INTRODUCTION

Over the past four decades China has become a global force in the world economy. China has contributed to approximately one third of world economic growth since 2005 (see Chart 27 in Dieppe, Gilhooly, Han, Korhonen, & Lodge, 2018). But having reached over 14% in 2007, real GDP growth slowed to about 6.4% in 2018 (see Figure A4 in the Appendix). The Chinese economy is maturing and rebalancing from import-intensive investment toward consumption. Dieppe et al. (2018) point out that the domestic imbalances in China are widening and may lead to a number of vulnerabilities. These fragilities include rapid credit growth, as well as increased complexity and leverage in the financial system. Also the emergence of a new coronavirus in China may lead to further slowdown of Chinese economy.
China plays a profound role in regional trade. It is a central point of the Asian supply chains. Thus, the slowdown of the Chinese economy is particularly troubling for its neighboring countries. In this paper we decided to concentrate on China’s spillover effects to Southeast Asia and Oceania countries.

The main contribution of this paper is the application of global vector autoregression (GVAR) model and a set of Bayesian vector autoregression (BVAR) models to quantify the implications of China’s slowdown for a number of economies, particularly in Southeast Asia and Oceania. The usage of a set of BVAR models in this context is a novel approach. We compare the two types of VAR models. Also we use a novel and large data set for 59 economies. Lastly, using Bayesian model averaging, we examine the structural features that determine the impact of the Chinese economy on other economies.

We use the GVAR model to assess the effects of negative demand shock in China that enables us to model the whole global economy and to capture economic linkages between countries. We implement the model with the original set of variables and time-varying link matrixes. Also as a robustness check we estimate a BVAR model for each economy separately. Each BVAR model includes Chinese variables as partially exogenous.

Our results show that the response of neighboring countries to negative demand shock in China is stronger and faster than the average response of other economies. The results from BVAR models seem to confirm the results from the GVAR model. According to our results Chinese Taipei is the most affected economy by negative GDP shock in China. Also Indonesia, Singapore, Hong Kong, Thailand, and Malaysia are strongly affected. Australia seems to be also affected but to a lesser degree. We find weak GDP response to China GDP shock for New Zealand and the Philippines. The response of GDP in South Korea and Japan is quite significant, but only according to the results from the GVAR model. Moreover, we find that spillovers are stronger to economies with less flexible exchange rates, a higher share of manufacturing in gross value added (GVA) and to economies which are larger.

The article is structured as follows. In the second section we describe related literature. In the third section we describe methods. The fourth section lists variables and their sources. In the fifth section we describe results, including a sensitivity analysis. The last section concludes.

2 | RELATED LITERATURE

China has become the largest market for Asian economies, surpassing Japan in 2005 and the United States in 2007 (Inoue, Kaya, & Ohshige, 2015). Because of the recession and anaemic growth in the United States and the euro zone, since 2008 the demand from advanced economies for Asia-Pacific exports has been decreasing. Asia-Pacific countries, however, have benefited from the surging Chinese domestic demand. Exports from Asia-Pacific countries to China have doubled over the last 5 years.

On the one hand China exerts significant effects on other Asian economies through direct trade linkages, and on the other hand China affects Asian economies indirectly through its impact on commodity prices. Chinese demand for metal and oil is high and increasing,2 because of high investment in the domestic economy and urbanization process in China. Osorio and Unsal (2013) by applying the GVAR model estimate both the direct and indirect channels.3 The authors estimate that within 2 years about 20% of the spillovers from positive demand shock in China are due to higher commodity prices. Also, indirect impacts transmit faster to inflation in Asian economies than direct impacts.

In the literature much attention has been directed to the international spillover effects of China’s slowdown. Using the GVAR model, Cashin, Mohaddes, and Raissi (2016) examine the impact of China’s slowdown and the higher global financial market volatility on other economies. It appears
that the negative output shock in China has the largest effect on less-diversified commodity exporters and ASEAN-5 countries (Indonesia, Malaysia, Singapore, and Thailand—without the Philippines). Following a 1 p.p. decrease of the real GDP growth in China, global growth decreases by 0.23 p.p. in the short term, and oil prices fall by 2.8 p.p. in the long term. Similarly, Sznajderska (2019) by estimating a different GVAR model shows that a 1 p.p. negative China GDP shock reduces global output by 0.22 p.p. in the short run, leading to a maximum 1 p.p. decrease in the global output in the longer term.

Blagrave and Vesperoni (2018) show that spillover effects are largest for countries with tighter trade links to China, particularly those in Asia. They analyze demand shocks for Chinese secondary and tertiary sectors separately. They apply a panel VAR model with China’s demand shocks, identified outside the model, as exogenous variables. Authors show that shocks to China’s secondary sector have much larger effects on partner export countries than shocks to China’s tertiary sector. In our study we do not take into account the tertiary sector, because we measure links between countries using DOTS statistics.

Also the Chinese stock market crash (2015–2016) shows that China is becoming more integrated with the regional financial markets. Abdullahi and Rui (2019), for instance, by investigating daily data between 2015 and 2016, show strong shock spillover effects from China to most Asia-Pacific stock markets (except New Zealand).

It is important to note that Chinese financial linkages are smaller than linkages through trade channels. Capital flows in and out of China are restricted legally. Despite capital controls, financial integration of China is de facto non-negligible (see Dieppe et al., 2018). Dieppe et al. note that the share of China and Hong Kong’s global gross asset and liability position in 2015 was approximately 8% (to compare with 10% share in global imports or 22% share in global energy consumption in 2015). Based on the data from BIS locational international banking statistics we may notice that the highest financial flows are between China and Hong Kong, followed by the euro area, the United States, the United Kingdom, Japan, Taiwan, Korea, Australia, and Canada, in descending order (see Figure A1 in the Appendix).

The important question is why some economies are affected more and some are less by China’s spillovers. We try to answer this question by looking at structural characteristics of the economies. Georgiadis is the author of two papers in which he shows that differences within the monetary transmission mechanism depend on the differences in the structural characteristics of the economies. He applies GVAR methodology with sign restrictions.

