Doojav, Gan-Ochir

Working Paper

Macroeconomic effects of COVID-19 in a commodity-exporting economy: Evidence from Mongolia

ADBI Working Paper, No. 1337

Provided in Cooperation with:
Asian Development Bank Institute (ADBI), Tokyo

Suggested Citation: Doojav, Gan-Ochir (2022) : Macroeconomic effects of COVID-19 in a commodity-exporting economy: Evidence from Mongolia, ADBI Working Paper, No. 1337, Asian Development Bank Institute (ADBI), Tokyo, https://doi.org/10.56506/AVHQ4043

This Version is available at:
https://hdl.handle.net/10419/267771

ADBI Working Paper Series

MACROECONOMIC EFFECTS OF COVID-19 IN A COMMODITY-EXPORTING ECONOMY: EVIDENCE FROM MONGOLIA

Gan-Ochir Doojav

No. 1337
August 2022

Asian Development Bank Institute

Gan-Ochir Doojav is Chief Economist of the Bank of Mongolia, Ulaanbaatar, Mongolia.

Suggested citation:

Doojav, G.-O. 2022. Macroeconomic Effects of COVID-19 in a Commodity-Exporting Economy: Evidence from Mongolia. ADBI Working Paper 1337. Tokyo: Asian Development Bank Institute. Available: https://doi.org/10.56506/AVHQ4043

Please contact the authors for information about this paper.

Email: doojav_ganochir@mongolbank.mn

Asian Development Bank Institute
Kasumigaseki Building, 8th Floor
3-2-5 Kasumigaseki, Chiyoda-ku
Tokyo 100-6008, Japan

Tel: +81-3-3593-5500
Fax: +81-3-3593-5571
URL: www.adbi.org
E-mail: info@adbi.org

Abstract

This paper examines macroeconomic effects and transmission mechanisms of COVID19 in Mongolia, a developing and commodity-exporting economy, by estimating a Bayesian structural vector autoregression on quarterly data. We find strong cross-border spillover effects of COVID-19. Our estimates suggest that the People's Republic of China's GDP and copper price shocks account, respectively, for three-fifths and one-fifth of the drop in real GDP in 2020Q1. The recovery observed for 2020Q2–2021Q1 is primarily due to positive external shocks. However, disruptions in credit and labor markets have been sustained in the economy. Two-thirds of the fall in employment in 2021Q1 could be attributed to adverse labor demand shocks. We also reveal novel empirical evidence for the balance sheet channel of the exchange rate, the financial accelerator effects, and an indirect channel of wage shock to consumer price passing through bank credit.

Keywords: COVID-19, demand and supply shocks, macroeconomic fluctuations, structural vector autoregression, Bayesian analysis

JEL Classification: C32, E6, E17, E27, E32, I15

Contents

1. INTRODUCTION

COVID-19 has triggered an extraordinary global economic shock, causing synchronized disruptions in economic activity and exacerbating socio-economic vulnerabilities across the world. The pandemic has affected emerging markets and developing economies (EMDEs) through various channels. The channels may include domestic health crises, disruptions in supply chains (production, trade, and travel), uncertainty-induced reductions in spending and investment, and unfavorable terms of trade shock as well as to a plunge in remittances from abroad and a tightening of financial conditions in domestic and global markets, with a resulting sharp reversal in capital flows and higher pressure on the exchange rate and credit spreads (Harjes et al. 2020). However, existing papers on the macroeconomic impact of the pandemic (i.e., McKibben and Fernando 2020; Ludvingson, Ma, and Ng 2020; Bekaert, Engstrom, and Ermolov 2020; Guerrieri et al. 2020; Baqaee and Farhi 2021) are more focused on advanced economies and less concentrated on the spillover effects of the global economic crisis on EMDEs. Moreover, designing policies to promote a sustainable, inclusive, and resilient recovery from the COVID-19 pandemic is a big challenge facing policymakers today.

