature. Specifically, we assume that

$$
\begin{equation*}
Q_{i r} \sim \mathcal{I} \mathcal{W}\left(\underline{v}_{i}, \underline{Q}_{i r}\right), \text { for } r=1, \ldots, k_{i}, \tag{2.13}
\end{equation*}
$$

where $\underline{v}_{i}$ is the prior degrees of freedom and $\underline{Q}_{i r}$ denotes a prior scale matrix. The normal prior on $\Psi$ and the set of inverted Wishart priors on $Q_{i}$ allow us to achieve shrinkage along two important dimensions. First, the prior on the initial state shrinks the parameters towards zero. Second, the inverted Wishart prior can be set such that the model is effectively pushed towards a constant coefficient specification, therefore controlling the degree of variation of the autoregressive parameters.

A set of normal priors are imposed on the initial state of $a_{i 0, t}, a_{i 0,0}$

$$
\begin{equation*}
\operatorname{vec}\left(a_{i 0,0}\right) \sim \mathcal{N}\left(\operatorname{vec}\left(\underline{a}_{i}\right), \underline{V}_{a_{i}}\right) \tag{2.14}
\end{equation*}
$$

where $\underline{a}_{i}$ and $\underline{V}_{a_{i}}$ denote the prior mean and prior variance covariance matrices of the initial state. Similarly to the prior on $Q_{i}$, we impose a set of inverted Wishart priors on $V_{i}$

$$
\begin{equation*}
V_{i r} \sim \mathcal{I} \mathcal{W}\left(\underline{m}_{i}, \underline{V}_{i r}\right), \text { for } r=1, \ldots, k_{i}, \tag{2.15}
\end{equation*}
$$

where $\underline{m}_{i}$ denotes the prior degrees of freedom and $\underline{V}_{i r}$ is the prior scaling matrix.
Finally, we use the prior setup proposed in Kastner and Frühwirth-Schnatter (2013) and subsequently used in Huber (n.d.) on the coefficients of the log-volatility process in Eq. (2.8). A normal prior is imposed on $\mu_{i l}\left(l=1, \ldots, k_{i}\right)$ with mean $\underline{\mu}_{i}$ and variance $\underline{V}_{\mu_{i}}$

$$
\begin{equation*}
\mu_{i l} \sim \mathcal{N}\left(\underline{\mu}_{i}, \underline{V}_{\mu_{i}}\right) \tag{2.16}
\end{equation*}
$$

For the persistence parameter $\rho_{i l}$ we elicit a beta prior

$$
\begin{equation*}
\frac{\rho_{i l}+1}{2} \sim \operatorname{Beta}\left(a_{0}, b_{0}\right), \tag{2.17}
\end{equation*}
$$

which implies

$$
\begin{aligned}
E\left(\rho_{i l}\right) & =\frac{2 a_{0}}{a_{0}+b_{0}}-1 \\
\operatorname{Var}\left(\rho_{i l}\right) & =\frac{4 a_{0} b_{0}}{\left(a_{0}+b_{0}\right)^{2}\left(a_{0}+b_{0}+1\right)} .
\end{aligned}
$$

For typical datasets arising in macroeconomics, the exact choice of the hyperparameters $a_{0}$ and $b_{0}$ in Eq. (2.17) is quite influential, since data does not tend to be very informative about the degree of persistence of log-volatilities.

We impose a non-conjugate gamma prior for $\varsigma_{i l}$,

$$
\begin{equation*}
\varsigma_{i l} \sim \mathcal{G}\left(1 / 2,1 / 2 B_{\sigma}\right) . \tag{2.18}
\end{equation*}
$$

This choice does not bound $\varsigma_{i l}$ away from zero, thus providing more shrinkage as typical conjugate inverted gamma priors. Moreover, such a prior setting can improve sampling efficiency considerably (Kastner and Frühwirth-Schnatter, 2013). Following Lopes et al. (2011), we impose a Cholesky structure at the individual country level, which provides significant computational gains when sampling from the posterior distributions of interest.

Using the prior setting described above, a Markov chain Monte Carlo (MCMC) algorithm to draw samples from the country-specific posterior distribution can be designed. Let us denote the full history of the time-varying elements in Eq. (2.9) up to time $T$ as

$$
\begin{aligned}
\operatorname{vec}\left(\Psi_{i}^{T}\right) & =\left(\operatorname{vec}\left(\Psi_{i 1}\right)^{\prime}, \ldots, \operatorname{vec}\left(\Psi_{i T}\right)^{\prime}\right)^{\prime} \\
a_{i}^{T} & =\left(a_{i 1}^{\prime}, \ldots, a_{i T}^{\prime}\right)^{\prime} \\
\lambda_{i}^{T} & =\left(\lambda_{i 1}, \ldots, \lambda_{i T}\right)^{\prime} .
\end{aligned}
$$

The MCMC algorithm consists of the following blocks

- $\operatorname{vec}\left(\Psi_{i}^{T}\right)$ and $a_{i}^{T}$ are sampled through the well known algorithm provided in Carter and Kohn (1994) and Frühwirth-Schnatter (1994).
- Conditional on $\operatorname{vec}\left(\Psi_{i}^{T}\right)$ and $a_{i}^{T}$, the variance-covariance matrices in Eq. (2.6) and Eq. (2.7) can be sampled from inverted Wishart distributions with precision matrices given by $\bar{V}_{i r}=\underline{V}_{i r}+\sum_{t=1}^{T}\left(a_{i t}-a_{i t-1}\right)\left(a_{i t}-a_{i t-1}\right)^{\prime}$ for Eq. (2.6) and $\bar{Q}_{i r}=\underline{Q}_{i r}+\sum_{t=1}^{T}\left(\operatorname{vec}\left(\Psi_{i t}\right)-\operatorname{vec}\left(\Psi_{i t-1}\right)\right)\left(\operatorname{vec}\left(\Psi_{i t}\right)-\operatorname{vec}\left(\Psi_{i t-1}\right)\right)^{\prime}$ for Eq. (2.7), and posterior degrees of freedom $\bar{m}_{i}=\underline{m}_{i}+T$ and $\bar{v}_{i}=\underline{v}_{i}+T$.
- The history of log volatilities is sampled using the algorithm outlined in Kastner and Frühwirth-Schnatter (2013). ${ }^{3}$

[^3]
## 3 Empirical application

The following section introduces the data used to estimate the model as well as the prior implementation. Using the TVP-SV-GVAR model structure presented in the previous section, we investigate first the volatility patterns of the underlying macroeconomic series. Second, we estimate the quantitative effect (impulse responses) of global economic shocks on US monetary policy (short-term interest rates). Third, we assess the spillover of shocks to US monetary policy on endogenous variables for a selected set of countries.

