International Evidence on Credit and Economic Activity*

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Abstract: We estimate a structural VAR on a balanced panel of 10 countries to examine different causal channels that lead to comovement between aggregate credit and GDP. Among all the six structural shocks in our model, we find that there is one that pushes aggregate credit up and then later depresses GDP growth, but its effects are small in most countries. All the other five structural shocks still generate positive or zero comovement between aggregate credit and GDP. The shocks in our model are identified via variation across countries in their relative size, with their global trend taken into account. We also model the dependence between initial conditions and country constants in our Bayesian estimation to avoid the small-T dynamic panel bias.

Keywords: impulse response function, structural vector autoregression, identification through heteroskedasticity, factor structure, dynamic panel. *JEL codes:* C11, C32, C33.

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1 Introduction

There has been longstanding arguments about whether credit expansion is good or bad for economic growth after 2008. Conventional wisdom usually regards a big credit-to-GDP ratio as a signal for output boost, when comparing income levels across countries. Classical textbooks also treat credit expansion as a measure of money stock expansion, which naturally boosts output under the Keynesian framework. On the contrary, the trauma from the Great Recession makes central bankers believe that disorderly credit expansion can be bad for the economy and thus emphasize the issue of debt sustainability ever since. When including data after 2008, many people provide evidence of damage from credit growth. It is interesting to figure out under what circumstances the credit expansion will be good or bad.

The contradictory findings between credit and GDP motivates a multiple-equation setup. The endogeneity among all the macroeconomic variables usually lead to having opposite reduced-form evidence when running a single-equation regression. The success of monetary structural VAR opens a door for distinguishing the opposite-sign causal relationship between macroeconomic variables, for example interest rate and inflation. Hence, the structural VAR setup has been be used in dis-tangling the different links between credit and GDP, and also examine their interaction with monetary policies, as in Brunnermeier et al. (2021). However, there are still not many papers discussing how to use structural VAR models in a cross-country dataset.

This paper tries to estimate a structural VAR to examine different causal channels that lead to comovement between aggregate credit and GDP. By using a balanced panel of 10 countries, we find that, among all the six structural shocks in our model, there is one that pushes aggregate credit up and then later depresses GDP growth, but its effects are small in most countries. All the other five structural shocks still generate positive or zero comovement between these two variables, in line with conventional thoughts. The shocks in our model are identified via variation across countries in the relative shock size, with the global trend of shocks taken into account and modeled as the global shock. In our Bayesian estimation framework, we also model the dependence between initial conditions and country constants to avoid the small-T dynamic panel bias.

This paper shows how to properly use a medium-scaled structural VAR model in a cross-country panel dataset. Our dataset covers 10 major economies for 25 years and includes 6 important macroeconomic variables. The model is specified parsimoniously to account for both the heterogeneity across countries and the common trend among them. Besides the country-level fixed effect, one key assumption in our model is the shock size varies across countries. We further split the shocks in each country into two components, i.e. global shocks and country shocks, to capture the global trend in the shock values, together with each country's idiosyncratic movement. In this way, we avoid the curse of dimensionality in the panel dataset, and explain rich dynamics within and across countries. To theoretically identify the model parameters, we utilize identification through heteroskedasticity in the cross-sectional dimension. Unlike Brunnermeier et al. (2021), this paper applies identification through heteroskedasticity when the shock size varies across countries, instead of varying across regimes in a specific country. Because each country has different loadings on the global shock and has different variances in their country shock, the impact matrix in our model can be theoretically point-identified following the scheme in Rigobon (2003).

Following the common routine in monetary structural VAR literature, our model is also estimated in a Bayesian framework. First, we impose conjugate prior on lag coefficients and country constants via dummy observation. Not only do we use the standard Minnesota prior as shrinkage for distant lag coefficients, but we also link the country constants with the initial conditions in each country's time series to avoid the dynamic panel bias in the lag coefficients. Second, we also directly impose dispersed non-conjugate prior on other parameters that we cannot derive the recognizable posterior distributions. Third, we optimize our MCMC algorithm to make posterior draws on a subset of the model parameters. In particular, we integrate out lag coefficients and country constants which have recognizable distribution densities, and then use Metropolis algorithm to draw the rest of the parameters that we cannot analytically integrate out.

In our main results, we analyze the comovement of aggregate credit and GDP growth, and also justify our model specification. We examine among all the six structural shocks in our model, and find that there is one shock coming from the real estate sector, which we label as real-estate shock, that leads to the unusual negative comovement of credit and GDP. However, the average effect of this shock is minimal compared to other sources of variation in credit and GDP. All the other structural shocks still generate the usual positive or zero comovement. This shows that the relationship we observe really depends on which structural shock is leading the variation in a certain period. We also present evidence of huge variation in the shock size across countries, from both the different loadings of global shocks and the different variances of country shocks, which helps to sharply identify our impact matrix. In addition, the global shock that we introduced into our model effectively captures the common trend in the shock terms from this cross-country panel dataset, without too complicated model parameterization.

We additionally run a few robustness checks for our main results. First, we twist the sample of countries and the sample periods to show that our main results are still preserved with another sample in the dataset. In particular, removing US from the sample does not change our main results, indicating it is reasonable to treat US as other countries in this panel VAR model. Second, we try to follow the convention in structural VAR to recursively define the shocks without using identification through heteroskedasticity, and we largely get the same results. This indicates that identification through heteroskedasticity introduces flexibility in specifying the impact matrix, without generating mysterious results at odds with the conventional methodology.

LITERATURE. Our empirical framework is inspired by Brunnermeier et al. (2021), which establishes a medium-scaled structural VAR on US data to study credit and GDP. That paper explores the different interactions of credit and GDP under different structural shocks, and noticed that the monetary policy can endogenously contribute to the negative comovement. Their model is also identified through heteroskedasticity, with the setup of multiple regimes in the US history. However, that paper only handles the time series data in the US, while our paper tries to extend the setup to the cross-country panel data and handle both the heterogeneity and the common trend across countries.

Numerous work has been proposed to find effects of credit growth in a cross-country panel data. Some old research work favors the traditional idea that credit expansion is good for the economy. Rajan & Zingales (1998) is one example showing the benefit of credit expansion in lowering financing cost of firms. However, the public opinion changed dramatically after 2008. Jordà et al. (2016) relies on a single-equation projection method in a long-run dataset to document the risk from the increased credit level. Mian et al. (2017) studies an unbalanced panel of 30 countries and find evidence for harmful household credit growth across countries. But their paper only sets up a reduced-form VAR model and did not try to model the global trend in the innovation terms. Thus, their conclusion is not exactly a causal interpretation of credit and GDP under different scenarios. Our paper tries to parsimoniously model the rich dynamics across countries and across time, and manage to provide a causal interpretation of comovement between credit and GDP.

The methodology for cross-country panel data has been long studied in the literature. Canova & Ciccarelli (2004) proposes a framework to stack multiple-country variables in a large-scaled VAR model. Because the curse of dimensionality quickly kicks in a large-scaled VAR model, researchers need to make some effort in specifying hierarchical prior to solve the problem. From a different perspective, Pesaran et al. (2004) tries to model the interdependence across countries by running a bunch of country-level VARX models, with the weighted average of foreign variables appearing in the equation as exogenous variables. However, the two step estimation routine of their framework makes it unfeasible to write a internally consistent likelihood formula to analyze the model parameters. In addition, neither of these two papers tries to explore the special issue of structural VAR modeling framework in a cross-country panel setup, i.e. the common trend across countries. We take a stance similar to Stock & Watson (2005) to build the factor structure in the error terms, to characterize the common trend across countries. But instead of only using output data across countries as in their paper, we try to build a model for six variables across countries and try to identify a structural VAR model. Although one can simply follow the conventional tricks to transform reduced-form VAR to structural form, such as running Cholesky decomposition on the variance-covariance matrix of the innovations, our paper tries to utilize the features of this panel data to more flexibly identify the structural parameters, while keeping the model parameterization parsimonious.