In his first paper, Georgiadis (2015) studies the transmission of the common euro area monetary policy across the individual euro area economies. The euro area countries in which a share of sectors with the demand sensitive to interest rate changes in the accumulated industry is bigger exhibit a stronger monetary transmission to real economic activity. Similarly, stronger transmission is observed in the countries with more real wages rigidities and/or fewer unemployment rigidities. In his second paper, Georgiadis (2016) studies spillover effects from the U.S. economy. The results of the study suggest that policymakers could mitigate the U.S. spillover effects by encouraging trade integration, financial market development, flexibility of exchange rates and by reducing labor market rigidities. Moreover, other policies, such as slowing the process of financial integration and industrialization or participation in the global value chains, could also reduce the spillover effects, but would probably decrease the level of long-run economic growth as well.

We analyze the factors which explain differences in spillovers similarly as Georgiadis (2015, 2016), by regressing maximum point impulse responses on structural characteristics of respective economies. However, due to having a large number of candidate characteristics compared to the number of observations, we have used Bayesian model averaging. A similar approach was used, for example, by
Havranek and Rusnak (2013) in order to analyze the transmission lags of monetary policy. In contrast to their analysis, we do not carry out a meta-analysis of existing studies.

3 | METHODS

3.1 | GVAR model

We use the global vector autoregressive model to investigate the impact of the Chinese economy on other economies. The GVAR model is estimated within two steps (see Dees, Mauro, Pesaran, & Smith, 2007; Pesaran, Schuermann, & Weiner, 2004). First, let us consider the VARX \((p_i, q_i)\) models for each country \((i = 1, \ldots, N; N\) is the number of countries), where \(p_i\) and \(q_i\) are lags lengths selected by SBC.

\[
x_{it} = \alpha_0 + \alpha_1 t + \Phi_{i1} x_{i,t-1} + \cdots + \Phi_{iq_i} x_{i,t-p_i} + \Lambda_{00} x_{i,t-q} + \cdots + \Lambda_{iq_i} x_{i,t-q} + \Psi_{00} \omega + \cdots + \Psi_{iq_i} \omega_{t-q} + u_{it},
\]

where \(x_{it}\) is a vector of domestic variables, \(x_{it}^*\) is a vector of foreign variables, \(\omega_i\) is a vector of dominant unit model variables (here: oil prices).

Note that \(\omega_i\) is treated as a foreign variable in the GVAR model and shares the same lag order as foreign variables.

Foreign variables are calculated as a weighted average of domestic variables:

\[
x_{it}^* = \sum_{j=0}^{N} \rho_{ij} x_{jt}, \text{ where } \rho_{ii} = 0,
\]

and \(\rho_{ij}\) are weights calculated on the basis of bilateral trade flows \((\sum_{j=0}^{N} \rho_{ij} = 1). k_i\) is the number of domestic variables and \(k_i^*\) is the number of foreign variables in \(i\)th country (here \(k_i^* = 2\)).

Following other studies we estimate the error correction form (VECMX \((p_i, q_i)\) models) of the VARX \((p_i, q_i)\) specification for each country (cf. Backé, Feldkircher, & Slacík, 2013; Bussière, Chudik, & Sestieri, 2012; Dees, Holly, Pesaran, & Smith, 2007; Inoue et al., 2015; Pesaran et al., 2004):

\[
\Delta x_{it} = c_{00} + \sum_{j=1}^{r_i} \gamma_{ij} ECT_{ij,t-1} + \sum_{p=1}^{q_i} \Phi_{ip} \Delta x_{i,t-p} + \sum_{q=0}^{q_i} \lambda_{iq} \Delta x_{i,t-q} + \sum_{q=0}^{q_i} \Psi_{iq} \Delta \omega_{t-q} + u_{it}.
\]

ECT are error correction terms and \(r_i\) is the number of cointegrating relations. Most of the variables are nonstationary with stationary first differences. The usage of VECM models allows us to capture long-run relationships that exists among the domestic and the country-specific foreign variables.

The dominant unit is modeled as:

\[
\omega_i = \mu_0 + \mu_1 t + \kappa_1 \omega_{t-1} + \cdots + \kappa_p \omega_{t-p} + \lambda_1 \bar{x}_{t-1} + \cdots + \lambda_q \bar{x}_{t-q} + \eta_t,
\]

where \(\bar{x}_t\) are feedback variables, constructed as a weighted average of variables included in the models for non-dominant units (see Smith and Galesi (2014) for details).

In the second step, the corresponding VARX models (Equation 1) are recovered from the estimated VECMX models. Then the individual country models are stacked into one model:

\[
G_0 x_{t} = a_0 + a_1 t + G_1 x_{t-1} + \cdots + G_p x_{t-p} + \Psi_0 \omega + \cdots + \Psi_q \omega_{t-q} + u_t,
\]
When solving the GVAR model Equations (1) and (2) are written in one equation, which is solved recursively.

Next we calculate the generalised impulse response functions (GIRFs), that were developed in Koop, Pesaran, and Potter (1996) and Pesaran and Shin (1998), and we calculate 90% bootstrap confidence bands. Because of the large number of variables in the GVAR model we cannot use the standard impulse response functions (IRFs) that assume orthogonal shocks. GIRFs do not depend on the ordering of the variables. GIRFs show how changes in Chinese GDP affect the other variables in the GVAR over time regardless of the source of the change. We do not know whether such a shock stems from a shift in the demand or supply of output in China or in other countries.

The baseline GVAR model includes five variables for each country: these are real GDP, CPI, stock price index, REER, and short-term interest rate. Furthermore, it includes oil prices as a global variable and real GDP and short-term interest rate as a foreign variable (see Equation 1). The model uses a time-varying matrix of trade flow (IMF DOTS). Also, we include a dominant unit to model oil prices with two feedback variables (real GDP and short-term interest rate).

We obtained a stable GVAR model, meaning convergent persistent profiles, eigenvalues lying in the unit circle, and non-explosive GIRFs. To arrive with a stable GVAR we reduced the number of cointegrating relations for Argentina from 5 to 1 relation. Also we decided to remove from the sample three economies that faced episodes of very high inflation, namely Venezuela, Turkey, and Bulgaria. When we included the three economies in the sample, many results were statistically insignificant.