### 3.1 Data overview, model specification and prior implementation

We rely on data provided by Dovern et al. (2015), that extend the dataset used in Dees et al. (2007a,b) with respect to variable coverage and time span. In what follows, we use quarterly data for 36 countries spanning the period from 1979:Q2 to 2013:Q4. The countries covered in our sample are shown in Table 1.
[Table 1 about here.]
The country-specific TVP-VAR models include real GDP growth $(\Delta y)$, the logdifference of the consumer price level $(\Delta p)$, the log-difference of the real exchange rate $(\Delta e)$ vis-á-vis the US dollar, short-term interest rates $\left(i_{s}\right)$ and the term spread, constructed as the difference between short-term and long-term interest rates ( $s$ ). ${ }^{4}$ Note that not all variables are available for each of the countries we consider in this study. With the exception of long-term interest rates, the cross-country coverage of all variables is, however, above $80 \%$. Long-term interest rate data are missing for emerging markets that are characterized by underdeveloped capital markets.

The vector of domestic variables for a typical country $i$ is thus given by

$$
\begin{equation*}
\boldsymbol{x}_{i t}=\left(\Delta y_{i t}, \Delta p_{i t}, \Delta e_{i t}, i_{s i t}, s_{i t}\right)^{\prime} . \tag{3.1}
\end{equation*}
$$

We follow the bulk of the literature by including oil prices (poil) as a global control variable. With the exception of the bilateral real exchange rate, we construct foreign counterparts for all domestic variables. The weights to calculate foreign variables are based on average bilateral annual trade flows in the period from 1980 to 2003, which denotes the end of our initial estimation sample. ${ }^{5}$ For a typical country $i$ the set of weakly exogenous and global control variables comprises the following variables,

$$
\begin{equation*}
\boldsymbol{x}_{i t}^{*}=\left(\Delta y_{i t}^{*}, \Delta p_{i t}^{*}, i_{s i t}^{*}, s_{i t}^{*}, \Delta p o i l^{*}\right)^{\prime} . \tag{3.2}
\end{equation*}
$$

[^4]The US model $(i=0)$ deviates from the other country specifications in that the oil price is determined within that country model and the trade weighted real exchange rate ( $\Delta e^{*}$ ) is included.

$$
\begin{align*}
\boldsymbol{x}_{0 t} & =\left(\Delta y_{0 t}, \Delta p_{0 t}, i_{s 0 t}, s_{0 t}, \Delta \text { poil }_{t}\right)^{\prime},  \tag{3.3}\\
\boldsymbol{x}_{0 t}^{*} & =\left(\Delta y_{0 t}^{*}, \Delta p_{0 t}^{*}, \Delta e_{0 t}^{*}, i_{s 0 t}^{*}, s_{0 t}^{*}\right)^{\prime} . \tag{3.4}
\end{align*}
$$

For all countries considered, we set the lag length of endogenous and weakly exogenous variables equal to one. Given the period spanned by our sample and the quarterly frequency of the data, this seems to be a reasonable choice.

We correct for outliers in countries that witnessed extraordinarily strong crisisinduced movements in some of the variables contained in our data. We opted to smooth the relevant time series in these cases rather than include step dummies. While step dummies might control for outliers within the specific country model, unusual effects might still be carried over to other country models via the trade-weighted foreign variables. Obviously, this is not the case when smoothing the series in the first place. More specifically, we defined outliers as those observations that exceed 1.5 times the interquartile range in absolute value.

Before proceeding to the empirical results let us discuss the specific choices of the hyperparameters needed to construct our prior distributions. Since the GVAR comprises of $N+1$ countries each country could be endowed with a country-specific set of hyperparameters. However, we simply assume that the hyperparameters are the same across countries, making prior elicitation much easier.

For the prior on the initial state $\Psi_{i 0}$ we set $\left.\operatorname{vec}\left(\underline{\Psi}_{i}\right)\right)=0$ and $\underline{V}_{\Psi_{i}}=10 I_{k_{i} m_{i}}$. Similarly we $\operatorname{set} \operatorname{vec}\left(\underline{a}_{j}\right)=0$ and $\underline{V}_{a_{i}}$ equal to a diagonal matrix with 10 on its main diagonal. This setup renders the prior on the initial conditions fairly uninformative and proves to be of minor importance for our empirical application.

The prior on the innovation variances of the state equations in Eq. (2.6) and Eq. (2.7) is set such that both $\underline{Q}_{i r}$ and $\underline{V}_{i r}$ are diagonal matrices where the main diagonal equals 0.001 and the prior degrees of freedom equal $k_{i}+1$. This choice is highly influential in practice and we have thus performed extensive robustness checks with respect to those hyperparameters. In contrast to Primiceri (2005), who elicit the prior on the variance of the state innovations using a pre-sample of data, we evaluate different hyperparameters on a grid of values, ranging from values which translate into a much tighter prior than Primiceri 2005's setup to a specification which is quite loose. Given that we are interested in allowing the data to be as much informative as possible with respect to the drifting behaviour of the coefficients we strongly favour hyperparameters that are loose but still impose enough discipline on the parameter dynamics such that the resulting posterior quantities are stable. The grid we evaluate is given by ( $0.00001,0.0001,0.001,0.005,0.01$ ) where we pick 0.001 as our reference value for both $\underline{Q}_{i r}$ and $\underline{V}_{i r}$. Higher values typically lead to posterior draws which are excessively unstable, leading to implausible impulse-response schedules.

Finally, the prior on the mean of the log-volatility equation is set such that $\underline{\mu}_{i}=0$ and $\underline{V}_{\mu_{i}}=10$, which is uninformative given the scale of our data. For the autoregressive parameter $\rho_{i l}$ we set $a_{0}$ and $b_{0}$ are set equal to 25 and 1.5 respectively. This prior places a lot of mass on high persistence regions of the parameter space. Since the data is usually not really informative about the autoregressive parameter the corresponding posterior distribution is strongly influenced by this choice. However, experimenting with other values that place more prior mass on stationary regions of $\rho_{i l}$ leads to qualitatively similar results. The last piece missing is the prior on $\varsigma_{i l}$, where we only have to specify $B_{\sigma}$, which is set equal to unity.