This paper also uses the existing tools from the literature of dynamic panel estimation. Since our model has the country constants like the fixed-effect model, and also has a small sample size like any typical macro dataset, the bias presented by Nickell (1981) is a valid concern. One solution, as shown in Sims (2000), is to model dependency of initial conditions with the fixed-effect constants, as the cross-sectional dimension grows. To model this dependency, one good example is to specify the correlated random effect as Liu (2022), in which the constants are assumed to have a linear relationship with initial conditions.[1] However, in order to easily add dummy observations, we follow the dummy observation representation of the cointegration prior (Sims & Zha, 1998), to model the initial conditions being centered around the implied mean of the model.

Outline. Section 2 describes the dataset and the model specification, together with the identification scheme in theory. Section 3 explains the steps in our Bayesian estimation procedures. Section 4 presents our main results regarding comovement of credit and GDP, variation in the shock size across countries, and benefits of having global shocks. Section 5 lists a few robustness checks that we experiment to show the robustness of our main results.

[1] One can derive the dummy observation representation for correlated random effects, but we avoid using this complicated dummy observation representation in order to make our model specification clear.

Section 6 concludes the main contributions of this paper and offers guidance for future research.

2 Data and model

This section presents the data and the model that we use in this paper. The details of the data, including the macroeconomic variables and the countries that we select, are listed in Section 2.1. We discuss the specification of our structural VAR model, which incorporates global shocks and country shocks, in Section 2.2. In terms of model identification, our identification through heteroskedasticity is illustrated in Section 2.3.

2.1 Data

We use a balanced panel of 10 countries, each with quarterly observations of 6 important macroeconomic variables.

Our dataset incorporates time series across countries in the BIS database and the IMF database. To get a long time series in a balanced panel, we focus on 10 countries with the highest data availability: Australia (AU), Canada (CA), Denmark (DK), United Kingdom (GB), Israel (IL), Japan (JP), Norway (NO), New Zealand (NZ), Sweden (SE), and United States (US). For each country, we gather the data of household credit, policy rate and property price index from the BIS website, and collect the data of GDP, GDP deflator from the IMF website. Moreover, we collect US commodity price index from FRED and adjust the US commodity price by each country's spot exchange rate to get each country's commodity price. In our balanced panel dataset that we finally use, we construct the variables of real property price, real GDP growth, policy rate, GDP deflator, commodity price, household credit in each country from 1995:Q1 to 2019:Q4.[2]

As an illustrative example, the historical paths of household credit in these 10 countries are showed in Figure 1. We can see there are huge discrepancies across countries. For example, Japan (JP) had credit contraction after 2000, US had a large credit decline after 2008, but most other countries have a upward-sloping path. The rich heterogeneity in credit paths can help us generalize our results to different country scenarios.

[2]When we feed the data into our model, we use policy rate with its decimal numbers, and use all the other variables with its logarithm.

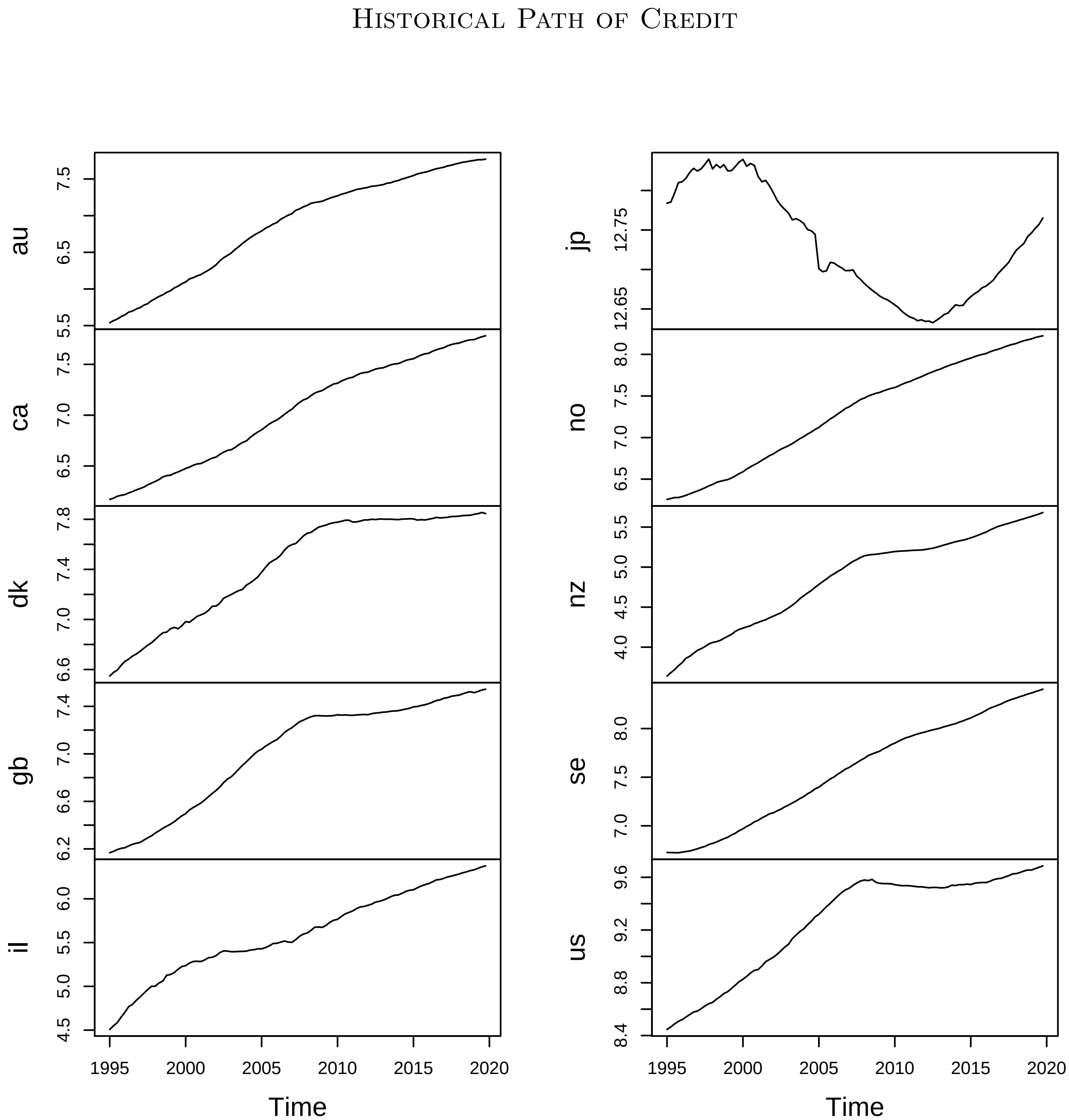

Figure 1: We collect the total household credit of each country in its domestic currency (billions). Each credit variable in our model is taken the logarithm of their levels.

2.2 Model specification

Our structural VAR model is specified parsimoniously to count for both the heterogeneity across countries and the global trend in shocks.

Consider country i's variables follow a structural VAR model:

$$Ay_{it} = c_i + B(L)y_{i,t-1} + \nu_{it}, i = 1, 2, \cdots, n, t = 1, 2, \cdots, T, \tag{1}$$

where y_{it} is a vector including $m = 6$ variables for country i at time t. All the countries share the slope coefficient $B(L)$ with $p = 8$ lags, but they have different country constants c_i. The shock term ν_{it} also contains $m = 6$ elements, i.e. $\nu_{it} = (\nu_{it}^1, \cdots, \nu_{it}^m)'$.[3] Particularly in the panel setup, we can expect some global trend in the shock term ν_{it}^j across i in each equation j at each time t, and thus the shock term ν_{it}^j can be further modeled with two components as:

$$\nu_{it}^j = \Gamma_i^j f_t^j + \eta_{it}^j, \tag{2}$$

where f_t^j is a 1-dim global shock in this factor representation and η_{it}^j is a 1-dim country shock.[4] As in any standard factor model, Γ_i^j is the country i's loading on the global shock f_t^j. We can stack the shocks across multiple equations in country i as:

$$\underbrace{\begin{bmatrix} \nu_{it}^1 \\ \vdots \\ \nu_{it}^m \end{bmatrix}}_{\nu_{it}} = \underbrace{\begin{bmatrix} \Gamma_i^1 & & \\ & \ddots & \\ & & \Gamma_i^m \end{bmatrix}}_{\Gamma_i} \underbrace{\begin{bmatrix} f_t^1 \\ \vdots \\ f_t^m \end{bmatrix}}_{f_t} + \underbrace{\begin{bmatrix} \eta_{it}^1 \\ \vdots \\ \eta_{it}^m \end{bmatrix}}_{\eta_{it}}, \tag{3}$$

which clearly illustrates the factor structure in ν_{it}.