In this context, this paper examines macroeconomic effects and the transmission mechanism of COVID-19 in Mongolia, a developing and commodity-exporting economy.[1] To analyze transmission channels of the COVID-19 pandemic, we extract macroeconomic shocks, including supply and demand shocks in the global economy, domestic real sector, credit market, labor market, exchange rate shock, and conventional and unconventional monetary policy and fiscal policy shocks. After verifying that our results are mainly in line with the existing evidence, we study macroeconomic fluctuations during the pandemic. Disentangling supply and demand shocks in crucial markets is essential for economic policy design during the pandemic. As the model includes several variables, a Bayesian structural vector autoregression (VAR) with normal-Wishart prior is used for estimation and inference to deal with overfitting and identification problems.

The present paper extends the literature in two distinct ways. First, evidence from this exercise will be highly relevant in identifying macroeconomic spillover effects in global commodity markets and the People's Republic of China's (PRC's) economy on EMDEs during COVID-19. Second, the paper provides a comprehensive analysis examining the impact of various external and domestic market-specific supply and demand shocks in the broader macroeconomy, including external sector, real sector, financial market, and labor market. Therefore, the analysis helps policymakers to adequately design economic policies during the pandemic.

Recent papers have attempted to quantify the macroeconomic effects of COVID-19 using different shock identifications. Ludvingson, Ma, and Ng (2020) examined the impact of the pandemic using costly and deadly disaster series by assuming that past natural disasters are local and come and go quickly, while COVID-19 is a global, multiperiod event. Bekaert, Engstrom, and Ermolov (2020) studied the effects of the

[1] Mongolia is a developing and commodity-exporting economy in the sense that mineral exports account for 80%–90% of total exports, 70%–80% of total FDIs come to the mining sector, and 80% of total exports go to the PRC. Because of COVID-19, the Mongolian economy shrank by 5.3% in 2020, and employment fell by 11.2% since the end of 2019. In the first three quarters of 2020, exports of goods and services contracted by 8% in real terms, the largest decline since the 2009 Global Financial Crisis (GFC). The contraction was due to weaker demand from the PRC, a temporary ban on exports in February–March 2020 to contain the risk of COVID-19, and a sharp fall in copper prices as the COVID-19 shock suppressed global demand (World Bank Group 2021).

pandemic by extracting aggregate demand and supply shocks from real-time survey data on inflation and real GDP. Guerrieri et al. (2020) claimed that economic shocks associated with COVID-19 may have features similar to supply shocks that more significantly trigger changes in aggregate demand than the shocks themselves. Baqaee and Farhi (2021) argued that COVID-19 is a messy combination of disaggregated sectoral supply and demand shocks propagated through supply chains to create different cyclical conditions in other parts of the economy. Our empirical approach aligns with these arguments since our VAR system includes all variables (i.e., external sector, real sector, financial sector, labor market, monetary and fiscal policies) capturing potential transmission channels of COVID-19 in EMDEs. For example, as the COVID-19 pandemic is global in nature, foreign gross domestic product (GDP), consumer price index (CPI), and commodity prices are included to capture the spillover effect of global demand, supply, and terms of trade shocks.

This paper relies on the structural VAR approach and focuses on a review of the relevant literature. Since it is challenging to include potential channels of COVID-19 in a structural model, existing papers mostly employ the VAR approach, the most popular time-series model in macroeconomics, to assess the impacts of the pandemic.[2] Empirical papers (i.e., Bekaert, Engstrom, and Ermolov 2020, Ludvingson, Ma, and Ng 2020) employ structural VARs and identify structural shocks based on Cholesky decompositions. Brinca, Duarte, and Castro (2020) measured labor demand and supply shocks at the sectoral level around COVID-19 by estimating a Bayesian structural VAR. Djurovic, Djurovic, and Bojaj (2020) assessed the macroeconomic effects of COVID-19 in Montenegro using a Bayesian VARX approach, and shocks were identified with a recursive method. Lenza and Primiceri (2020) proposed a solution to manage a sequence of extreme observations, such as those recorded during COVID-19, when estimating VAR and showed that exclusion of the data from the pandemic may be acceptable for parameter estimation. Gharehgozli et al. (2020) used a two-step VAR model to forecast and estimate the effect of the COVID-19 outbreak on New York's GDP for the first and second quarters of 2020. Bobeica and Hartwig (2021) showed that for both single equation models (Phillips curves) and Vector Autoregressions (VARs), estimated parameters changed notably with the pandemic. They found that a large Gaussian VAR with a higher degree of prior shrinkage mitigated the problem of changing parameters after adding the COVID-19 observations.