### 3.2 The volatility of macroeconomic shocks: A global dimension

In this section we investigate the volatility of the variables considered in this paper, measured by the (normalized) posterior mean of the standard deviation. Figure 1 plots the volatility of output growth for four regional groups and in addition a selection of countries in each group: (a) Western Europe (Germany, Spain, France, Norway and Great Britain), (b) Asia (China, India, Indonesia, Korea and Thailand), (c) Latin America (Brazil, Chile, Peru, Mexico and Argentina), and (d) other Developed Economies (US, Canada, Japan, Australia and New Zealand). The figure shows the median of volatility in red and in addition the volatility for the selection of countries (see legend below each panel). We can observe the decline in the volatility of GDP growth in Western Europe and other Developed Economies until the middle of the 2000's. After 2007 we see a sharp increase in output volatility due to the start of the Great Recession, followed by a gradual return to lower volatility recently. Economies in Latin America and Asia had episodes of increased volatility of GDP growth also during crises in the 1980's and 1990's, respectively. Some emerging economies (Thailand, Korea and Argentina) has also sharp increases in volatility following the global financial crisis.
[Fig. 1 about here.]
Figure 2 shows the volatility of inflation for the same four regional groups and selection of countries in each group as in Fig. 1. The median country in Western Europe and other Developed Economies in subplots (a) and (d) had falling volatility of inflation in until the mid 2000's (cf. the so-called Great Moderation). However, some countries such as France, Norway or Australia has bouts of increased volatility towards the end of this period. Economies in Asia shown in panel (b) had much more pronounced volatility of inflation in the 1980s and especially during the East Asian crisis in the 1990s. Panel (c) shows that volatility of inflation in many economies in Latin America was much larger during the 1980s and early 1990s which makes relative volatility almost flat in more recent years.
[Fig. 2 about here.]
Figure 3 shows the volatility of short-term interest rates for the same four regional groups and selection of countries in each group as in Fig. 1. In addition to the decline
in median volatility of short term rates until the mid-2000's in Western European and Developing economies echoing falling inflation rates in Fig. 2, a number of interesting episodes stand out. In panel (a) Norway has a sharp increase in interest rate volatility related to turbulence of the European Exchange Rate Mechanism (ERM) in the early 1990's. ${ }^{6}$ Japan had an increase in volatility of short rates in the late 1990's and early 2000's. Economies in Asia and Latin America had sharp spikes in volatility of short term interest rates during crises episodes in the 1980's and 1990's.
[Fig. 3 about here.]
Finally, Fig. 4 shows the volatility of real exchange rates for the four regional groups and selection of countries in each group. Panel (a) show the sharp rise in volatility of real exchange rates around the ERM crisis in the early 1990's and again during the recent recession in Europe after 2008. Economies in Asia shown in panel (b) had particular volatile exchange rates during the East Asian crisis in the late 1990's and Latin American countries shown in panel (c) in the 1980's, but also during other times.

$$
\text { [Fig. } 4 \text { about here.] }
$$

In the context of identifying the changing effect of US monetary policy on the global economy, it is therefore important that our model accounts for stochastic volatility to capture salient features of the time series involved (see (Cogley and Sargent, 2002)).

### 3.3 The international dimension of US monetary policy over time

In this section we investigate how systematic monetary policy changed over time with respect to international economic activity. Typically, the reaction function of the US Fed is modelled as a linear function of purely domestic quantities. For instance, reaction functions based on a simple Taylor rule (Taylor, 1993) assume that the Fed sets the policy rate according to a simple linear function consisting of inflation expectations, the output gap and possibly the effective exchange rate (Taylor, 2002; Clarida et al., 1998). Thus by establishing a rule-based behaviour it is theoretically ruled out that the Fed reacts to international economic developments. In addition, the assumption of a linear monetary policy reaction function implies that the central bank is conducting monetary policy independently from the prevailing state of the economy, i.e. the reaction function is the same in boom- and bust phases, a rather strong assumption.

To establish a relationship between the central banks' behaviour and macroeconomic developments abroad we assume that the policy instrument is set according to

$$
\begin{equation*}
\mathfrak{i}_{t}=\mathfrak{f}_{t}\left(\Omega^{t}\right)+\epsilon_{t}, \tag{3.5}
\end{equation*}
$$

where $\mathfrak{i}_{t}$ denotes the policy rate, $\mathfrak{f}_{t}\left(\Omega^{t}\right)$ is a non-linear function of the information set of the central bank up to time $t$ and $\epsilon_{t}$ denotes a monetary policy shock with zero mean

[^5]and unit variance. The vast majority of the literature assumes that $\mathfrak{f}_{t}=\mathfrak{f}$ for all $t$ and $\Omega^{t}$ includes only information related to domestic economic quantities (Christiano et al., 1999).

In the GVAR model outlined in Section 2 the inclusion of weakly exogenous variables implies that $\Omega^{t}$ now also includes information on international output, interest rates, prices, exchange rates and term spreads. This allows us to investigate the behaviour of the Fed related to shocks to the aforementioned quantities.

We investigate the dynamic behaviour of the Fed by investigating the following four cases

1. A one standard error shock to international real activity.
2. A one standard error shock to international inflation.
3. A one standard error shock to international short-term interest rates.
4. A one standard error appreciation of the real effective exchange rate of the US.

Shocks to international real activity, inflation, short-term interest rates and the real effective exchange rate of the US are constructed by shocking the errors of the corresponding equations in all countries except the US. Since structural identification is problematic in the presence of such a large number of shocks, we resort to generalized impulse response functions (Pesaran and Shin, 1998).

Figure 5 depicts the posterior mean of the impulse responses of the US short-term interest rate to the different shocks described above across time. Several findings are worth emphasizing. Figure 5(a) displays US short-term interest rate responses to a global output shock. Note output responses show only little variation over time, thus indicating that short-term rates increase by around 8 basis points (bp), petering out rather fast afterwards. While we do not report confidence bounds it is worth emphasizing that this response is significant within the first two quarters, becoming insignificant thereafter.

By contrast, responses to a global inflation shock (see Fig. 5(b)) exhibit a larger degree of time variation. Note that the short-term interest rates increased by around 4 basis points after three to four quarters for most periods considered, except for beginning of the sample and the period ranging from approximately 1990 to 1997. The somewhat stronger response in the beginning of the sample marks the first half of Paul Volckers term as Fed chairman, where monetary policy started to react much more aggressively to fight inflationary developments. In the period from 1990 to 1997 interest rates increased by around 9 basis points to a global inflation shock. The first gulf war led to a sharp decrease in US economic activity and the Fed reacted by lowering interest rates. In addition, the past performance of the Fed led to a decline in its credibility for low inflation. Interestingly, however, our results suggest that the Fed reacted stronger to external inflation shocks within that period. Contrasting this global supply shock with a purely domestic supply shock (not shown) reveals that the Fed's actual response
to US based supply shocks was lower for that part of the sample, with the response to an external shock being much stronger.

Figure 5(c) reveals that US short-term interest rates only showed minor reactions with respect to a global interest rate shock, outlining the leading role US monetary policy has for the world economy. However, especially within the first half of the eighties, the Fed lowered interest rates aggressively, mirroring increased short-term interest rates abroad. Since rising short-term interest rates abroad are accompanied by rising nominal exchange rates vis-á-vis the US dollar, conventional macroeconomic theory suggests that the Fed also increases interest rates such that the uncovered interest rate parity holds. However, our finding implies that the Fed actually responded by lowering interest rates in the midst of the eighties, thus providing further stimulus to counterbalance the detrimental effects a global monetary policy shock might have on external demand.
[Fig. 5 about here.]
Finally, Fig. 5(d) shows the reaction of short-term rates with respect to an appreciation of the US real effective exchange rate. We see that especially in the beginning of the sample the Fed reacted aggressively, lowering interest rates by around 10 basis points to lower the external value of the US dollar. The responses become significantly smaller afterwards, reacting only marginally from the midst of the eighties onward.