For the shock distribution, we assume:

$$\begin{aligned} f_t^j &\overset{\text{iid}}{\sim} \mathcal{N}(0, 1), \forall t, j, \\ \eta_{it}^j &\overset{\text{iid}}{\sim} \mathcal{N}(0, (\Lambda_i^j)^2), \forall i, t, j, \end{aligned} \tag{4}$$

[3] To clearly distinguish the equation index j with the country index i and time index t, this paper always uses a superscript for the equation index j.

[4] To stay in line with the setup of VAR literature, we assume one global shock and one country shock per equation. However, it is possible to extend our setup to include multiple global shocks and one country shock per equation.

which indicates all the shocks in (2) are orthogonal to each other, independent across time, and thus have causal interpretation. Only the shocks in (2) are called as structural shocks in our model, in which the global shock captures the synchronized trend in ν_{it}^j across i, and the country shock represents the idiosyncratic source of variation. Note that in (4), f_t^j is normalized to have standard deviation of 1, and η_{it}^j is normalized to have an average standard deviation of 1 across countries, i.e. $\frac{1}{n}\sum_i \Lambda_i^j = 1$. For simplicity, we also use the aggregate notation $\Lambda_i = \text{diag}(\Lambda_i^1, \cdots, \Lambda_i^m)$.[5]

2.3 Identification

The way we identify our structural VAR model is mainly through variation of the shock size across countries, with both global shocks and country shocks taken into account.

The identification of the impact matrix A is the key problem in any structural VAR model, and we identify it in a flexible way via the identification through heteroskedasticity. Unlike imposing recursive ordering and force some elements in A to be zero, we allow all the elements in A to be non-zero. Our identification scheme works when the shock size varies a lot across countries, including both the loaded global shock and the idiosyncratic country shock. By assuming the same impact matrix A in (1), the variation of the shock size can help distinguish different structural shocks in different equations of (1).

Now we explain how the identification through heteroskedasticity works in our model setup. Consider the reduced-form innovation of y_{it} and define the variance-covariance matrix of reduced-form innovation as:

$$\Sigma_i = \text{Var}(y_{it}|y_{i,(t-\infty):(t-1)}) = \text{Var}(A^{-1}\nu_t) = A^{-1}\,\text{Var}(\nu_{it})A^{-1'}, \tag{5}$$

Moreover, we can further derive the variance of ν_{it} from (3),

$$\text{Var}(v_{it}) = \text{Var}(\Gamma_i f_t + \eta_{it}) = (\Gamma_i)^2 + (\Lambda_i)^2, \tag{6}$$

where $\text{Var}(v_{it})$ clearly has a diagonal structure due to the same structure in Γ_i and Λ_i, and it corresponds to the structural definition of the global shocks and the country shocks.

Finally, we can follow the technique of identification through heteroskedasticity by applying eigenvalue decomposition. where Σ_i is supposed to be identified directly from the data,

[5] For simplicity, we later also use the aggregate notation Λ, Γ, c to denote the corresponding set of Λ_i, Γ_i, c_i across i.

as one part of the reduced-form specification. After we collect $\{\Sigma_i\}_{i=1}^n$ across countries, we will notice that for any two countries i_1 and i_2:

$$\Sigma_{i_1}^{-1}\Sigma_{i_2} = A'((\Gamma_{i_1})^2 + (\Lambda_{i_1})^2)^{-1}((\Gamma_{i_2})^2 + (\Lambda_{i_2})^2)A^{-1'}, \tag{7}$$

which pins down the impact matrix A by computing eigenvalue decomposition.[6]

Once we pin down the elements in A, which equivalent pins down the definition of structural shocks in each equation, the rest of the parameters can also be identified using conventional routines. First, the reduced-form specification together with the identified A can identify the slope coefficient $B(L)$ and the country constants c_i. Second, with the identified A, we can back out the shock term ν_{it} and then identify Γ_i and Λ_i as the factor loading and idiosyncratic variance from standard factor models.

3 Estimation procedure

This section explains our Bayesian estimation procedure in this paper. In Section 3.1, we show the technique of using dummy observations as a convenient way to impose prior on autoregressive coefficients and country constants. We also discuss other priors we directly impose on the rest of the parameters that we cannot analytically integrate out in Section 3.2. The brief outline of our MCMC algorithm for making posterior draws is listed in Section 3.3.

3.1 Dummy observations

As a way to apply shrinkage and express prior belief, we use dummy observations to govern the prior of the slope coefficients and the country constants.

The prior on the slope coefficients and the country constants is conditional on A, Γ_i and Λ_i, and thus can be viewed as handling the shrinkage on the reduced-form specification of each equation. Following Sims & Zha (1998), we use three types of dummy observations for each country i:

[6] This identification scheme still pins down up to relabeling of rows, as the literature has noticed. But following Brunnermeier et al. (2021), we impose a dispersed prior on A to nudge the main diagonal of A to be larger than the off diagonal, in order to get around of the relabeling issue.

1. Cointegration: one dummy observation[7]

$$\lambda_1 \cdot A\bar{y}_i = \lambda_1 \cdot c_i + \lambda_1 \cdot \sum_{l=1}^{p} B_{\cdot,\cdot,l}\bar{y}_i + \nu_{i,t_1^*}, \tag{8}$$

where the initial condition denotes $\bar{y}_i = \frac{1}{p}\sum_{l=1}^{p} y_{i,1-l}$, which captures the initial levels of country i's variables.[8] The usage of this cointegration prior can model the dependence between country constants and initial conditions, and can thus address the dynamic panel bias as shown in Sims (2000).[9]

2. Single unit-root: one dummy observation for each variable j

$$\lambda_2 \cdot A(\bar{y}_i \circ e_j) = \lambda_2 \cdot \sum_{l=1}^{p} B_{\cdot,\cdot,l}(\bar{y}_i \circ e_j) + \nu_{i,t_2^*}, \tag{9}$$

where $\circ$ means element-wise product and e_j means a zero vector only with 1 in index j, i.e. we are selecting the j-th element of a vector.

3. Minnesota (random-walk) prior: one dummy observation for each lag l of each variable j

$$\begin{aligned} \lambda_{31} \cdot A(\hat{\sigma} \circ e_j) &= \lambda_{31} \cdot B_{\cdot,\cdot,1}(\hat{\sigma} \circ e_j) + \nu_{i,t_3^*}, \quad \text{if } l = 1, \\ 0 &= \lambda_{31} l_{32}^{\lambda} \cdot B_{\cdot,\cdot,l}(\hat{\sigma} \circ e_j) + \nu_{i,t_3^*}, \quad \text{if } l > 1, \end{aligned} \tag{10}$$

where $\hat{\sigma}$ is a rough estimate of the standard deviation of the reduced-form residuals in the VAR model on y_{it}.

When imposing these dummy observations as the prior, we need to tune the hyper-parameters to control the tightness of the prior. Here we select $\lambda_1 = 0.2/\sqrt{m}$, $\lambda_2 = 0.2/\sqrt{m}$, $\lambda_{31} = 0.1/\sqrt{m}$ and $\lambda_{32} = 1$, to keep the prior reasonably loose and control the magnitude of the residuals in these dummy observations. Since we add these three types of dummy observations for each country i, the division by $\sqrt{m}$ in these hyper-parameters makes sure that we are not going to impose a tighter and tighter prior as the number of countries m

[7]Here one dummy observation means one set of variable values in the multiple-equation system as in (1).

[8]We use t^* to denote the auxiliary time index in dummy observations.

[9]Although our dataset has 10 countries and 100 real observations for each country, which is not similar to the usual "big n small T" setup in panel data, the bias from the dynamic panel is still a valid concern given any finite T.

grows.