The order of the VARX* models as well as the number of cointegration relationships are presented in Table A1 in the Appendix. The cointegration results are based on the trace statistic, which has better small sample power results compared to the maximum eigenvalue statistic.

3.2 Robustness of the results—BVAR models

We apply the Bayesian VAR models to check the robustness of the results from the GVAR model. BVAR models are estimated for each country separately. We estimate the models on first differences (all variables except of interest rate are in first differences) to ensure maximum comparability to GVAR model.

\[ \Delta x_t = a_0 + \beta_1 \Delta x_{t-1} + \ldots + \beta_k \Delta x_{t-k} + \gamma \Delta z_t + \epsilon_t, \]

\( x_t \) is a vector of endogenous variables, \( z_t \) is a vector of exogenous variables, and it corresponds to foreign variables and the dominant unit in the GVAR model, \( \epsilon_t \sim N(0, \Sigma) \) is a vector of residuals.
We identify shocks using the Cholesky decomposition, which is easier to reasonably implement within the BVAR framework, than within the GVAR framework. The specification of the BVAR models is chosen to be as similar to the GVAR model as possible.

The endogenous variables are as follows: Chinese GDP ($y_{China}$), Chinese interest rate ($i_{China}$), domestic GDP ($y$), domestic price level ($p$), domestic interest rate ($i$), domestic stock price index ($s$), and domestic real effective exchange rate ($r$). The order of variables for the Cholesky identification is as written above. The exogenous variables are foreign GDP (without China) ($y_{foreign}$), foreign price level (without China) ($p_{foreign}$), and oil price level (oil). The choice of variables is similar to Peersman and Smets (2001). The number of lags is 4.

Note that in the models for Algeria, Croatia, Saudi Arabia, and Romania, stock price indexes are not included due to the unavailability of data.

We use Minnesota prior with parameters presented in Table 1.

Auto-regressive coefficient is equal to 0.8, because our variables are known to be stationary (see Dieppe, van Roye, & Legrand, 2016). The rest of the hyperparameters are chosen on the basis of suggestions in Canova (2007).

We implement block exogeneity to create partial exogeneity within our set of endogenous variables. We want domestic variables ($y, p, i, s, r$) to have no impact on Chinese variables ($y_{China}, i_{China}$) (see Table 2).

### 3.3 Bayesian model averaging

Next after computing GDP responses in respective economies to China’s GDP impulse from both GVAR and BVAR models, we attempt to explain them by the countries’ structural characteristics. In principle, we estimate the parameters of the following linear regression models:

| TABLE 1 | Hyperparameters for Minnesota prior |
|----------|------------------------------------|
| Auto-regressive coefficient          | 0.8               |
| Overall tightness $\lambda_1$        | 0.2               |
| Cross-variable weighting $\lambda_2$ | 0.5               |
| Lag decay $\lambda_3$                | 2                 |
| Exogenous variable tightness $\lambda_4$ | 100,000           |

| TABLE 2 | Exogeneity block |
|----------|------------------|
| $y_{China}$ | $i_{China}$ | $y$ | $p$ | $i$ | $s$ | $r$ |
| $y_{China}$ | $i_{China}$ | $y$ | $p$ | $i$ | $s$ | $r$ |
| $y_{China}$ | 1 | 1 |
| $i_{China}$ | 1 | 1 |
| $y$ | 1 | 1 |
| $p$ | 1 | 1 |
| $i$ | 1 | 1 |
| $s$ | 1 | 1 |
| $r$ | 1 | 1 |

*Note: The value of 1 in row $i$ and column $j$ of the table means that variable $i$ has no effect on variable $j$.***
\[ y_i = \mathbf{x}_i' \mathbf{\beta} + \epsilon_i, \]

where \( y_i \) is an impulse response (either from the GVAR or from the BVAR model), \( \mathbf{x}_i \) is a vector of structural characteristics for each economy, \( \mathbf{\beta} \) is a vector of coefficients and \( \epsilon_i \) is an error term.

As a dependent variable, we take the maximum effect within 20 quarters (5 years) after an impulse.

We consider as many as 18 (16–17 at the same time) structural characteristics within the following groups:

- the structure of international trade (shares of: agriculture, fuels and mining products, and manufacturing in trade with China),
- the structure of GVA (shares of: agriculture, industry, manufacturing and services in GVA),
- financial openness (Chinn-Ito index, where the higher the value, the higher the capital account openness),
- the size of international investment position (the sum of international investment position assets and liabilities to GDP ratio),
- distance (between capitals of respective economies and Beijing),
- exchange rate regime (according to the classification of Klein and Shambaugh (2008), where 1 indicates a fixed and 0—a flexible exchange rate),
- trade openness (the sum of exports and imports to GDP ratio),
- size (GDP in PPP, constant prices),
- development (GDP per capita in PPP, constant prices),
- participation in global value chains (GVC)—with China and total,
- tariffs (weighted average).

As we describe in the next section, we consider 40 economies, so if we included all the above mentioned variables in linear regression models at the same time we would be left with just above 20° of freedom, which does not appear to be acceptable. We could estimate a model with each structural characteristic separately, but that would put us at risk of getting biased estimates (due to the omitted-variable bias).

Therefore, we decided to use the Bayesian model averaging approach, where first we estimate linear regression models with different sets of independent variables, and then we average parameters over models, with weights proportional to posterior probabilities of respective models being correct (assuming one of them is correct).\(^{11}\)

Formally, a model-averaged Bayesian point estimator is the following:

\[
E[\mathbf{\beta}_1|D] = \sum \tilde{\mathbf{\beta}}^{(k)}_1 p(M_k|D),
\]

where \( E[\mathbf{\beta}_1|D] \) is the posterior distribution of a parameter \( \mathbf{\beta}_1 \), \( \tilde{\mathbf{\beta}}^{(k)}_1 \) is the posterior mean of the parameter \( \mathbf{\beta}_1 \) under model \( M_k \), and \( P(M_k|D) \) is the posterior probability that \( M_k \) is the correct model, given that one of the models considered is correct. For more details on Bayesian model averaging see, for example, Raftery, Painter, and Volinsky (2005).