### 3.4 Dynamic effects of a contractionary US monetary policy shock

Last we investigate the international responses of an unexpected monetary policy tightening in the USA. The shock is normalized to a 50 basis points increase on impact throughout the sample period. The results are summarized in Figs. (6) to (13). The plots show the posterior for selected countries along with the cross-country means (in red) and associated $25 \%$ and $75 \%$ credible sets (in orange). Responses are shown for three distinct horizons, after one quarter $(t=1)$, after 8 quarters $(t=8)$ and after 12 quarters $(t=12)$.

Figures 6 and 7 show the output response for selected developed economies and Western European economies. The reaction of output in developed economies is very homogeneous, both across the countries and over time. In all three different time horizons considered, the output reaction is negative and for most countries lies within the credible set. Taken at face value this indicates a very persistent effect of spillovers generated from a US monetary policy shock on output and corroborates findings of Feldkircher and Huber (2015b) who use a linear version of the Bayesian GVAR model. While responses are in general very homogeneous, two countries stand out: on the one hand, Canada's response is even stronger than the domestic reaction of output in the USA itself. On the other hand, Australia seems very insulated from the monetary policy shock. The response in selected Western European economies is also very homogeneous and - compared to the group of developed economies - smaller in magnitude. Spillovers from the monetary policy shock are also very persistent, however this is mostly the case
from the mid-1990s onward. There is much more time variation in responses when turning to emerging economies. In Asia, and with the exception of China, all countries respond negatively to the monetary tightening in the USA. While these effects are present also after 8 quarters, in the long-run credible sets include the zero response. Note also that credible sets for this group of countries are much wider than for developed and Western European economies. Some countries countries show a clear downward trend in responses, while for others spillover effects became less pronounced in the most recent period of the sample. In China and India the trend in responses even turns from less pronounced to more pronounced and vice versa. All this information would be lost in a linear setting. In Latin America, output responses are also very persistent, which is in line with findings of Feldkircher and Huber (2015b). While credible sets are wide, most responses show the pattern becoming more pronounced in the most recent period of our sample.
[Fig. 6 about here.]
[Fig. 7 about here.]
Responses of inflation are depicted in Figs. (8) to (9). On impact the domestic response of inflation in the USA is negative. Hence our model is rich enough to yield responses that do not create a price puzzle which lends further confidence to the overall results. In the medium term, however, inflation in the USA adjusts and becomes positive, which is in contrast to responses of its peers. Again, Canada shows the most pronounced response to the US monetary tightening - even after 3 years the effect is pronounced and negative. In general, responses of inflation show more time-variation compared to output responses. However, credible sets are also much wider including zero responses throughout the sample period and for all three impulse response horizons. A similar picture arises in Western European economies: inflation responds negative throughout the sample period and across countries. However, credible sets are large and responses in the medium-term hover around zero for most of the sample period. With respect to time variation, for most of the economies a downward shift in response has set in around 2005. In line with findings for output responses, reactions of inflation show much more variation over time for emerging compared to advanced economies. In emerging Asia, the monetary tightening triggers negative reactions of inflation on impact, while responses in the medium term are accompanied by wide credible sets including the zero response. On impact, Korea and Indonesia are most insulated from the shock. In the medium-term China responds most strongly with responses hovering around the lower credible bound throughout the sample period. Impact responses in Latin America tend to be even more diverse. On the one hand, responses on impact are positive in Peru, Chile and Mexico with the latter exceeding the upper credible set nearly throughout the sample period. On the other hand, responses are negative in Brazil and Argentina hitting the lower credible set throughout the sample period. In the medium-term responses are insignificant across all countries considered in this group. Nevertheless there is considerable time variation in the reaction of inflation, particularly
at the beginning of the sample period in which some countries experienced times of hyperinflation.
[Fig. 8 about here.]
[Fig. 9 about here.]
Figures 10 and 11 show the response of interest rates with respect to the monetary policy shock. Comovements of interest rates have been identified as an important transmission channel of macroeconomic shocks in Feldkircher and Huber (2015b). While the response of US short-term rates has been fixed to +50 bp on impact, spillovers for most other developed economies are meager. An exception to this is Canada, whose short-term rates tick up strongly in response to the US monetary policy tightening. In the medium-term, interest rates in Canada and the USA still increase, while responses of interest rates for the remaining countries are close to zero. Since responses are so diverse, the regional mean might not be informative in case of short-term interest rates. With the exception of Spain, impact responses in Western Europe are positive and credible sets are well above zero. In Spain, responses are more similar to the rest of the group in the second part of the sample. In the medium-term credible sets are wide throughout the region. Moreover and with respect to time variation, responses vary considerably over the period covered for most of the countries emphasizing the importance to consider a non-linear framework. While in most of advanced economies, interest rates move in parallel with US short-term rates, interest rates in emerging economies tend to decrease in response to the contractionary US monetary policy shock. With the exception of Indonesia, all economies in emerging Asia respond negatively on impact and accompanying credible sets are tight. After 8 quarters responses are still negative, but only significant in the most recent period of the sample. Also note that time variation of responses is pronounced. For example, responses in Korea are positive in the first part of the sample, after which they turn persistently negative. A similar picture arises for responses of short-term rates in Latin America. Here, on impact shortterm rates decrease for all countries but Mexico and Chile in the most recent period of the sample. In the medium-term interest rates still respond negatively underlining the importance of the financial channel in transmitting external shocks from the USA (Canova, 2005). Mexico and Chile deviate also in the medium term from its peers in Latin America. For both countries responses are strongly time varying and positive throughout the sample period. Other countries, like Argentina, also show pronounced variations of responses over time.
[Fig. 10 about here.]
[Fig. 11 about here.]
Last, Figs. (12) and (13) show the responses of the real exchange rate vis-á-vis the US dollar. As expected, responses are positive on impact indicating a real appreciation
of the US dollar after as a consequence of the interest rate increase. Also consistent with our findings so far, Canada is most affected, while Australia's currency seems resilient to the US interest rate shock. This patterns also holds in the medium-term. Strikingly, the effect of the monetary policy shock on real exchange rates seems to be increasing over time, for all countries but Australia. This implies that the dollar is now more strongly appreciating as a consequence of an interest rate increase than at the beginning of our sample period. Qualitatively a similar picture arises considering developed economies in Western Europe. On impact, all currencies weaken against the US dollar. These effects are most pronounced for the United Kingdom, which shares traditionally strong trade and financial linkages with the USA. In the medium term, credible sets start to widen. However, the effects of monetary policy on exchange rates also become more pronounced over the period considered and are especially tightly estimated from the mid 2000s onward. In emerging Asia, currencies weaken against the US dollar on impact, after 8 quarters and after 12 quarters. Over all three forecast horizons, effects are most pronounced for Korea, while the other countries show a very homogeneous response. In line with results for advanced economies, responses increase gradually with the sample period indicating a stronger sensitivity of the currencies in the most recent period of the sample. Also Latin American currencies weaken against the US dollar on impact and credible sets are tight. In the medium term credible sets widen and include the zero response for all currencies considered. Similar to results for the other regions, currencies tend to react more strongly in response to a US monetary policy shock in the most recent period of the sample. However, and in contrast to responses of currencies in emerging Europe, in Latin America reactions seem to be less gradual. To be more specific, around 2000 responses of the real exchange rate started to rise significantly, while in the most recent period responses moved sidwards or even declined.
[Fig. 12 about here.]
[Fig. 13 about here.]