Only a few papers have investigated the international spillover effects of the pandemic on EMDEs through changes in commodity markets and the PRC's economy. Based on a global Bayesian VAR model with five major economic blocs (the US, the PRC, the euro area, other advanced economies, and other emerging market economies), Kohlscheen, Mojon, and Rees (2020) showed that the macroeconomic spillovers and spillbacks of pandemic-type recessions were substantial. Adam, Hensridge, and Lee (2021) found that the disruption from domestic economic slowdowns caused by early and stringent lockdowns was augmented by the global economic slowdown, which has reduced countries' import capacity and resulted in a severe squeeze on domestic absorption in sub-Saharan Africa. Sawada and Sumulong (2021) found that the impact of COVID-19 in developing Asian economies has been significant, and these impacts primarily originate from declines in domestic demand, tourism, and global spillovers. Coulibaly (2021) examined spillover effects of COVID-19 on the consumer price index

[2] A few exceptions include Mihailov (2020), who chose adverse labor supply shocks in an estimated DSGE model as a proxy for the COVID-19 pandemic lockdown; McKibben and Fernando (2020), who used a global hybrid DSGE/CGE general equilibrium model; and Barrot, Grassi, and Sauvagnat (2021) and Baqaee and Farhi (2021), who employed quantitative multisector models.

(CPI) for the West African Economic and Monetary Union (WAEMU) and found that the confirmed cases, world food prices, and oil prices positively affected the CPI. Barrett et al. (2021) investigated the possible persistent effects (scarring) and the channels of the COVID-19 pandemic, and found that deep recessions often leave long-lived scars, particularly on productivity. They highlighted that EMDEs are expected to suffer more scarring than advanced economies, while the degree of expected scarring varies across countries depending on the structure of economies and the size of the policy response. Wang and Han (2021) examined spillover effects of the US economic slowdown induced by the COVID-19 pandemic on energy, economy, and environment in other countries. They showed that the pandemic caused a sharp decline in carbon emissions and energy consumption in the US, having a more significant impact on embodied energy exports of Canada, the PRC, Mexico, the European Union, and the Russian Federation. Ha, Kose, and Ohnsorge (2021) found that the decline in global inflation during the pandemic (the 2020 global recession) was the most muted and shortest-lived of the global recessions over the past 50 years and the increase in inflation since May 2020 has been the fastest. They also showed that the decline in global demand from January–May 2020 was four-fifths driven by the collapse in global demand and another one-fifth driven by plunging oil-prices, with some offsetting inflation pressures from supply disruptions.

The rest of the paper is structured as follows. Section 2 presents a benchmark specification of a structural Bayesian VAR model for the Mongolian economy. Section 3 describes the data used in this paper and reports the main findings of the benchmark estimations. Section 4 provides robustness checks. Finally, Section 5 concludes the paper with policy implications.

2. A STRUCTURAL VAR MODEL FOR THE MONGOLIAN ECONOMY

Structural vector autoregression (SVAR) models have been extensively used to examine the effects of macroeconomic shocks. A SVAR describing the dynamics of economic relations takes the form

$$\mathbf{A}\mathbf{y}_t = \mathbf{B}\mathbf{y}_{t-1} + \mathbf{u}_t \quad (1)$$

for $\mathbf{y}_t$, which is a $n \times 1$ vector of observed variables at date $t = 1, \dots, T$, $\mathbf{A}$ is an $n \times n$ matrix summarizing their contemporaneous structural relations, $\mathbf{y}_{t-1}$ is a $(k \times 1)$ vector (with $k = mn + 1$) containing a constant and m lags of $\mathbf{y}$ $((\boldsymbol{y}'_{t-1}, \boldsymbol{y}'_{t-2}, \dots, \boldsymbol{y}'_{t-m}, 1)')$, $\mathbf{B}$ is a $k \times k$ matrix summarizing constants and lagged structural relations, and $\mathbf{u}_t$ is $n \times 1$ vector of structural shocks that are assumed to be i.i.d. $\mathcal{N}(0, \mathbf{D})$ and mutually uncorrelated (i.e., $\mathbf{D}$ is diagonal).