In this way, we construct the above-mentioned set of dummy observations for each country and model the country constants with their initial conditions. The dummy observation of cointegration penalizes the country constant if it implies a steady state too far away from the initial conditions, since those cases occur when the huge bias of the country constants kicks in to mechanically use the mean-reversion trend to fit the persistent time series. This is a special concern in dynamic panel data, since we have a lot of country constants and the time span is not extremely long.

3.2 Other priors on parameters

In addition to dummy observations, we also impose other priors directly on parameters A, Λ_i, Γ_i.

Since it is difficult to derive a recognizable posterior distribution for A, Λ_i, Γ_i in (1) - (2), we directly use non-conjugate prior for these parameters. For each element in A, we use a Gaussian prior:

$$p(A_{jk}) = \mathcal{N}(1\{j = k\} \cdot 100, 200^2), \tag{11}$$

where the dispersed prior slightly push the diagonal of A to the positive region and to be slightly larger than the off diagonal, in order to get around the well-known relabeling issue of A. For Λ_i, given the normalization of having its average equal to 1 across i, we impose a scaled Dirichlet prior on Λ_i in each equation j:

$$p(\Lambda_1^j, \cdots, \Lambda_n^j) \propto \mathrm{Dir}(2, \cdots, 2). \tag{12}$$

Finally for Γ_i, we use a truncated Gaussian prior. However, to avoid introducing sharp discontinuity in the posterior density, we first use a untruncated Gaussian prior for Γ in each equation j to make posterior draws, and then later map the draws to the target region where the average of Γ_i in each equation j are normalized to be positive:

$$p(\Gamma_1^j, \cdots, \Gamma_n^j) \propto \mathcal{N}(0, 1), \quad \text{if } \frac{1}{n}\sum_{i=1}^{n} \Gamma_i^j > 0 \tag{13}$$

Here the prior on Γ indicates that ex ante we expect the global shock component is as large as the country shock component for an average country. All the prior has been set to be relatively dispersed to cover the possible range of parameter values.

3.3 MCMC algorithm

We set up a MCMC algorithm, which fully utilizes the structure of this model, to make posterior draws. There are two parts in evaluating the posterior distribution for our MCMC algorithm:

1. Integrate out the parameters with recognizable posterior distribution, i.e. integrating c_i and $B(L)$ given A, Λ_i and Γ_i,[10]

$$p(Y|A,\Lambda,\Gamma) = \int_{c,B} p(c, B(L)|A,\Lambda,\Gamma) \cdot p(Y|c, B(L), A, \Lambda, \Gamma) \cdot dc \cdot dB, \tag{14}$$

   Since it is to verify the posterior distribution of c_i and $B(L)$ given other parameters is Gaussian, we can easily integrate out c_i and $B(L)$ to get the marginal likelihood for A, Λ, Γ.[11]

2. Directly evaluate posterior for parameters that cannot be integrated out,

$$p(A,\Lambda,\Gamma|Y) \propto p(A)p(\Lambda)p(\Gamma)p(Y|A,\Lambda,\Gamma), \tag{15}$$

   where $p(Y|A,\Lambda,\Gamma)$ is obtained from (14).

To make the MCMC algorithm computationally efficient, we apply Metropolis method on (15) to only draw A, Λ, Γ. We execute a long MCMC series for these three parameters, and then later draw c and $B(L)$ given these three parameters from a Gaussian posterior when analyzing impulse responses and shock sizes. Our MCMC algorithm generates 100,000 draws, from which we later thin to keep only 100 draws for the inference results. Further details are discussed in Appendix A.

4 Main results

This section presents the main results from estimating our structural VAR model. The comovement between credit and GDP, under scenarios of different structural shocks, are

[10] For simplicity, we also use the aggregate notation of Λ, Γ, c to denote the set of Λ_i, Γ_i, c_i across i.

[11] We denote all the real observations as Y, and all the dummy observations as Y^* in our illustration.

Posterior Modal Estimate of Impact Matrix

	real property	real GDP	policy rate	commodity price	GDP deflator	household credit
real-estate shock	92.94	-1.11	0.08	2.57	0.46	-1.00
output shock	-1.99	105.35	-0.93	0.37	0.79	-0.50
monetary shock	-0.58	-1.30	105.54	0.14	-0.40	-0.44
commodity shock	3.83	0.81	0.26	31.94	-2.95	-0.09
price shock	2.88	2.14	-0.33	-1.26	103.43	-0.47
credit shock	-3.47	-1.08	-0.32	0.36	-1.25	105.05

Table 1: Each row represents one equation in our model.

described in Section 4.1. We also compare the shock size across different countries, in terms of their loaded global shocks and their idiosyncratic country shocks, as in Section 4.2. Furthermore, we show the benefits of including global shocks into our model in Section 4.3.

4.1 Comovement of credit and GDP

We analyze the comovement of credit and GDP, with the occurrence of different structural shocks, to unveil the various causal channels underlying the documented relationship.

Since we identify the impact matrix through heteroskedasticity, we allow all the elements of our impact matrix to be non-zero. Our estimate of A at the posterior peak is presented in Table 1. The impact matrix has small entries off-diagonal, capturing the small correlations across variables. Its main-diagonal entries are much larger, and thus we label the shocks in line with the variable names.

We document the impulse responses of credit and GDP, together with other included macroeconomic variables, as in Figure 2. Since we have six equations, we will have six types of structural shocks, where each type has its global shock component and its country shock component. Here we examine the responses when an average country has a one-standard-deviation move for each type of structural shocks, where its standard deviation includes the variation of both its global shock component and its country shock component, in order to demonstrate which type of shocks explains most of the variation for most countries.

Across all the six structural shocks, we find the shock from the real estate sector largely drives the negative comovement of credit and GDP. Here, since the first shock in Figure 2 pushes up the property price a lot, we can thus label the first shock as the real-estate shock. This real estate shock generates an increasing trend in credit, but the response of GDP is hump-shaped, with a negative GDP growth rate after 1 year. In addition, we note that the policy rate endogenously rises shortly after this real-estate shock, which contributes to this negative relationship. This seems the only exceptional pattern across all the impulse responses, because all the other five structural shocks are either generating positive comovement or no comovement between credit and GDP, which matches the convectional opinions before 2008. For example, the monetary policy shock (the third shock in Figure 2) will lower GDP and credit at the same time, which is the typical effect of monetary tightening.

The exceptional negative relationship explains the puzzle in contradictory opinions about credit growth. First, the shocks coming from different sectors will lead to different comovement, and the real estate shock plays an important role whenever we observe bad effects of credit growth. Second, the magnitude of variation caused by this real estate shock is small, compared to other sources of variation in credit and GDP, which explains why we did not collect much evidence on bad credit growth before 2008. Third, it is noteworthy that the monetary policy rate endogenously responds to the real estate shock, which drives down GDP after 1 year. Any analysis omitting this endogenous interaction might lead to puzzling conclusions.

4.2 Size of global shocks and country shocks

We show that there is huge heterogeneity in the shock size across countries, in terms of both the global shock component and the country shock component.

First, we present the size of idiosyncratic country shocks, i.e. the posterior peak value of Λ, as in Table 2. We notice that the second shock, i.e.output shock, has similar sizes across countries. On the contrary, the third shock, i.e. monetary policy shock, is more than 100 times larger in some countries than the others.