## 4 Closing remarks

This paper developed a time-varying parameter global VAR with stochastic volatility. We demonstrate the virtues of our approach by considering the changing international transmission of US based monetary policy shocks. Moreover, to shed some light on the question how the Fed responds to international shocks we also simulate four global shocks and investigate the response of the policy rate.

Our results may be summarized as follows. First, we find significant international spillovers with respect to US monetary policy that appear to be increasing over time. This effect is especially pronounced for output, exchange rates and interest rates. In addition, international responses of output are rather persistent, corroborating the findings in Feldkircher and Huber (2015a). Second, investigating the international dimension of US monetary policy reveals that the responses of the Fed with respect to global
inflation, short-term interest rate and exchange rate shocks have changed remarkably over time, all coinciding with periods of regime shifts of US fiscal- and monetary policy. Finally, investigating the volatility of exogenous shocks across the globe reveals that our model is capable of capturing several country-specific crises, thus providing enough flexibility in terms of modeling macroeconomic outliers.

As possible avenues of further research the introduction of shrinkage priors in the spirit of Frühwirth-Schnatter and Wagner (2010) could help to obtain more precise parameter estimates. More specifically since in the present contribution we set the same set of hyperparameters across countries, it might be important to allow for more flexibility along this dimension. Thus by using a hierarchical approach we could let the data inform us on how much shrinkage is needed at the country level.

## References

Binder, Michael and Marco Gross, "Regime-switching global vector autoregressive models," 2013.
Boivin, Jean, "Has U.S. Monetary Policy Changed? Evidence from Drifting Coefficients and Real-Time Data," Journal of Money, Credit and Banking, August 2006, 38 (5), 1149-1173.
Canova, Fabio, "The transmission of US shocks to Latin America," Journal of Applied Econometrics, 2005, 20 (2), 229-251.

- and Luca Gambetti, "Structural changes in the US economy: Is there a role for monetary policy?," Journal of Economic Dynamics and Control, February 2009, 33 (2), 477-490.

Carter, Chris K and Robert Kohn, "On Gibbs sampling for state space models," Biometrika, 1994, 81 (3), 541-553.
Christiano, Lawrence J, Martin Eichenbaum, and Charles L Evans, "Monetary policy shocks: What have we learned and to what end?," Handbook of macroeconomics, 1999, 1, 65-148.
Clarida, Richard, Jordi Galı, and Mark Gertler, "Monetary policy rules in practice: some international evidence," european economic review, 1998, 42 (6), 10331067.

Cogley, Timothy and Thomas J. Sargent, "Evolving Post-World War II U.S. Inflation Dynamics," in "NBER Macroeconomics Annual 2001, Volume 16" NBER Chapters, National Bureau of Economic Research, Inc, May 2002, pp. 331-388.
_ and Thomas J Sargent, "Drifts and volatilities: monetary policies and outcomes in the post WWII US," Review of Economic dynamics, 2005, 8 (2), 262-302.
Cuaresma, Jesús Crespo, Martin Feldkircher, and Florian Huber, "Forecasting with Bayesian Global Vector Autoregressive Models: A Comparison of Priors," Working Papers 189, Oesterreichische Nationalbank (Austrian Central Bank) March 2014.

Dees, Stephane, Filippo di Mauro, Hashem M. Pesaran, and L. Vanessa Smith, "Exploring the international linkages of the euro area: a global VAR analysis," Journal of Applied Econometrics, 2007, 22 (1).
_ , Sean Holly, Hashem M. Pesaran, and Vanessa L. Smith, "Long Run Macroeconomic Relations in the Global Economy," Economics - The Open-Access, Open-Assessment E-Journal, 2007, 1 (3), 1-20.
Dovern, J., M. Feldkircher, and F. Huber, "Does Joint Modelling of the World Economy Pay Off? Evaluating Multivariate Forecasts from a Bayesian GVAR," Working Paper 200/2015, OeNB 2015.
Dovern, Jonas and Björn van Roye, "International transmission and business-cycle effects of financial stress," Journal of Financial Stability, 2014, 13 (0), 1 - 17.
Des, Stphane, Hashem Pesaran, Vanessa Smith, and Ron P. Smith, "Supply, demand and monetary policy shocks in a multi-country New Keynesian Model," Working Paper Series 1239, European Central Bank September 2010.

Eichenbaum, Martin and Charles L. Evans, "Some Empirical Evidence on the Effects of Shocks to Monetary Policy on Exchange Rates," Quarterly Journal of Economics, November 1995, 110 (4), 975-1009.
Eickmeier, Sandra and Tim Ng, "How do credit supply shocks propagate internationally? A GVAR approach," Discussion Paper Series 1: Economic Studies 2011,27, Deutsche Bundesbank, Research Centre 2011.
Feldkircher, M., I. Moder, and F. Huber, "Towards a New Normal - How Different Paths of US Monetary Policy Affect World GDP," January 2015. Oesterreichische Nationalbank, mimeo.
Feldkircher, Martin and Florian Huber, "Changes in US Monetary Policy and its Transmission over the last Century," 2015. Oesterreichische Nationalbank, mimeo.
_ and _ , "The international transmission of US shocks - Evidence from Bayesian global vector autoregressions," European Economic Review, 2015, forthcoming.
Frühwirth-Schnatter, Sylvia, "Data augmentation and dynamic linear models," Journal of time series analysis, 1994, 15 (2), 183-202.
_ and Helga Wagner, "Stochastic model specification search for Gaussian and partial non-Gaussian state space models," Journal of Econometrics, 2010, 154 (1), 85-100.
Huber, Florian, "Density Forecasting using Bayesian Global Vector Autoregressions with Common Stochastic Volatility," Technical Report.
Kastner, Gregor and Sylvia Frühwirth-Schnatter, "Ancillarity-sufficiency interweaving strategy (ASIS) for boosting MCMC estimation of stochastic volatility models," Computational Statistics \& Data Analysis, 2013.
Kim, Soyoung, "International transmission of U.S. monetary policy shocks: Evidence from VAR's," Journal of Monetary Economics, October 2001, 48 (2), 339-372.
Lopes, Hedibert F, RE McCulloch, and RS Tsay, "Cholesky stochastic volatility," Technical Report 2011.
Omori, Yasuhiro, Siddhartha Chib, Neil Shephard, and Jouchi Nakajima, "Stochastic volatility with leverage: Fast and efficient likelihood inference," Journal of Econometrics, 2007, 140 (2), 425-449.
Peersman, Gert, "What caused the early millennium slowdown? Evidence based on vector autoregressions," Journal of Applied Econometrics, 2005, 20 (2), 185-207.
Pesaran, M. Hashem and Yongcheol Shin, "Generalized impulse response analysis in linear multivariate models," Economics Letters, January 1998, 58 (1), 17-29.
_ , Til Schuermann, and S. M. Weiner, "Modeling Regional Interdependencies Using a Global Error-Correcting Macroeconometric Model," Journal of Business and Economic Statistics, American Statistical Association, 2004, 22, 129-162.
Primiceri, Giorgio E, "Time varying structural vector autoregressions and monetary policy," The Review of Economic Studies, 2005, 72 (3), 821-852.
R Development Core Team, R: A Language and Environment for Statistical Computing R Foundation for Statistical Computing 2011. ISBN 3-900051-07-0.
Rodgers, David P, "Improvements in multiprocessor system design," in "ACM SIGARCH Computer Architecture News," Vol. 13 IEEE Computer Society Press