The reduced-form VAR associated with the structural model (1) is

$$\mathbf{y}_t = \boldsymbol{\Phi}\mathbf{y}_{t-1} + \boldsymbol{\varepsilon}_t \quad (2)$$

$$\boldsymbol{\Phi} = \mathbf{A}^{-1}\mathbf{B} \quad (3)$$

$$\boldsymbol{\varepsilon}_t = \mathbf{A}^{-1}\mathbf{u}_t \quad (4)$$

The matrices $\boldsymbol{\Phi}$ and $\boldsymbol{\Omega} = \mathrm{E}(\boldsymbol{\varepsilon_t}\boldsymbol{\varepsilon_t'}) = \mathbf{A^{-1}D}\left(\mathbf{A^{-1}}\right)'$ consist of reduced-form parameters, while $\mathbf{A}$ and $\mathbf{B}$ are structural parameters.

Once structural shocks, $\mathbf{u_t}$, are identified using an assumption for $\mathbf{A^{-1}}$ (i.e., a Choleski factorization), the resulting structural VAR has a structural moving average representation taking the form

$$\mathbf{y_t} = \sum_{\mathrm{h}=0}^{\infty} \boldsymbol{\psi}_{\mathrm{h}} \mathbf{u}_{\mathrm{t-h}} \tag{5}$$

with impact effect of shock *j* measured by the *j*-th diagonal entry of $\boldsymbol{\psi_0}$, which is also the standard deviation of shock *j*.[3] The dynamic effect of a one-time change in structural shock $\mathbf{u_t}$ on the VAR variables $\mathbf{y_{t+h}}$ are summarized by $\boldsymbol{\psi_h}$ matrices, which are called impulse response functions of the structural VAR.

In our VAR specification, the vector of endogenous variables, $\mathbf{y}_{\mathrm{t}}$, comprises 15 variables. Several aspects of the selection of variables are worth mentioning. First, the benchmark specification includes key foreign variables to properly assess the impacts of external shocks on domestic macroeconomic fluctuations. The foreign variables include copper price, oil price, the PRC's GDP, and the PRC's CPI. Mineral exports account for 90%of total exports, of which 45 percentage points are solely attributed to copper exports. Thus, the copper price is a good proxy for reflecting the effects of the global commodity price cycle. Though Mongolia extracts a small amount of crude oil, all domestic petroleum products are imported from the Russian Federation and the PRC. Therefore, the oil price is a sort of demand shock on the real sector and can be a negative supply shock since a rise in petroleum price leads to a hike in consumer prices by raising supply chain costs. To analyze the effects and transmission of oil price, we include the price in the system. IMF (2020) provides details about how falls in oil and other commodity prices at the beginning of COVID-19 could affect the macroeconomy and banking sector. Moreover, Mongolian exports to the PRC account for about 90% of total exports. Hence, the PRC's GDP and CPI are used to identify foreign demand and supply shocks. Existing studies (i.e., Gan-Ochir and Davaajargal 2019) have found that these foreign variables play a vital role in explaining and predicting domestic business cycle fluctuations. Second, as the economy has faced a sudden flood and stop of mining sector foreign direct investment (FDI) over the last decade, FDI inflow is included to identify its role in macroeconomic fluctuations. The inclusion of exchange rate allows us to analyze the effects of exchange rate shocks and the role of the exchange rate in the transmission of external and domestic shocks. In the model, we chose nominal exchange rate as Mongolian tögrög (MNT) against US dollar instead of renminbi (RMB) because the US dollar still accounts for 7075% of export revenues, import payments, and foreign exchange transactions. Statistics on foreign exchange transactions show that RMB's share is less than 15% in the economy. Third, the policy rate, which is the central bank's balance sheet indicator, and government expenditure are included in conventional monetary policy (CMP), unconventional monetary policy (UMP), and fiscal policy. Fourth, critical domestic variables, such as GDP, CPI, exchange rate, bank loan, and the spread between the lending rate and policy rate, are included to capture macroeconomic and financial developments. GDP and CPI are used to distinguish domestic aggregate demand and supply shocks, while the bank loan and the spread are essential to isolate loan demand and loan supply shocks in the banking sector. The inclusion of the banking sector variables also helps to identify UMP shocks (balance sheet shocks) and reflects that