Now we turn to each country's loading on the global shock, i.e. the posterior peak value of Γ, as shown in Table 3. First, most countries have positive loadings, which means they follow the global trend in the same direction. This coincides with our usual observations that the world economy comoves together. Second, a certain country can follow the global trend in the shock, and go against the global trend in the other shock. For example, Canada (CA) has big positive loadings on shock 4 (global commodity shock) and shock 5 (global

Impulse Responses under Average Shock Size

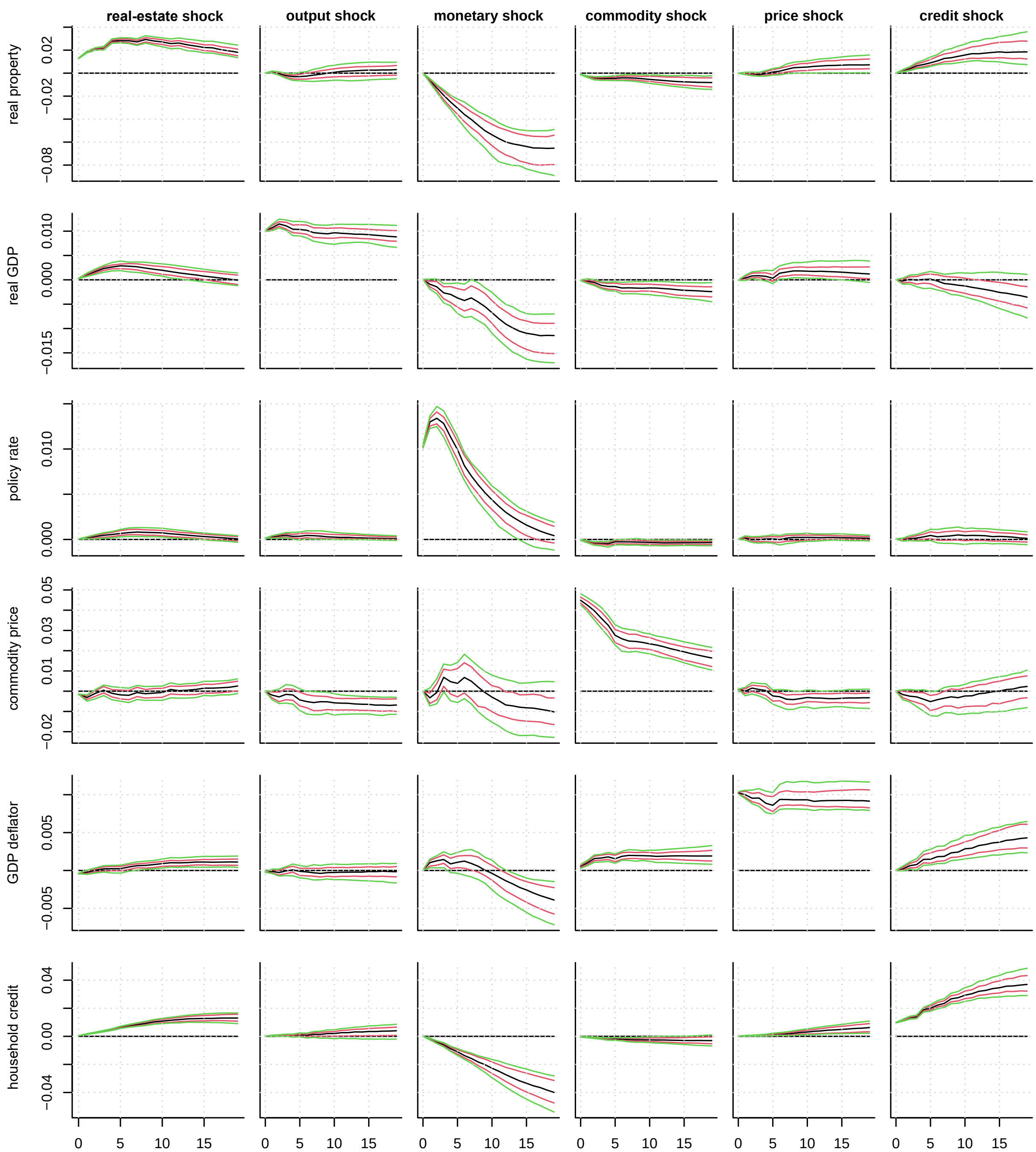

Figure 2: The 68% and 90% credible bands are plotted in red and in green. We feed in a one-std shock (including both variation of global and country shocks) for each type of structural shock in an average country, which equals to the average shock size across countries.

Posterior Modal Estimate of Standard Deviation in Country Shock

	AU	CA	DK	GB	IL	JP	NO	NZ	SE	US
real-estate shock	1.22	1.11	1.14	0.03	1.14	0.83	1.54	1.01	1.21	0.76
output shock	0.54	0.48	0.82	0.35	0.88	1.09	3.59	1.02	0.76	0.48
monetary shock	0.24	0.25	0.28	0.19	7.39	0.07	0.45	0.60	0.21	0.32
commodity shock	1.30	0.90	0.78	1.00	0.93	2.02	0.94	1.38	0.09	0.66
price shock	0.83	0.79	0.54	0.75	1.07	0.34	4.00	1.05	0.50	0.12
credit shock	0.57	0.49	1.01	0.52	5.04	0.73	0.25	0.47	0.25	0.67

Table 2: Each row is normalized to have average of 1, in order to pin down the scale of each structural equation.

price shock), but big negative loading on shock 6 (global credit shock). Third, across all the different shocks, shock 4 (global commodity shock) has the largest cross-country linkages. Since shock 4 (commodity shock) is mainly from the commodity market, it makes sense to have strong synergy in this shock, given the integration of the global commodity market and the way in which we construct each country's commodity price index.

We can now compare the variation of shock sizes in each country's global shock component and country shock component. Figure 3 compares the standard deviation of the global shock component and country shock component across countries. We pick the real-estate shock and monetary policy shock here as two illustrative examples (See Appendix B for this comparison in other shocks). First, we notice huge variation in contribution of global shocks vs. country shocks. For example, GB's real-estate shocks relies heavily on the global trend, while IL's monetary policy shocks are mostly idiosyncratic. Second, the importance of the global trend differs across types of shocks. For most countries, the global trend plays a limited role for real-estate shocks, while the global trend imposes a stronger synergy in monetary policy shocks. Third, there is no clear pattern showing the complementary or substitution between the global component and country component, because we do not see the standard deviation of these two components always moving in the same or opposite direction.

Posterior Modal Estimate of Loading on Global Shock

	AU	CA	DK	GB	IL	JP	NO	NZ	SE	US
real-estate shock	0.37	0.06	0.40	1.53	0.11	-0.03	0.28	-0.13	0.41	0.14
output shock	-0.04	0.23	0.28	0.19	0.39	0.44	0.03	-0.04	0.44	0.22
monetary shock	0.26	0.23	0.17	0.33	0.23	0.02	0.29	0.19	0.30	0.24
commodity shock	0.99	0.49	1.28	0.73	0.51	0.42	1.15	1.03	1.50	0.01
price shock	0.41	0.44	0.21	0.05	-0.21	-0.25	0.73	0.12	0.00	0.06
credit shock	0.11	-0.12	-0.36	-0.01	0.17	0.02	0.12	0.19	-0.07	0.06

Table 3: Each row is normalized to have average above 0, in order to uniquely pin down the sign of global shocks.

Standard Deviation of Global & Country Shock Component

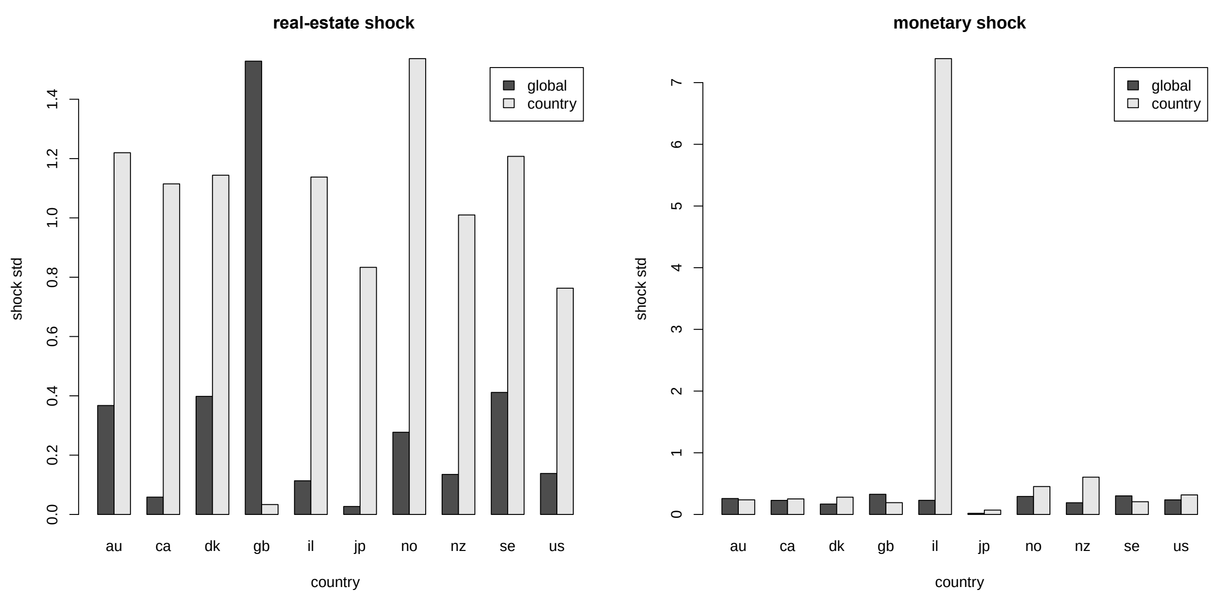

Figure 3: This bar plot shows the standard deviation of the global shock component and country shock component across countries. The standard deviation of global shock component is the absolute value of Γ. The standard deviation of country shock component, i.e. Λ, is normalized to have an average of 1 across countries.