When interpreting the results we focus on posterior inclusion probabilities of each variable being in the model.

Finally, it should be noted that, on top of using two variants of the dependent variable (either from the GVAR or from the BVAR models), we also try two sets of regressors: one with a weight in trade with China, and one with proxies for it based on the gravitational model of trade—GDP in PPP and
distance. The latter specification does not directly include any deterministic relationship between responses and trade weights due to the construction of the GVAR model itself. The remaining variables are used in both sets.

In the baseline model we explain responses from the GVAR model by the set of variables including GDP in PPP and distance, while the remaining three variants make up a sensitivity analysis.

4 | DATA

Our sample consists of 59 economies, where the 19 euro area countries are grouped into one economy. We use quarterly observations. The data span from 1995Q1 to 2017Q4.

The primary data source for GDP, price level (CPI), and short-term interest rate was the IMF IFS. If for any country these data were not available we used the OECD MEI database. If the data were still not available we used national sources of data, and next annual data from the IMF WEO (with Chow-Lin interpolation). In cases of data on stock market indexes the primary data source was MSCI. If the data were not available we used the data sources listed above.

The data on real effective exchange rates (REER) for each country was taken from the Bank of International Settlements (BIS). The monthly data were aggregated to quarterly frequency. An increase in the REER index indicates an appreciation.

Detailed data sources for each country are presented in Table 3.12

Real GDP, CPI, stock market indexes, and REER are 2010 indices (2010 = 100). These variables are in logarithms.

Oil prices were taken from FRED, as an average from Brent, West Texas Intermediate and Dubai Fateh indexes.

We used the World Economic Outlook database of the IMF for construction of the country-specific PPP-GDP weights. We took the average from 1995 to 2017 from the annual data on purchasing power parity in billions of international dollars.

The matrices of trade flows were constructed on the basis of International Monetary Fund statistics, namely the Direction of Trade Statistics (DOTS). These are annual data, so they allow the construction of trade flows matrix for each year separately and subsequent estimation of the model with time-varying link matrices. It is important to note, that the data for Chinese Taipei as a reporting country were not available. The data for Chinese Taipei were available only as a counterpart country. Thus, we made the symmetry assumption here (meaning that, for example, the value of export and import from China to Taipei equals the value of export and import from Taipei to China). Also there were no data for South Africa from 1995 to 1997 and we decided to replace the empty spaces using data from 1998.

We took data on the structure of international trade from the WTO. The structure of GVA, measures of trade openness, size, development and tariffs were taken from the World Bank. We used the updated versions of databases from Chinn and Ito (2006), and Klein and Shambaugh (2008) for financial openness and exchange rate regimes, respectively. The size of international investment positions was taken from the IMF, distances were from the Distance Calculator webpage (www.distancecalculator.net) and the participation in global value chains—from the OECD.

We computed an average over the period 1995–2015 for each variable. Due to the large number of missing observations in data on structural characteristics we removed Algeria, the euro area, Israel, and Taiwan from the BMA analysis. These economies, however, were included in the GVAR and BVAR models.
| Country       | real GDP       | price level       | stock price index | REER  | short-term interest rate |
|--------------|----------------|-------------------|-------------------|-------|-------------------------|
| Algeria      | IMF WEO        | IMF IFS           | –                 | BIS   | IMF IFS                 |
| Argentina    | IMF IFS + IMF WEO | national       | MSCI + IMF IFS   | BIS   | IMF IFS                 |
| Australia    | OECD           | IMF IFS           | MSCI              | BIS   | IMF IFS                 |
| Brazil       | IMF IFS + IMF WEO | IMF IFS          | MSCI              | BIS   | IMF IFS                 |
| Bulgaria     | IMF IFS + national | IMF IFS         | –                 | BIS   | IMF IFS + OECD          |
| Canada       | IMF IFS + OECD  | IMF IFS           | MSCI              | BIS   | IMF IFS + OECD          |
| Chile        | OECD + national | IMF IFS           | MSCI              | BIS   | IMF IFS + OECD          |
| China        | national       | IMF IFS           | MSCI              | BIS   | national*               |
| Chinese Taipei | national     | national          | MSCI              | BIS   | National                |
| Colombia     | IMF IFS + OECD  | IMF IFS           | MSCI              | BIS   | IMF IFS                 |
| Croatia      | IMF IFS + IMF WEO | IMF IFS          | –                 | BIS   | IMF IFS + national      |
| Czech Republic | IMF IFS + IMF WEO | IMF IFS      | MSCI + OECD       | BIS   | IMF IFS                 |
| Denmark      | IMF IFS        | IMF IFS           | MSCI              | BIS   | IMF IFS                 |
| euro area    | IMF IFS        | IMF IFS + OECD    | MSCI              | BIS   | IMF IFS + OECD          |
| Hong Kong SAR | IMF IFS        | IMF IFS           | MSCI              | BIS   | IMF IFS                 |
| Hungary      | IMF IFS        | IMF IFS           | MSCI              | BIS   | OECD                    |
| Iceland      | IMF IFS + IMF WEO | IMF IFS          | OECD + IMF IFS    | BIS   | IMF IFS                 |
| India        | OECD + IMF WEO  | IMF IFS           | MSCI              | BIS   | IMF IFS + national      |
| Indonesia    | IMF IFS + OECD  | IMF IFS           | MSCI              | BIS   | IMF IFS + OECD          |
| Israel       | IMF IFS        | IMF IFS           | MSCI              | BIS   | OECD                    |
| Japan        | IMF IFS + OECD  | IMF IFS           | MSCI              | BIS   | IMF IFS + OECD          |
| Korea        | IMF IFS        | IMF IFS           | MSCI              | BIS   | IMF IFS                 |
| Malaysia     | IMF IFS + national | IMF IFS        | MSCI              | BIS   | IMF IFS                 |
| Mexico       | IMF IFS + OECD  | IMF IFS           | MSCI + OECD       | BIS   | IMF IFS                 |
| Country       | real GDP       | price level  | stock price index | REER | short-term interest rate |
|--------------|----------------|--------------|-------------------|------|--------------------------|
| 25 New Zealand | IMF IFS       | IMF IFS      | MSCI              | BIS  | OECD                     |
| 26 Norway     | IMF IFS       | IMF IFS      | MSCI              | BIS  | OECD                     |
| 27 Peru       | IMF IFS + national | IMF IFS | MSCI + national  | BIS  | IMF IFS + national       |
| 28 Philippines | IMF IFS + OECD | IMF IFS      | MSCI              | BIS  | IMF IFS                  |
| 29 Poland     | IMF IFS + OECD | IMF IFS      | MSCI              | BIS  | IMF IFS                  |
| 30 Romania    | IMF IFS       | IMF IFS      | –                 | BIS  | IMF IFS                  |
| 31 Russia     | IMF IFS       | IMF IFS      | MSCI + national   | BIS  | IMF IFS + OECD           |
| 32 Saudi Arabia | IMF IFS + IMF WEO | IMF IFS | –                 | BIS  | IMF IFS + national       |
| 33 Singapore  | IMF IFS + national | IMF IFS | MSCI              | BIS  | IMF IFS                  |
| 34 South Africa | IMF IFS + OECD | IMF IFS      | MSCI              | BIS  | IMF IFS                  |
| 35 Sweden     | IMF IFS       | IMF IFS      | MSCI              | BIS  | IMF IFS + OECD           |
| 36 Switzerland | IMF IFS       | IMF IFS      | MSCI              | BIS  | IMF IFS + OECD           |
| 37 Thailand   | IMF IFS       | IMF IFS      | MSCI              | BIS  | IMF IFS                  |
| 38 Turkey     | IMF IFS       | IMF IFS      | MSCI              | BIS  | OECD + national          |
| 39 United Kingdom | IMF IFS   | IMF IFS      | MSCI              | BIS  | IMF IFS                  |
| 40 United States | IMF IFS     | IMF IFS      | MSCI              | BIS  | IMF IFS + OECD           |
| 41 Venezuela  | IMF IFS + IMF WEO | IMF IFS + IMF WEO | national  | BIS  | IMF IFS                  |