1985, pp. 225-231.
Rue, Håvard, "Fast sampling of Gaussian Markov random fields," Journal of the Royal Statistical Society: Series B (Statistical Methodology), 2001, 63 (2), 325-338.
Sahay, Ratna, Vivek Arora, Thanos Arvanitis, Hamid Faruqee, Papa N'Diaye, Tommaso Mancini-Griffoli, and an IMF Team, "Emerging Market Volatility: Lessons from the Taper Tantrum ," Staff Discussion Note, IMF SDN/14/09, International Monetary Fund 2014.
Sims, Christopher A. and Tao Zha, "Were There Regime Switches in U.S. Monetary Policy?," American Economic Review, 2006, 96 (1), 54-81.
Taylor, John B., "Discretion versus policy rules in practice," Carnegie-Rochester Conference Series on Public Policy, December 1993, 39 (1), 195-214.
_ , "The Monetary Transmission Mechanism and the Evaluation of Monetary Policy Rules," in Norman Loayza, Klaus Schmidt-Hebbel, Norman Loayza (Series Editor), and Klaus Schmidt-Hebbel (Series, eds., Monetary Policy: Rules and Transmission Mechanisms, Vol. 4 of Central Banking, Analysis, and Economic Policies Book Series, Central Bank of Chile, July 2002, chapter 2, pp. 021-046.

Table 1: Country coverage of GVAR model

| Europe | Other Developed | Emerging Asia | Latin America | Mid-East and Africa |
| :--- | :--- | :--- | :--- | :--- |
| Austria (AT) | Australia (AU) | China (CN) | Argentina (AR) | Turkey (TR) |
| Belgium (BE) | Canada (CA) | India (IN) | Brazil (BR) | Saudi Arabia (SA) |
| Germany (DE) | Japan (JP) | Indonesia (ID) | Chile (CL) | South Africa (ZA) |
| Spain (ES) | New Zealand (NZ) | Malaysia (MY) | Mexico (MX) |  |
| Finland (FI) | United States (US) | Korea (KR) | Peru (PE) |  |
| France (FR) |  | Philippines (PH) |  |  |
| Greece (GR) | Singapore (SG) |  |  |  |
| Italy (IT) | Thailand (TH) |  |  |  |
| Netherlands (NL) |  |  |  |  |
| Portugal (PT) |  |  |  |  |
| Denmark (DK) |  |  |  |  |
| Great Britain (GB) |  |  |  |  |
| Switzerland (CH) |  |  |  |  |
| Norway (NO) |  |  |  |  |
| Sweden (SE) |  |  |  |  |
| Notes: ISO-2 country codes in parentheses. Empirical results shown for coun- |  |  |  |  |
| tries in bold. |  |  |  |  |

Fig. 1: Volatility of GDP growth


Fig. 2: Volatility of Inflation


Notes: The plots depict the posterior mean of standardized volatility across regions over the estimation sample

Fig. 3: Volatility of short-term interest rates


Notes: The plots depict the posterior mean of standardized volatility across regions over the estimation sample

Fig. 4: Volatility of real exchange rates


Notes: The plots depict the posterior mean of standardized volatility across regions over the estimation sample.

Fig. 5: US short-term interest rate responses to global shocks


Notes: The plots depict the posterior mean response (in basis points) of the short-term interest rates with respect to the four global shocks defined in the text over time. Results are based on 500 posterior draws.

Fig. 6: Output responses to a 50 basis point (bp) monetary policy shock in the USA


Notes: The plots show the posterior for selected countries along with the cross-country means (in red) and associated $25 \%$ and $75 \%$ credible sets (in orange). Responses are based on 500 posterior draws, shown for three distinct horizons, namely after one quarter $(t=1)$, after 8 quarters $(t=8)$ and after 12 quarters $(t=12)$.

Fig. 7: Output responses to a 50 basis point (bp) monetary policy shock in the USA


Notes: The plots show the posterior for selected countries along with the cross-country means (in red) and associated $25 \%$ and $75 \%$ credible sets (in orange). Responses are based on 500 posterior draws, shown for three distinct horizons, namely after one quarter $(t=1)$, after 8 quarters $(t=8)$ and after 12 quarters $(t=12)$.

Fig. 8: Inflation responses to a +50 basis point (bp) monetary policy shock in the USA


Notes: The plots show the posterior for selected countries along with the cross-country means (in red) and associated $25 \%$ and $75 \%$ credible sets (in orange). Responses are based on 500 posterior draws, shown for three distinct horizons, namely after one quarter $(t=130$ after 8 quarters $(t=8)$ and after 12 quarters $(t=12)$.

Fig. 9: Inflation responses to a +50 basis point (bp) monetary policy shock in the USA


Notes: The plots show the posterior for selected countries along with the cross-country means (in red) and associated $25 \%$ and $75 \%$ credible sets (in orange). Responses are based on 500 posterior draws, shown for three distinct horizons, namely after one quarter $\left(t=131^{3}\right.$ after 8 quarters $(t=8)$ and after 12 quarters $(t=12)$.

Fig. 10: Short-term interest rate responses to a +50 basis point (bp) monetary policy shock in the USA


Notes: The plots show the posterior for selected countries along with the cross-country means (in red) and associated $25 \%$ and $75 \%$ credible sets (in orange). Responses are based on 500 posterior draws, shown for three distinct horizons, namely after one quarter $\left(t=132^{\text {after }} 8\right.$ quarters $(t=8)$ and after 12 quarters $(t=12)$.

Fig. 11: Short-term interest rate responses to a +50 basis point (bp) monetary policy shock in the USA


Notes: The plots show the posterior for selected countries along with the cross-country means (in red) and associated $25 \%$ and $75 \%$ credible sets (in orange). Responses are based on 500 posterior draws, shown for three distinct horizons, namely after one quarter $\left(t=133^{\text {after }} 8\right.$ quarters $(t=8)$ and after 12 quarters $(t=12)$.

Fig. 12: Real exchange rate responses to a +50 basis point (bp) monetary policy shock in the USA


Notes: The plots show the posterior for selected countries along with the cross-country means (in red) and associated $25 \%$ and $75 \%$ credible sets (in orange). Responses are based on 500 posterior draws, shown for three distinct horizons, namely after one quarter $\left(t=134^{\text {after }} 8\right.$ quarters $(t=8)$ and after 12 quarters $(t=12)$.