4.3 Comparison with and without global shocks

Including global shocks brings many benefits into our model, including describing the global trend, identifying the model, and improving the model fit.

We document the time series of implied global shock, as in Figure 4. Here we consider both the uncertainty from the model parameters and from the latent shocks. In our specification, the global shock can be interpreted as contemporaneous spillover of shocks across countries. For example, central banks will decide the policy rate next period and introduce some unexpected surprise across time. But when they are in the process of determining the policy rate for next period, they might have meetings with other central banks to communicate, and thus create some global trend in the monetary policy shock next period, which is captured by the global monetary policy shock listed in the graph. After taking out the global trend, the remaining variation in each country's monetary policy is supposed to be idiosyncratic. We plot the country shocks of monetary policy as an example in Figure 5. Across countries, we no longer see dramatic dips in the country shocks of monetary policy around 2008, because the common dip is interpreted as a global shock, and the idiosyncratic deviation from this common dip will show up as the country shock. Thus, most of the common trend across countries has been absorbed into the global shock component, leaving the country shock component closer to being orthogonal.[12]

Introducing the global shock into our model has multiple benefits. First, it explicitly models the global component and country component in the shock terms, and effectively captures the global trend. This preserves the causal interpretation in our structural model, because we can now discuss the response of either a global shock or a country shock, without worrying the synergy of shocks across countries. Second, the global shock brings another layer of shock size variation across countries. As we have seen in Section 4.2, the loadings on the global shock in each country vary dramatically, which can help the identification scheme to work in addition to the variations in sizes of country shocks, as we can rely on both the change of Γ_i and Λ_i in (7). Third, the goodness of model fit mildly increases after the usage of global shocks, indicating it is crucial to specify the right cross-country correlation structure to fit the data. Table 4 lists the logarithm of marginal data density using models

[12]Here we cannot expect the orthogonality to be perfect, because the model specification is still parsimonious and cannot fully interpret every correlation across countries. As shown in Appendix C, if we impute the country shocks of monetary policy at the posterior peak and compute the correlation matrix, we can still find a few big correlations. However, compared to the model without global shocks, our model has done a good job in tackling down most of the big correlations.

Implied Values of Global Shocks

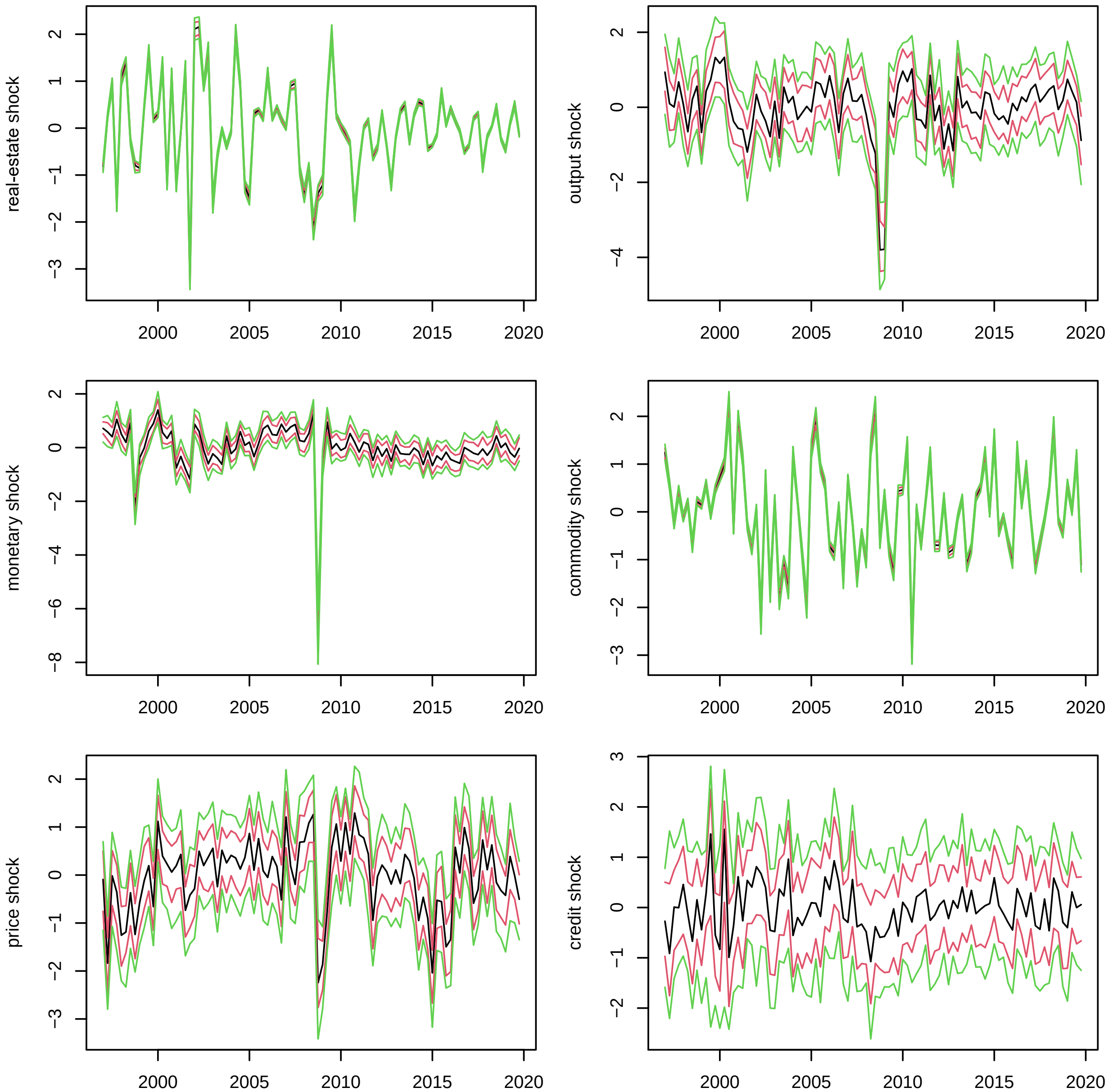

Figure 4: The 68% and 90% credible bands are plotted in red and in green. Both the uncertainty from the model parameters and the latent shock values are incorporated. Each global shock is normalized to have mean 0 and standard deviation 1.