Note: We decided to use Lending Rate of Financial Institutions, 1 year or less from Macrobond for China.
5 | EMPIRICAL RESULTS AND DISCUSSION

5.1 | The output spillover effects from China to Southeast Asia and Oceania

In this section we describe the influence of negative demand shock in China on a set of economies. We report output elasticities for specific countries following a 1% negative GDP shock in China.

Figure 1 presents the negative demand shock in China from the GVAR model, which is equal to 1 p.p. decrease in Chinese GDP on impact, and an average response of the whole global economy and an average response of Southeast Asia and Oceania.

The negative demand shock in China is standardized to 1 p.p. (Figure 1a). The shock is permanent. The presented GIRFs are bootstrap mean estimates with the associated 90% bootstrap error bounds.

The maximum response of the whole global economy to 1 p.p. negative demand shock in China is equal to $-0.157$ p.p. after 7 quarters. The maximum response of Southeast Asia and Oceania to 1 p.p. negative demand shock in China is $-0.262$ p.p. after 4 quarters. Thus, the response of neighboring countries is much stronger and faster than the average response of other economies.

Concerning Southeast Asia and Oceania, according to the results from the GVAR model, the strongest response of domestic GDP to negative GDP shock in China is observed in Chinese Taipei ($-0.505$ p.p. after 6 quarters). Next we list the countries from the most to the least affected: the strongest response of domestic GDP is observed in Singapore ($-0.430$ p.p. after 4 quarters), Indonesia ($-0.383$ p.p. after 8 quarters), Thailand ($-0.317$ p.p. after 3 quarters), Hong Kong ($-0.280$ p.p. after 3 quarters), Japan ($-0.269$ p.p. after 9 quarters), Malaysia ($-0.259$ p.p. after 4 quarters), Philippines ($-0.246$ p.p. after 5 quarters), and South Korea ($-0.269$ p.p. after 2 quarters). Hong Kong, Singapore and Taipei have strong financial linkages with China (see Figure 5). It is worth noting that Chinese Taipei is a smaller financial centre than Hong Kong and Singapore, but it has greater trade links with the mainland. This may be the reason for its strong GDP reaction. Indonesia is a major exporter of coal and industrial metals to China. Whereas Thailand, Malaysia, the Philippines, and South Korea are major exporters of industrial supplies (including base metals) and capital goods to China. Japan is the main Chinese export market.

A similar result is found by Inoue et al. (2015), who found that negative Chinese GDP shock impacts commodity exporters, like Indonesia, to the greatest extent, and also export dependent economies, like Japan, Malaysia, Singapore, and Thailand. They find a counterintuitive reaction for Philippines.

Within the studied region the weakest reaction is observed in New Zealand ($-0.144$ p.p. after 6 quarters) and Australia ($-0.099$ p.p. on impact). It may be a bit surprising, because Australia has about a third of its exports headed for China (see Figure A3 in the Appendix).

The output reaction is statistically significant in Chinese Taipei, Hong Kong, Japan and, South Korea (see Figure 2).

The obtained results are in line with Cashin et al. (2016), who reported that negative output shock has a large and statistically significant impact on all ASEAN-5 countries (except for the Philippines), with output elasticities ranging between $-0.23\%$ and $-0.35\%$. Also Bussière et al. (2012) show that Asian countries benefit the most from a positive shock to Chinese imports. They reported that a one-standard-error shock to Chinese imports, which is an increase of 1.9% at the time of the impact, has an economically significant effect on other Asian countries, with real output increase in Korea, Singapore, and Thailand by 0.4% after 1 year, and a lower but still considerable real output increase in Japan and New Zealand by 0.2%.
FIGURE 1  Impulse response functions from the GVAR model. Bootstrap mean estimates with 90% bootstrap error bounds [Colour figure can be viewed at wileyonlinelibrary.com]
5.2 Robustness analysis—the results from BVAR models

In order to check the robustness of our results we estimate a series of BVAR models. Specification of the models is described in Section 2.2. We check whether the difference between the IRFs obtained from the GVAR model and the IRFs obtained from the BVAR model for each country separately is statistically significant. To do so we subtract the IRFs and the confidence bands obtained from the two models. The results are presented in Table 4. It appears that there are considerable differences between maximum responses and maximum response horizons across the economies between the two types of models.