[3] In the case of Choleski factorization (i.e., $\mathbf{D} = \boldsymbol{I}$), the impact period impulse response is given by $\boldsymbol{\psi_0} \equiv \mathbf{A^{-1}}$.

the banking system's healthiness plays an essential role in a monetary policy's effectiveness. For instance, the spread reflects macroeconomic and financial risks, and conditioning on the spread is vital to disentangle exogenous changes in the balance sheet indicator from endogenous responses to financial risks and uncertainties.[4] If banks are capital constrained and have financial fragility issues, they cannot convert the extra liquidity into more lending to the private sector. In such a case, the central bank injects liquidity, but banks are not able or willing to lend to households and firms due to their fragility; thereby, the effects on economic activity are more subdued. Finally, employment and wage are included in the system to distinguish labor demand and labor supply shocks as the COVID-19 pandemic harshly hit the labor market.

As our empirical analysis involves a more extensive data set, we estimate the model using the Bayesian approach, which helps to deal with the over-parameterization problem by imposing prior beliefs on the parameters. In Bayesian econometrics, every parameter of interest is treated as a random variable characterized by an underlying probability distribution. The aim is thus to identify these distributions to produce estimates and carry inferences on the model. The principle of Bayesian analysis is to combine the prior information about the distribution of these parameters (the prior distribution) with the information contained in the data (the likelihood function) to obtain an updated distribution accounting for both these sources of information, known as the posterior distribution.

The simplest and a frequently used form of prior distributions for VAR models is known as the Minnesota prior as advocated by Litterman (1980). In this framework, it is assumed that the VAR variance–covariance matrix $\mathbf{\Omega}$ is known. Hence, the only object left to estimate is the vector of parameters $\phi = vec(\mathbf{\Phi})$. Although the Minnesota prior offers a simple way to derive the posterior distribution of the VAR coefficients, it suffers from the main drawback of assuming that $\mathbf{\Omega}$ is known. One possibility to relax this assumption is to use a Normal-Wishart prior distribution. In this setting, it is taken that both ϕ and $\mathbf{\Omega}$ are unknown.

Therefore, a Normal-Wishart prior is employed in this paper. Under the assumption that ϕ and $\mathbf{\Omega}$ are unknown, the likelihood function $f(y|\phi, \mathbf{\Omega})$, where $y = vec(\boldsymbol{y})$ for data can be recognized as the kernel of a multivariate normal distribution for ϕ and the kernel of an inverse Wishart distribution for $\mathbf{\Omega}$, both centered around ordinary least squares (OLS) estimators. Therefore, the choice of similar prior distributions for ϕ and $\mathbf{\Omega}$ could yield distributions of the same families for the posterior distribution. Such identical families for the prior and the posterior are known as conjugate priors.

The Normal-Wishart prior is given by

$$\phi|\mathbf{\Omega} \sim \mathcal{N}\left(\tilde{\phi}, \mathbf{\Omega} \otimes \tilde{\Psi}\right), \mathbf{\Omega} \sim iW\left(\tilde{\mathbf{\Omega}}, \alpha\right) \quad (6)$$

with prior mean and variance $E(\phi) = \tilde{\phi}$, $\alpha > n$, and $Var(\phi) = (\alpha - n - 1)^{-1}\tilde{\mathbf{\Omega}} \otimes \tilde{\Psi}$, $\alpha > n + 1$, where α is the prior degrees of freedom.

For the choice of $\tilde{\phi}$, a typical conventional Minnesota scheme will be adopted as

$$\tilde{\phi}_{l,ij} = \begin{cases} \delta_i, i = j, l = 1 \\ 0, \text{otherwise} \end{cases} \quad (7)$$

[4] UMP measures of the BOM have been intended to increase credit supply and reduce lending rates during the credit crunch period rather than responding to financial turbulence. Given a bank-centric financial system, the BOM's UMP (i.e., large-scale subsidized lending to the real sector through banks) can stimulate the economy by increasing new loans and reducing lending rates.