Implied Values of Country Shocks in Monetary Policy

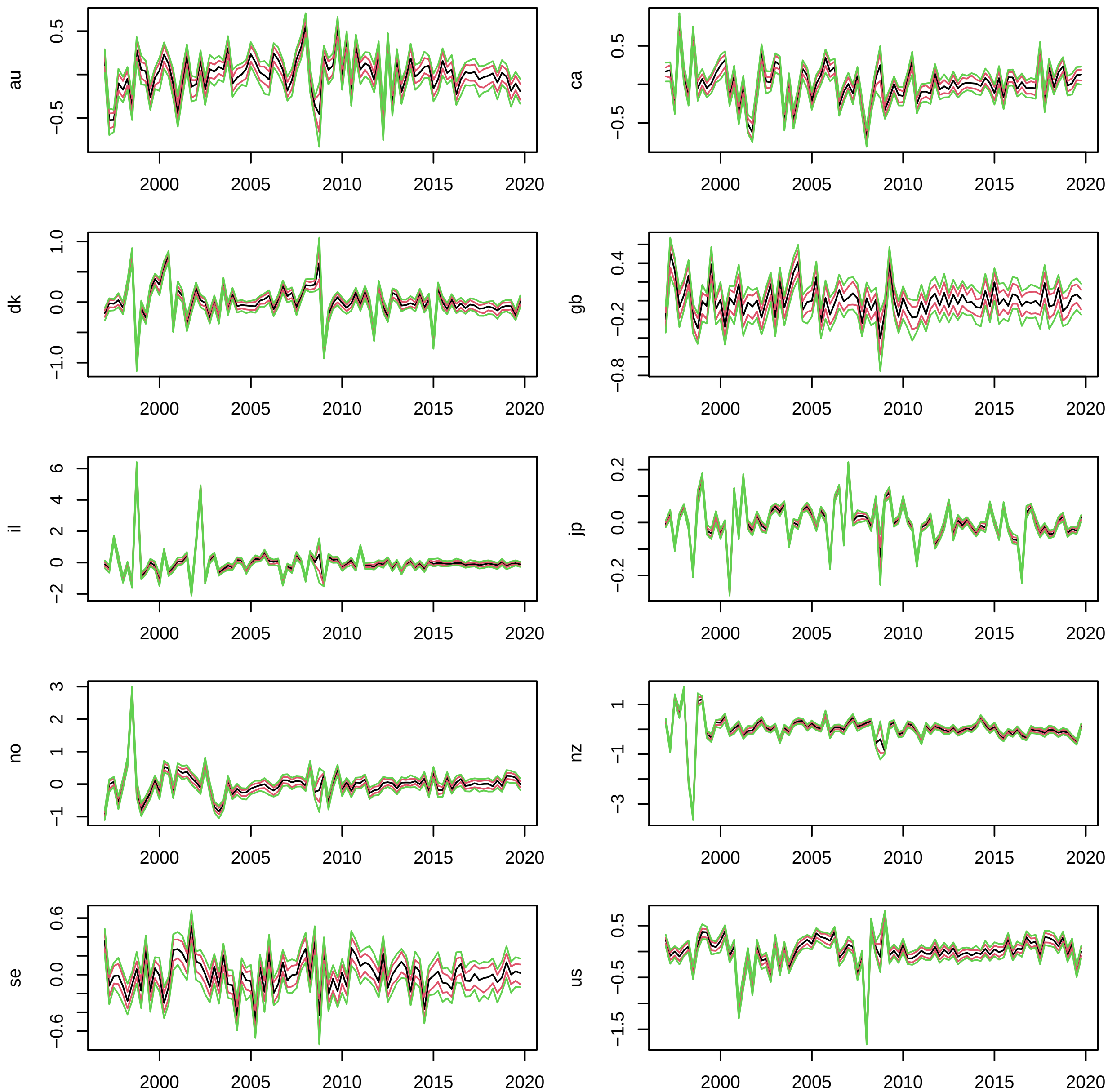

Figure 5: The 68% and 90% credible bands are plotted in red and in green. Both the uncertainty from the model parameters and the latent shock values are incorporated. Each country shock is normalized to have mean 0 and average standard deviation 1 across countries.

Model fit with / without global shocks

	log of marginal data density
with global shocks	16379.7
without global shocks	16377.2

Table 4: We report the logarithm of marginal data density, computed from bridge sampling with a Gaussian proposal density around the posterior peak, using 100 posterior draws.

with and without global shocks.[13] Although using the global shocks remarkably increases the likelihood[14] and easily rejects the null in a frequentist likelihood-ratio test, our Bayesian analysis gives a more conservative conclusion, showing there is only mild increase in the model fit, especially in the case of testing a large amount of free parameters, i.e. the 60 parameters of Γ.[15]

5 Robustness checks

This section implements a few robustness checks on our data and model. In Section 5.1, we change the countries and the periods in our sample to show our main results are still robust. In Section 5.2, we use the conventional identification scheme, by recursively defining shocks and ignoring global trends, to show that the impulse response results are also robust.

5.1 Alternative sample

To test the robustness of our main results, we change the sample by altering the selection of countries and the sample period. First, we allow shorter time series to expand the dataset to 13 countries from 2000:Q1 to 2019:Q4. Our main results are preserved. Second, we remove US in our baseline specification, and re-estimate the model, which generate similar results. This means it is feasible to treat US the same as other countries, as long as we have modeled the cross-country heterogeneity and the global trend in our panel data.

[13] For the model without global shocks, we simply force $\Gamma = 0$, and thus the model only has idiosyncratic country shocks, i.e. $\nu_{it}^{j} = \eta_{it}^{j}$ as in standard panel structural VAR models.

[14] The log-likelihood increases by more than 300, which is much larger than $\chi^2_{60,0.95}$.

[15] Although the increase of log marginal data density by 2.5 would imply the model with global shocks is 12 times more likely, the rule of thumb in Bayesian high-dim model comparison would view this as an mild increase, given we are testing two distinct models, with no other models in between.

5.2 Conventional identification scheme

To show that our identification scheme gives results in line with conventional identification scheme, we re-estimate our model without global shocks and define structural shocks recursively. The implementation simply treats (1) as a standard panel structural VAR model with country fixed effects, and estimate the pooled variance-covariance of ν_{it}. Then we use Cholesky decomposition to back out the impact matrix and examine the impulse response. The response largely coincides with our main results, indicating our identification scheme in the main results is allowing extra flexibility while not generating anything completely mysterious.

6 Conclusion and directions for future research

We estimate a structural VAR on a balanced panel of 10 countries to examine different causal channels that lead to comovement between aggregate credit and GDP. The model is specified to account for heterogeneity across countries and to capture the global trend. We show this model can be identified through heteroskedasticity, with the variation in the size of loaded global shocks and country shocks. Among all the six structural shocks in our model, we find that there is one from the real estate sector, that pushes aggregate credit up and then later depresses GDP growth, but its effects are small in most countries. All the other five structural shocks still generate the positive or zero comovement between aggregate credit and GDP. The results also imply huge variation in shock sizes across countries. The inclusion of the global shocks effectively captures the global trend of shocks across countries.

There are some interesting extensions of our model specification. First, researchers can specify both the shock size variation across countries and across time. This is going to combine our paper with (Brunnermeier et al., 2021), and use the cross section and time series information to identify the impact matrix. In addition, this type of models will have rich dynamics that can characterize the extremely large shock values around 2008 and even after the pandemic. Second, one can extend our specification by introducing dynamic structures of global shocks. The example of 2008 Financial Crisis shows that the pace of rates cut will largely be synchronized across countries, but might have some time mismatches around 1 quarter. Having lagged terms of global shocks appearing in our model will answer the question that how soon each country follow the global trend, for example, in the common rates cut. Third, one can try some sub-models between our model with global shocks and the model without global shocks. Our analysis shows that adding global shocks for each structural equation brings in too many free parameters, which is not favored using Bayesian information criteria. Simply adding global shocks for equations with large cross-cournntry correlation will be promising.

Appendix A Details on MCMC algorithm

The details of our MCMC algorithm are listed here.

We first optimize the MCMC algorithm by integrating out c and $B(L)$ in the likelihood. Since we use dummy observations to express prior on c and $B(L)$, we need to integrate the likelihood twice to get the correct posterior. Denote the real observations as Y and the dummy observations as Y^*. In addition, the prior that the dummy observations generates is

$$p(c, B(L)|A, \Lambda, \Gamma) = \frac{p(Y^*|c, B(L), A, \Lambda, \Gamma)}{\int_{c,B} p(Y^*|c, B(L), A, \Lambda, \Gamma) dc \cdot dB}. \tag{A.1}$$

Thus the likelihood with c and $B(L)$ integrated out both in the real and dummy observations is

$$\begin{aligned} p(Y|A, \Lambda, \Gamma) &= \int_{c,B} p(c, B(L)|A, \Lambda, \Gamma) \cdot p(Y|c, B(L), A, \Lambda, \Gamma) dc \cdot dB \\ &= \int_{c,B} \frac{p(Y^*|c, B(L), A, \Lambda, \Gamma)}{\int_{c,B} p(Y^*|c, B(L), A, \Lambda, \Gamma) dc \cdot dB} p(Y|c, B(L), A, \Lambda, \Gamma) dc \cdot dB \\ &= \frac{\int_{c,B} p(Y, Y^*|c, B(L), A, \Lambda, \Gamma) dc \cdot dB}{\int_{c,B} p(Y^*|c, B(L), A, \Lambda, \Gamma) dc \cdot dB} \end{aligned} \tag{A.2}$$

After integrating out c and $B(L)$, we are left with parameters, i.e. A, Λ, Γ, which cannot easily integrate out, and hence we turn to Metropolis algorithm to directly make posterior draws on this smaller set of parameters. We run a pilot series of 10,000 Metropolis draws from the posterior peak, and update the variance-covariance matrix in our Gaussian proposal density. Then we start a formal series of 100,000 Metropolis draws for our main results. We check the convergence of our MCMC draws by using the traceplot of our posterior density. When computing impulse responses or implied shock values, our routine is taking a posterior draw of A, Λ, Γ and then analytically draw c and B given the value of A, Λ, Γ.