We find out that there are statistically significant differences between the IRFs for 8 out of the 37 analyzed economies, that is for 22% of analyzed economies (8th column of Table 4). However, if we omit the first quarter (the reaction on impact), for the following quarters the difference between the reaction obtained from the GVAR model and the reaction obtained from the BVAR model is statistically different for 4 out of 37 analyzed economies, that is for 11% of the analyzed economies (9th column of Table 4). This is a good result, that seem to indicate that the results from BVAR models confirm the results from the GVAR model.

Nevertheless the comparison of the two models is a bit problematic and should be analyzed with caution. First, the confidence bands are quite wide (see Figure 3). Second, the GDP shock is different within the two models (compare, for example, Figures 1a and 4). The shock is very similar for each of the 37 estimated BVAR models (see Figure 4). But the Chinese GDP shocks in BVAR model are much stronger than the Chinese GDP shock in GVAR model. It is important to note, however, that the shocks are equal on impact, we standardize them so that they are equal to 1 p.p. on impact.

For example, for Australia the Chinese GDP shock stabilizes at the level of 1.56 p.p. in the BVAR model, whereas the shock stabilizes at the level of 1.01 p.p. in the GVAR model. Note that the shocks are permanent in both specifications. The maximum response of domestic GDP in Australia is stronger in the BVAR model (−0.17 p.p.) than in the GVAR model (−0.99 p.p.).
### Table 4: Comparison of the results from GVAR and BVAR models

| GVAR | BVAR | Difference | Stat. significance |
|------|------|------------|--------------------|
| Max response | Max response | Max response horizon | Stat. significance | Difference | Stat. significance | Difference without first quarter |
| Algieria | 0.0004 | 16 | no | 0.0007 | 2 | yes | No | No |
| Argentina | 0.0039 | 7 | no | 0.0133 | 4 | yes | No | No |
| Australia | 0.0010 | 0 | no | 0.0017 | 20 | yes | No | No |
| Brazil | 0.0048 | 13 | yes | 0.0060 | 20 | yes | No | No |
| Canada | 0.0003 | 6 | no | 0.0034 | 5 | yes | Yes | No |
| Chile | 0.0005 | 3 | no | 0.0020 | 0 | yes | No | No |
| Chinese Taipei | 0.0050 | 6 | yes | 0.0140 | 20 | yes | No | No |
| Colombia | 0.0014 | 12 | no | 0.0007 | 20 | yes | No | no |
| Croatia | 0.0008 | 17 | no | 0.0108 | 20 | yes | Yes | yes |
| Czech Republic | 0.0012 | 5 | no | 0.0066 | 20 | yes | No | no |
| Denmark | 0.0011 | 7 | no | 0.0002 | 7 | no | No | no |
| euro area | 0.0013 | 4 | yes | 0.0025 | 20 | yes | No | no |
| Hong Kong | 0.0028 | 3 | yes | 0.0026 | 4 | no | No | no |
| Hungary | 0.0013 | 11 | no | 0.0005 | 0 | no | No | no |
| Iceland | 0.0035 | 0 | yes | 0.0059 | 20 | yes | No | no |
| India | 0.0024 | 11 | yes | 0.0001 | 4 | no | Yes | no |
| Indonesia | 0.0038 | 8 | no | 0.0048 | 11 | yes | No | no |
| Israel | 0.0017 | 12 | no | 0.0031 | 0 | yes | No | no |
| Japan | 0.0024 | 6 | yes | 0.0001 | 0 | no | No | no |
| Korea | 0.0019 | 2 | yes | 0.0017 | 20 | no | No | no |
| Malaysia | 0.0026 | 4 | no | 0.0057 | 6 | yes | No | no |
| Mexico | 0.0013 | 13 | no | 0.0098 | 0 | yes | Yes | no |
| Country      | GVAR       | BVAR       | Difference | Difference without first quarter |
|-------------|------------|------------|------------|----------------------------------|
|             | Max response | Max response | Stat. significance | Max response | Max response | Stat. significance |          |                                 |          |
| New Zealand | −0.0011     | 6          | no         | 0.0000     | 9          | no         | Yes        | yes               |          |
| Norway      | −0.0001     | 14         | no         | −0.0024    | 20         | no         | No         | no                |          |
| Peru        | −0.0002     | 11         | no         | 0.0000     | 5          | yes        | Yes        | no                |          |
| Philippines | −0.0025     | 5          | no         | 0.0007     | 0          | no         | No         | no                |          |
| Poland      | 0.0005      | 7          | no         | −0.0017    | 3          | no         | No         | no                |          |
| Romania     | −0.0018     | 7          | no         | −0.0157    | 20         | yes        | Yes        | yes               |          |
| Russia      | −0.0051     | 10         | yes        | −0.0023    | 4          | no         | No         | no                |          |
| Saudi Arabia| −0.0069     | 20         | yes        | −0.0103    | 20         | yes        | No         | no                |          |
| Singapore   | −0.0043     | 4          | no         | −0.0042    | 20         | yes        | No         | no                |          |
| South Africa| −0.0005     | 10         | no         | −0.0017    | 0          | yes        | No         | no                |          |
| Sweden      | −0.0007     | 2          | no         | −0.0023    | 6          | yes        | No         | no                |          |
| Switzerland | −0.0011     | 7          | no         | −0.0085    | 7          | yes        | No         | no                |          |
| Thailand    | −0.0032     | 3          | no         | −0.0032    | 3          | yes        | Yes        | yes               |          |
| United Kingdom | −0.0007 | 3          | no         | −0.0007    | 3          | yes        | No         | no                |          |
| United States | −0.0021   | 11         | yes        | −0.0036    | 3          | yes        | No         | no                |          |
Therefore, the differences between the IRFs obtained from the two models do not necessarily stem from a different reaction of domestic GDP, but may be the result of differences in the trajectories of Chinese GDP shock.