This implies that we set δ_i values for own first lag ($i = j$, $l = 1$, where i is for equation, j is for variable, l is for lag considered by the coefficient) coefficients and 0 for cross-variable and exogenous coefficients. Based on the empirical fact that most observed macroeconomic variables seem to be characterized by a unit root, Litterman (1986) suggested that $\delta_i = 1$ for its own first lag. However, as highlighted by Dieppe, Legrand, and Roye (2018), in the case of variables known to be stationary, this unit root hypothesis may not be suitable, so that a value around $\delta_i = 0.8$ may be preferred.

In terms of $\widetilde{\Phi}$, a Minnesota type of variance matrix can be adopted as (see, e.g., Karlsson 2012)

$$\widetilde{\Psi}_{l,ij} = \left(\frac{1}{\sigma_j^2}\right)\left(\frac{\lambda_1}{l^{\lambda_3}}\right)^2 \tag{8}$$

$$\boldsymbol{\Omega}_{ij} \otimes \widetilde{\Psi}_{l,ij} = \begin{cases} \left(\frac{\lambda_1}{l^{\lambda_3}}\right)^2, i = j \\ \left(\frac{\sigma_i^2}{\sigma_j^2}\right)\left(\frac{\lambda_1}{l^{\lambda_3}}\right)^2, \text{otherwise} \end{cases} \tag{9}$$

where λ_1 is overall tightness parameter, λ_3 is a scaling coefficient controlling the speed at which coefficients for lags greater than 1 converge to 0 with greater certainty, and σ_j^2 and σ_j^2 denote the OLS residual variance of the autoregressive models estimated for variables i and j. The parameter, λ_1 controls the importance given to the priors. If $\lambda_1 = 0$, the model is the same as the OLS model. For bigger values of λ_1, more importance is given to the priors and less importance to the data. In this paper, we manually set the hyperparameters based on values commonly employed by empirical papers rather than searching for optimal combinations. However, the optimal choice of the hyperparameters can be approached via Bayesian VARs with hierarchical prior selection as suggested by Kuschnig and Vashold (2021). The use of hierarchical modeling for the same topic is left for future research.

Following Kadiyala and Karlsson (1997), $\widetilde{\boldsymbol{\Omega}}$ can be defined as

$$\widetilde{\boldsymbol{\Omega}} = (\alpha - n - 1)\boldsymbol{\Omega} \tag{10}$$

The prior degrees of freedom α is simply defined as

$$\alpha = n + 2 \tag{11}$$

Given the above priors, posterior distributions for ϕ ($\phi|\boldsymbol{\Omega}, \boldsymbol{y} \sim \mathcal{N}(\bar{\phi}, \boldsymbol{\Omega} \otimes \bar{\Psi})$) and $\boldsymbol{\Omega}$ ($\boldsymbol{\Omega}|\boldsymbol{y} \sim iW(\bar{\boldsymbol{\Omega}}, T + \alpha)$) can be determined as shown in Kadiyala and Karlsson (1997). The hyperparameters of prior distributions are carefully selected in Section 3.2.

In isolating structural macroeconomic shocks, $\mathbf{u}_t$, the most common identification scheme for $\mathbf{D}$ and $\mathbf{A^{-1}}$ is Choleski factorization, which assumes that $\mathbf{D} = \boldsymbol{I}$ and $\mathbf{A^{-1}}$ is the Choleski factor of the covariance matrix of residual in the reduced form VAR, $\boldsymbol{\Omega}$. However, the assumption that $\mathbf{D} = I$ may constitute an excessively restrictive hypothesis. This assumption implies that all the structural shocks have similar unit variance; however, the variance may differ from unit to unit, and different shocks may have very different sizes. As a simple solution to this problem, a triangular factorization is used in this paper. In this identification scheme, i) $\mathbf{D}$ is diagonal, but not identity, and the zeros below the diagonal impose $n(n-1)/2$ constraints; and (ii) $\mathbf{A^{-1}}$ is a lower triangle, and its main diagonal is made of ones, and the zeros above the main diagonal