Fig. 13: Real exchange rate responses to a +50 basis point (bp) monetary policy shock in the USA


Notes: The plots show the posterior for selected countries along with the cross-country means (in red) and associated $25 \%$ and $75 \%$ credible sets (in orange). Responses are based on 500 posterior draws, shown for three distinct horizons, namely after one quarter $\left(t=135^{2}\right.$ after 8 quarters $(t=8)$ and after 12 quarters $(t=12)$.

## Appendix A Sampling from the posterior of the log volatilities

This appendix provides a brief overview of the MCMC algorithm put forward in Kastner and Frühwirth-Schnatter (2013).

We rewrite Eq. (2.5) as

$$
\begin{equation*}
A_{i 0, t}^{-1} y_{i t}-\left(I_{k_{i}} \otimes x_{i t}^{\prime}\right) \operatorname{vec}\left(\Psi_{i t}\right)=\tilde{y}_{i t}=D_{i t}^{\frac{1}{2}} u_{i, t} \tag{A.1}
\end{equation*}
$$

Here $u_{i, t} \sim \mathcal{N}\left(0, I_{k_{i}}\right)$ and $D_{i t}=\left(D_{i t}^{\frac{1}{2}}\right)^{\prime} D_{i t}^{\frac{1}{2}}$. Kastner and Frühwirth-Schnatter consider $\lambda_{i j, t}$ in its centered parametrization given in Eq. (2.8) and in its non-centered form given by

$$
\begin{equation*}
\ln \left(\tilde{\lambda_{i j, t}}\right)=\rho_{i j} \ln \left(\tilde{\lambda_{i j, t-1}}\right)+\epsilon_{i j, t} \text { for } j=1, \ldots, k_{i}, \tag{A.2}
\end{equation*}
$$

where $\epsilon_{i j, t}$ is a standard normal error term.
Let us consider the $j$ th equation of Eq. (A.1). Squaring and taking logs yields

$$
\begin{equation*}
\tilde{y}_{i j, t}^{2}=\ln \left(\lambda_{i j, t}\right)+\ln \left(u_{i j, t}^{2}\right) \text { for } j=1, \ldots, k_{i} \text {. } \tag{A.3}
\end{equation*}
$$

Since $\ln \left(u_{i, t}^{2}\right) \sim \log \chi^{2}(1)$, we follow Omori et al. (2007) and use a mixture of normal distribution to design the sampling procedure. This renders Eq. (A.3) conditionally Gaussian, i.e. $\ln \left(u_{i j, t}^{2} \mid r_{j, t}\right) \sim \mathcal{N}\left(m_{r_{i j, t}}, s_{r_{i j, t}}^{2}\right)$. The indicators controlling the mixture components prevailing at time $t$ are labeled as $r_{i j, t} \in\{1, \ldots, 10\} . m_{r_{i, t}}$ and $s_{r_{i j, t}}^{2}$ denote the mean and variance of the corresponding mixture normal component, respectively.

Conditional on $r_{i j, t}$, we can rewrite Eq. (A.3) as a (conditionally) Gaussian linear state space model,

$$
\begin{equation*}
\tilde{y}_{i j, t}^{2}=m_{r_{i j, t}}+\lambda_{i j, t}+\zeta_{i j, t}, \tag{A.4}
\end{equation*}
$$

where $\zeta_{i j, t} \sim \mathcal{N}\left(0, s_{r_{i j, t}}^{2}\right)$.
We simulate the history of $\log$ volatilities and the parameters of the state equation according to the following algorithm outlined in Kastner and Frühwirth-Schnatter (2013). The algorithm proceeds as follows:

1. Sample $\ln \left(\lambda_{i j,-1}\right) \mid r_{i j}, \mu_{i j}, \rho_{i j}, \varsigma_{i j}, \Psi_{i t}, A_{i 0, t}$ or $\ln \left(\tilde{\lambda}_{i j,-1}\right) \mid r_{i j}, \rho_{i j}, \zeta_{i j}, \Psi_{i t}, A_{i 0, t}$ all without a loop (AWOL). In the spirit of Rue (2001), it is possible to state $\ln \left(\lambda_{i j,-1}\right)=$ $\left(\ln \left(\lambda_{i j, 2}\right), \ldots, \ln \left(\lambda_{i j, T}\right)\right)^{\prime}$ in terms of a multivariate normal distribution

$$
\begin{equation*}
\ln \left(\lambda_{i j,-1}\right) \sim \mathcal{N}\left(\Omega_{\lambda_{i j}}^{-1} c_{i}, \Omega_{\lambda_{i, j}}^{-1}\right) \tag{A.5}
\end{equation*}
$$

In a similar fashion the distribution of the full state vector $\tilde{\lambda}_{i j,-1}=\left(\tilde{\lambda}_{i j, 2}, \ldots, \tilde{\lambda}_{i j, T}\right)$ is given by

$$
\begin{equation*}
\ln \left(\tilde{\lambda}_{i j,-1}\right) \sim \mathcal{N}\left(\tilde{\Omega}_{\lambda_{i j}}^{-1} \tilde{c}_{i}, \tilde{\Omega}_{\lambda_{i j}}^{-1}\right) \tag{A.6}
\end{equation*}
$$

Here the posterior moments are given by

$$
\Omega_{\lambda_{i j}}=\left(\begin{array}{ccccc}
\frac{1}{s_{r_{i j, 2}}}+\frac{1}{\varsigma_{i j}^{2}} & \frac{-\rho_{i j}}{\varsigma_{i j}^{2}} & 0 & \cdots & 0  \tag{A.7}\\
-\frac{\rho_{i}}{\varsigma_{i j}^{2}} & \frac{1}{s_{r_{i, 3}}^{2}}+\frac{1+\rho_{i j}}{\varsigma_{i}^{2}} & -\frac{\rho_{i j}}{\varsigma_{i j}} & \ddots & \vdots \\
0 & -\frac{\rho_{i j}}{\varsigma_{i j}^{2}} & \ddots & \ddots & 0 \\
\vdots & \ddots & \ddots & \frac{1}{s_{r_{i j, T-1}}^{2}}+\frac{1+\rho_{i j}}{\varsigma_{i j}^{2}} & \frac{-\rho_{i j}}{\varsigma_{i j}^{2}} \\
0 & \cdots & 0 & -\frac{\rho_{i j}}{\varsigma_{i j}^{2}} & \frac{1}{s_{r_{i j, T}}^{2}}+\frac{1}{\varsigma_{i j}^{2}}
\end{array}\right)
$$

and

$$
c_{i j}=\left(\begin{array}{c}
\frac{1}{s_{r_{i j, 2}}^{2}}\left(\tilde{y}_{i j, 2}^{2}-m_{r_{i j, 2}}\right)+\frac{\mu_{i j}\left(1-\rho_{i j}\right)}{\varsigma_{i j}^{2}}  \tag{A.8}\\
\vdots \\
\frac{1}{s_{r_{i j, T}}}\left(\tilde{y}_{i j, T}^{2}-m_{r_{i j, T}}\right)+\frac{\mu_{i j}\left(1-\rho_{i j}\right)}{\varsigma_{i j}^{2}}
\end{array}\right)
$$