Concerning Southeast Asia and Oceania, according to the results from the BVAR models, the strongest response of domestic GDP to negative GDP shock in China is observed in Chinese Taipei (−1.40 p.p.), and next in Singapore (−1.03 p.p.), Thailand (−0.85 p.p.), Malaysia (−0.57 p.p.), Indonesia (−0.48 p.p.), Hong Kong (−0.26 p.p.), and Australia (−0.17 p.p.). According to the results the IRFs from the BVAR model are statistically significant on impact. If we omit the first quarter, the GDP reaction becomes statistically insignificant for Hong Kong, Japan, New Zealand, the Philippines, and South Korea. In Japan the reaction is very weak. In the Philippines we find a counterintuitive positive reaction of domestic GDP to negative Chinese GDP shock.

Thus, both the GVAR and BVAR models show that Chinese Taipei is the most affected economy by negative GDP shock in China. The results for Japan from the GVAR model and from the BVAR model are very different. Both specifications point to very weak and statistically insignificant output reaction in New Zealand.
Lastly, it is important to notice that both the results from the GVAR model and the results from the BVAR model show that the United States are quite severely affected by the slowdown in the Chinese economy. The maximum reaction of domestic GDP in the United States is equal to 0.2 p.p. after 11 quarters according to the GVAR model or 0.36 p.p. after 3 quarters according to the BVAR model.

### 5.3 Factors differentiating responses to a China GDP impulse

Figure 5 shows posterior inclusion probabilities of each structural characteristic being in the model from the baseline BMA analysis (based on results from GVAR, without the weight in trade with China among regressors). They are the highest for the exchange rate regime (94.5%), GDP in PPP (98.0%), the share of manufacturing in international trade (81.1%), the size of international investment position (78.5%), and the share of manufacturing in GVA (80.0%).

![Figure 4](https://wileyonlinelibrary.com)
Figure 6 shows the results in a different way. Rows correspond to variables and columns correspond to models. The wider the column, the higher the probability of a given model. Models are ordered so that the first one has the highest probability. If a variable enters a given model, it is in red (a positive impact) or in blue (a negative impact) in a cell. Otherwise—it is in white. When interpreting the results it should be noted that responses are to a negative impulse. The relationship between the strength of the response to a China GDP impulse is negatively related with the exchange rate regime (the less flexible the exchange rate, the stronger the response), GDP in PPP and the size of international investment position, and positively related with the share of manufacturing in international trade.
Figures 7–10 show the results from the remaining variants of the BMA analysis (responses from GVAR with the weight in trade with China among regressors, responses from BVARs with or without the weight in trade). Some of them give a high probability of being in the model for participation in GVC with China (a negative relationship), and measures of trade and financial openness (a negative and a positive relationship, respectively).

Averaging over the results above, among the most important factors differentiating responses to a China GDP impulse are: the exchange rate regime, the structure of the economy and its size, with more rigid exchange rates, higher shares of manufacturing in GVA and larger sizes of the economy associated with stronger spillovers. Below we try to interpret these results.

**FIGURE 7** Posterior inclusion probabilities—alternative

**FIGURE 8** Graphical results of BMA analysis—alternative 1 (GVAR, with weight in trade with China) [Colour figure can be viewed at wileyonlinelibrary.com]
The economies with floating exchange rates should be more resistant to a decrease in China's GDP, because if it leads to a decrease in domestic GDP, then domestic currency should depreciate leading to a later increase in domestic GDP.

The share of industry in China's value added was about 41% in 2015, whereas the average for all other countries in our sample was 31%, similarly the share of manufacturing in China's value added was about 83% in 2015, whereas the average for all other countries in our sample was 67%. It means that manufacturing is the most important component of China's trade, thus, the slowdown of Chinese economy transmits more strongly to economies with higher shares of manufacturing in GVA.

It appears that the size of economy correlates with the weight in trade with China. It means that China trades more with larger economies. Therefore, larger economies are more affected by negative demand shocks from China.
In this study we develop the GVAR model to investigate how a slowdown in Chinese economy may affect other economies. We use a novel data set that spans from 1995Q1 to 2017Q4 and covers 59 economies. We apply time-varying trade weights. Also, we estimate a set of BVAR models to check the robustness of the results.

We decided to concentrate on Southeast Asia and Oceania, because this region seems to be the most dependent from China. Indeed, our results show that the maximum response of the whole global economy to 1 p.p. negative demand shock in China is equal to $-0.157$ p.p. after 7 quarters, while the maximum response of Southeast Asia and Oceania is equal to $-0.262$ p.p. after 4 quarters. Thus, the response of neighboring countries is much stronger and faster than the average response of other economies.

According to our results from both the GVAR and the BVAR models Chinese Taipei is the most affected economy by negative GDP shock in China. Also Indonesia, Singapore, Hong Kong, Thailand, and Malaysia are strongly affected. Australia seems to be also affected but to a lesser degree. We find a weak GDP response to China GDP shock for New Zealand and the Philippines. The response of GDP in South Korea and Japan is quite significant, but only according to the results from the GVAR model.

Thus, our results suggest that there exist strong economic linkages between the Asian economies. Bussière et al. (2012), for example, also confirm the presence of a strong Asian business cycle and an increased vertical specialization in international trade among Asian economies.

The results from the BVAR models seem to confirm the results from the GVAR model. We find out that there are statistically significant differences between the IRFs in 22% of analyzed economies, but if we omit the first quarter the differences appear only in 11% of the analyzed economies. But there are considerable differences between maximum responses and maximum response horizons across the economies between the two types of models.

In the final step of our analysis, we used Bayesian model averaging in order to check how structural characteristics may explain the differences in the response of the analyzed economies to a negative Chinese GDP shock. We found that spillovers are stronger to economies with less flexible exchange rates, a higher share of manufacturing in GVA and to economies which are larger.