Appendix B Shock size variation in global and country components

Here we list out the comparison of the standard deviation in the global shock component and the country shock component, similar to Section 4.2

Standard Deviation of Global & Country Shock Component

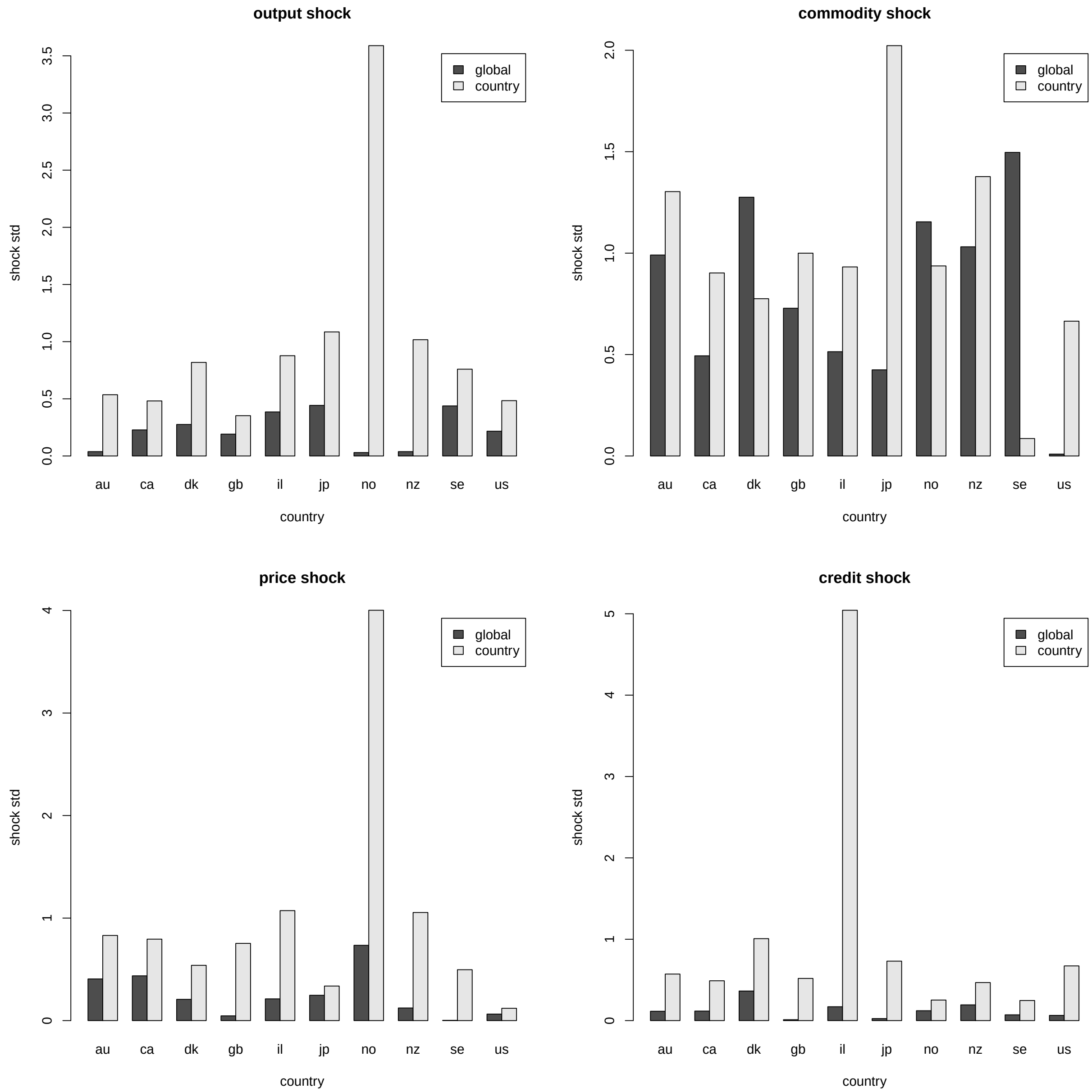

Figure B.1: This bar plot shows the standard deviation of the global shock component and country shock component across countries. The standard deviation of global shock component is the absolute value of Γ. The standard deviation of country shock component, i.e. Λ, is normalized to have an average of 1 across countries.

Appendix C Cross correlation in monetary policy shocks

Here we impute the country shock values at the posterior peak, and compute the sample correlation matrix. We then compare the correlation matrix using the model with global shocks and the model without global shocks, to check how many big correlation entries have been absorbed by the global shocks.

Cross correlation in country shocks in monetary policy

(a) Model with global shocks

	AU	CA	DK	GB	IL	JP	NO	NZ	SE	US
AU	1.00	-0.22	-0.15	-0.31	0.13	0.15	-0.14	0.15	-0.09	-0.05
CA	-0.22	1.00	0.10	-0.26	0.15	-0.11	0.04	-0.11	-0.27	0.23
DK	-0.15	0.10	1.00	-0.11	-0.24	-0.36	0.34	-0.25	-0.12	-0.21
GB	-0.31	-0.26	-0.11	1.00	-0.18	0.03	-0.08	-0.01	-0.33	-0.17
IL	0.13	0.15	-0.24	-0.18	1.00	0.11	-0.13	0.30	-0.04	0.11
JP	0.15	-0.11	-0.36	0.03	0.11	1.00	-0.37	0.29	0.01	0.10
NO	-0.14	0.04	0.34	-0.08	-0.13	-0.37	1.00	-0.57	-0.07	-0.19
NZ	0.15	-0.11	-0.25	-0.01	0.30	0.29	-0.57	1.00	0.04	0.09
SE	-0.09	-0.27	-0.12	-0.33	-0.04	0.01	-0.07	0.04	1.00	-0.29
US	-0.05	0.23	-0.21	-0.17	0.11	0.10	-0.19	0.09	-0.29	1.00

(b) Model without global shocks

	AU	CA	DK	GB	IL	JP	NO	NZ	SE	US
AU	1.00	0.40	0.29	0.59	0.17	0.18	0.30	0.32	0.58	0.46
CA	0.40	1.00	0.34	0.50	0.14	0.06	0.39	0.09	0.43	0.53
DK	0.29	0.34	1.00	0.41	-0.16	-0.12	0.46	-0.05	0.36	0.17
GB	0.59	0.50	0.41	1.00	-0.02	0.13	0.40	0.26	0.68	0.49
IL	0.17	0.14	-0.16	-0.02	1.00	0.08	-0.06	0.32	0.09	0.13
JP	0.18	0.06	-0.12	0.13	0.08	1.00	-0.06	0.22	0.16	0.18
NO	0.30	0.39	0.46	0.40	-0.06	-0.06	1.00	-0.28	0.38	0.17
NZ	0.32	0.09	-0.05	0.26	0.32	0.22	-0.28	1.00	0.31	0.28
SE	0.58	0.43	0.36	0.68	0.09	0.16	0.38	0.31	1.00	0.38
US	0.46	0.53	0.17	0.49	0.13	0.18	0.17	0.28	0.38	1.00

Table 5: Both tables show the sample correlation matrix of implied country monetary policy shocks at the posterior peak. The first one uses the model with global shocks, while the second uses the model without global shocks.

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