The moments for the non-centered case are given by $\tilde{\Omega}_{i}=\varsigma_{i j}^{2} \Omega_{h_{i j}}$ and $\tilde{c}_{i j}=$ $\varsigma_{i j}^{2} c_{i j}$. The initial states of $\ln \left(\lambda_{i j, 1}\right)$ and $\ln \left(\tilde{\lambda}_{i j, 1}\right)$ are obtained from the respective stationary distributions.
2. Sample the parameters of the state equations for both parameterizations. Due to the lack of conjugacy of the prior setup outlined in the main body, we combine Gibbs steps with Metropolis Hastings (MH) steps. We employ simple MH steps for the parameters of the state equations in (2.8) and (A.3). In the centered parametrization case, we sample $\mu_{i j}$ and $\rho_{i j}$ jointly using a Gibbs step and $\varsigma_{i j}^{2}$ is updated through a simple MH step. For the non-centered parametrization, $\rho_{i j}$ is sampled by means of a MH step and the remaining parameters are obtained by Gibbs sampling.
3. Sample the mixture indicators through inverse transform sampling. Finally, the indicators controlling the mixture distributions employed are obtained by inverse transform sampling in both cases. This step can be implemented by noting that $\tilde{y}_{i j, t}^{2}-\ln \left(\lambda_{i j, t}\right)=\tilde{u}_{i j, t}$ with $\tilde{u}_{i j, t} \sim \mathcal{N}\left(m_{r_{i j, t}}, s_{r_{i j, t}}^{2}\right)$. Posterior probabilities for each $r_{i j, t}$ are then given by

$$
\begin{equation*}
p\left(r_{i j, t}=c \mid \bullet\right) \propto p\left(r_{i j, t}=c\right) \frac{1}{s_{i j, k}} \exp \left(-\frac{\left(\tilde{u}_{i j, t}-m_{i j, k}\right)}{2 s_{i j, t}^{2}}\right) \tag{A.9}
\end{equation*}
$$

where $p\left(r_{i j, t}=c\right)$ is the weight associated with the $c t$ component.
In the implementation of the present algorithm we simply draw the parameters under both parametrization and depending on the relationship between the innovation variances of Eq. (A.1) and Eq. (2.8) we decide ex-post whether we should discard draws obtained from the centered parametrization or keep them. This constitutes the
interweaving part of the algorithm. For further details we refer the reader to Kastner and Frühwirth-Schnatter (2013). ${ }^{7}$

## A. 1 Computational aspects

Since our sampling scheme treats countries and equations as isolated estimation problems, parallel computing can be exploited to carry out inference in the TVP-GVAR model. Such a modeling strategy proves to be an efficient means of estimating highdimensional GVARs with drifting parameters, while imposing parametric restrictions only on the international linkages that take place through the weakly exogenous variables.

More specifically the combination of the Cholesky structure in Eq. (2.2) and the presence of the weakly exogenous variables permit equation-by-equation and country-by-country estimation. This gives rise to an estimation strategy that relies heavily on parallel computation to obtain parameter estimates for Eq. (2.11). The first strategy views the GVAR model as a system of $k$ unrelated regression models, which can be spread across $c$ processors. In this strategy the maximum speedup gained by parallelization is given by

$$
\begin{equation*}
\text { Maximum Speedup }=\frac{1}{\frac{f}{c}+(1-f)} \tag{A.10}
\end{equation*}
$$

Here, $f$ denotes the fraction of the problem which can be parallelized. Eq. (A.10) is known as Amdahl's law (Rodgers, 1985) in computer science. If $f$ equals unity the task at hand is called embarassingly parallel, making it perfectly suitable for parallel computing. In the GVAR setting, $f$ is close to unity. We say close to unity since we also have to take into account the costs of distributing the information across the different processing units. In addition, it is worth emphasizing that since we impose a triangular structure on the model and the number of endogenous variables per country model differs (note that in general, $k_{i} \neq k_{j} \forall j, i$ ), the number of parameters differs from equation to equation. If we denote the number of parameters of each equation in a given country $i$ as $N_{i}=m_{i}+s_{i}$ ), with $s_{i j}$ being the number of free elements in the $j$ th row of $A_{i 0, t}$, a bottleneck arises because the maximum computation time is bounded by the time required to estimate the equation with the maximum number of parameters, $N^{*}=\max \left(N_{0}, \ldots, N_{k}\right)$. However, given the fact that $k_{i}$ is approximately of the same order for all $i$ and the maximum number of $m_{i}$ is $k_{i}-1$, with $k_{i}$ being of order four to six in the present application this is only a minor shortcoming of our approach.

So if the number of CPU cores $c$ equals $k$ estimation time almost boils down to estimating the equation with the maximum number of parameters $N^{*}$. After obtaining parameter estimates for all equations we simply have to perform the algebra outlined above to obtain the posterior distribution of the parameters in Eq. (2.11).

[^6]
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[^1]:    ${ }^{1}$ Binder and Gross (2013) propose a regime-switching GVAR structure to assess nonlinearities in the global transmission of shocks. However, as outlined above, the literature on US monetary policy finds rather gradual changes in the coefficients attached to US monetary policy rules and in the volatility of macroeconomic variables. This is in contrast to large one-off swings of coefficients and variances which are implied by regime-switching model. Other contributions have focused on stochastic volatility dynamics but do not address changes in coefficients (Dovern et al., 2015).

[^2]:    ${ }^{2}$ The assumption of a diagonal $D_{t}$ simplifies the computational burden of model estimation enormously, since the $k_{i}$ equations can be viewed as separate estimation problems and hence easily parallelized to achieve computational gains. See the Appendix for further details on the computation.

[^3]:    ${ }^{3}$ Further details of the sampling algorithm by Kastner and Frühwirth-Schnatter (2013) can be found in the Appendix.

[^4]:    ${ }^{4}$ For a more detailed description, consider ?? in Appendix ??.
    ${ }^{5}$ Note that recent contributions (Eickmeier and Ng, 2011; Dovern and van Roye, 2014) suggest using financial data to compute foreign variables related to the financial side of the economy (e.g., interest rates or credit volumes). Since our data sample starts in the early 1980s, reliable data on financial flows - such as portfolio flows or foreign direct investment - are not available. See the appendix of Feldkircher and Huber (2015b) for a sensitivity analysis with respect to the choice of weights.

[^5]:    ${ }^{6}$ Norway behaved qualitatively similar, but not quite as extreme as Sweden (not shown) where short rates were increase to 500 percent.

[^6]:    ${ }^{7}$ The steps described here are implemented using the stochvol package in R , a language and environment for statistical computing (R Development Core Team, 2011).