**ACKNOWLEDGMENTS**

This work was supported by the National Science Center under Grant No. 2016/21/D/HS4/02798. The authors are grateful for helpful comments of conference participants at EcoMod 2019 in Ponta Delgada.

**DATA AVAILABILITY STATEMENT**

The data that support the findings of this study are openly available in Mendeley at https://data.mendeley.com/datasets/jr8n8hnrw9/draft?a=9fecca2f-5853-4058-9117-2e1d23f744d3.

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**ENDNOTES**

1. Investment slowed from over 17% in 2000 (12) to 3% in 2015, while private consumption slowed from 13% in 2000 (12) to 9% in 2015.

2. China consumed about 50% of copper and aluminium (2016), 60% of iron ore, and 12% of oil (2015), produced globally.
It appears that the level of inflation is most strongly affected in Indonesia and next in Malaysia, India, Philippines, Thailand, Singapore, and Korea. While Hong Kong, New Zealand, Australia, and Japan are less affected.

These statistics do not include Hong Kong.

A special administrative region of China. Hong Kong is a major renminbi center.

In 2012, an agreement was signed between the central banks of China and Taiwan enabling direct settlement of their currencies. As a result, Taiwan has become a local Chinese renminbi center.

We estimate a GVAR model using the modified GVAR 2.0 toolbox.

Persistent profiles show the time profiles of the effects of either variable or system specific shocks on the cointegration relations in the GVAR model. The value of persistent profiles is unity on impact and, if the vector under investigation is indeed a cointegration vector, it should tend to zero as the time horizon tends to infinity.

We estimate BVAR models using the modified BEAR 4.2 toolbox.

Initially we considered 39 structural characteristics, but we deleted 5 of them because of many missing data and next we deleted 16 of them because of a high correlation with other data from a similar group.

We used the bicreg function in the BMA package in R.

The data that support the findings of this study are openly available in Mendeley at https://data.mendeley.com/datasets/jr8n8hnwrw9/draft?a=9fecca2f-5853-4058-9117-2e1d23f744d3.

Table 6 expands abbreviations in Figures 5-10.

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APPENDIX

FIGURE A1  Counterparties resident in China. Total assets and liabilities for all sectors (USD millions) located in BIS reporting country in 2018. Source: own calculations based on BIS locational statistics (see Bácę et al., 2013) [Colour figure can be viewed at wileyonlinelibrary.com]
FIGURE A2  The sum of exports and imports from China (USD millions). Source: own calculations based on Direction of Trade Statistics, IMF; sum of goods, value of exports, FOB and goods, value of imports, CIF [Colour figure can be viewed at wileyonlinelibrary.com]
**FIGURE A3** Exposure to China. Percentage of exports to China in 2017. *Source:* own calculations based on Direction of Trade Statistics, IMF; sum of goods, value of exports, FOB and goods, value of imports, CIF [Colour figure can be viewed at wileyonlinelibrary.com]

**FIGURE A4** Real GDP growth rate in China. *Source:* own calculations based on China GDP Total (at Constant Price, 2015), CNY series from Macrobonds [Colour figure can be viewed at wileyonlinelibrary.com]
| Country            | VARX* order | Number of coint. relations |
|--------------------|-------------|----------------------------|
| Algiers             | 1           | 2                          |
| Argentina           | 1           | 1                          |
| Australia           | 2           | 1                          |
| Brazil              | 1           | 2                          |
| Canada              | 1           | 1                          |
| Chile               | 1           | 3                          |
| China               | 1           | 2                          |
| Chinese Taipei      | 1           | 2                          |
| Colombia            | 1           | 3                          |
| Croatia             | 1           | 3                          |
| Czech Republic      | 1           | 2                          |
| Denmark             | 1           | 2                          |
| euro area           | 1           | 3                          |
| Hong Kong           | 1           | 3                          |
| Hungary             | 1           | 2                          |
| Iceland             | 1           | 3                          |
| India               | 1           | 2                          |
| Indonesia           | 2           | 2                          |
| Israel              | 1           | 2                          |
| Japan               | 1           | 1                          |
| Korea               | 1           | 4                          |
| Malaysia            | 1           | 2                          |
| Mexico              | 1           | 2                          |
| New Zealand         | 1           | 1                          |
| Norway              | 1           | 1                          |
| Peru                | 1           | 3                          |
| Philippines         | 1           | 3                          |
| Poland              | 1           | 3                          |
| Romania             | 1           | 2                          |
| Russia              | 1           | 4                          |
| Saudi Arabia        | 1           | 1                          |
| Singapore           | 1           | 1                          |
| South Africa        | 1           | 3                          |
| Sweden              | 1           | 2                          |
| Switzerland         | 1           | 3                          |
| Thailand            | 1           | 3                          |
| United Kingdom      | 1           | 1                          |
| United States       | 1           | 2                          |
### Table A2  Expansions of abbreviations in Figures 5–10

| Abbreviation | Variable |
|--------------|----------|
| agr_int_tra  | Share of agriculture in international trade |
| agr_gva      | Share of agriculture in GVA |
| chinn_itio   | Chinn-Ito index |
| exc_rat_reg_kspeg | Exchange rate regime |
| fue_min_int_tra | Share of fuels and mining products in international trade |
| gdp_per_cap_ppp_con | GDP per capita, PPP, constant prices |
| gvc_chi      | Participation in GVC with China |
| gvc_wor      | Participation in GVC, total |
| ind_gva      | Share of industry in GVA |
| man_int_tra  | Share of manufacturing in international trade |
| man_gva      | Share of manufacturing in GVA |
| ser_gva      | Share of services in GVA |
| tariff_wei_mea | Tariffs, weighted mean |
| Weight       | Weight in trade with China |
| exp_imp_gdp  | Sum of exports and imports in relation to GDP |
| iip_ass_lia_gdp | Sum of IIP assets and liabilities in relation to GDP |
| Distance     | Distance between capital of respective economies and Beijing |
| gdp_ppp_con  | GDP, PPP, constant prices |