combined with the diagonal of ones generates another $n(n+1)/2$ set of constraints. Combining the $n(n-1)/2$ constraints on $\mathbf{D}$ with the $n(n+1)/2$ constraints on $\mathbf{A^{-1}}$ results in n^2 constraints that exactly identify $\mathbf{D}$ and $\mathbf{A^{-1}}$. Like the Choleski method, the triangular factorization identification scheme assumes that some variables have no immediate response to certain structural shocks.

Bayesian estimation and shock identification are made using the BEAR toolbox, a flexible MATLAB routine developed by Dieppe, Legrand, and Roye (2018).

3. DATA, CHOICE OF HYPERPARAMETERS, AND EMPIRICAL RESULTS

3.1 Data

Our benchmark VAR is estimated in (log) levels over the sample period 2006Q3–2021Q1. In the case of Mongolia, quarterly data for the labor market is only available from the third quarter of 2006. In the benchmark specification, the vector of endogenous variables, $\mathbf{y}_t$, is comprised of the following 15 variables: The log of seasonally adjusted PRC real GDP (GDP_{CH}), the log of PRC CPI (CPI_{CH}), the log of the copper price index (P_{copper}), the log of the oil price index (P_{oil}), the log of FDI inflows (FDI), the log of seasonally adjusted real government expenditure (*GEXP*), the log of seasonally adjusted domestic real GDP (GDP), the log of domestic CPI (all items, 2015=100) (CPI), the log of the nominal exchange rate (expressed in MNT/USD) (ER), the log of the (annual) policy rate (PR), the log of the central bank's domestic assets excluding other assets (DA), the spread between the lending rate and policy rate (SP), the log of bank loan outstanding (L), the log of seasonally adjusted total employment (EMP) and the log of national average wage (W).

The PRC's GDP and CPI were observed from Federal Reserve Economic Data (FRED) of the Federal Reserve Bank of St. Louis,[5] while copper price index and Brent crude oil price index were collected from the Primary Commodity Price System of the IMF database. Domestic GDP, CPI, government expenditure, total employment, and national average wage were retrieved from the National Statistical Office. All remaining data were obtained from the Statistical Bulletin of the Bank of Mongolia (BOM).

The Bayesian approach is better equipped to estimate the large VAR model based on a relatively short sample. However, as highlighted in the literature, Bayesian estimates are sensitive to the specification of prior distribution when conducting estimation on small samples. We set standard hyperparameters of prior distributions to deal with the issues, as discussed in section 3.2.

3.2 Choice of Hyperparameters

Values typically found in the literature were chosen for the overall tightness, $\lambda_1 = 0.1$,[6] and the lag decay, $\lambda_3 = 2$. As suggested by Bobeica and Hartwig (2021), the choice of

[5] The PRC's real GDP is calculated as a ratio of seasonally adjusted current price GDP in the PRC (CHNGDPNQDSMEI) to CPI, all items for the PRC, index 2015=100 (CHNCPIALLQINMEI), data are collected from FRED economic data of the Federal Reserve Bank of St. Louis.

[6] Dieppe, Legrand, and Roye (2018) suggested setting λ_1 for the normal-Wishart prior at a smaller value than for the Minnesota prior to compensate for the lack of extra shrinkage from λ_2, which controls tightness on cross-variable parameters in the case of Minnesota prior. Our choice of $\lambda_1 = 0.1$ is much

higher degrees of prior shrinkage helps to mitigate the problem of changing parameters after adding the COVID-19 observations. For the autoregressive coefficient prior, δ_i, we set $\delta_i = 0.8$ as selected by Sznajderska and Kapuściński (2020) for quarterly data. Lag length was determined based on the formal Bayesian model comparison, where the ratio of posterior probabilities is used as the main criteria. Log marginal likelihoods for $\mathcal{M}_1$:BVAR(1), $\mathcal{M}_2$:BVAR(2), $\mathcal{M}_3$:BVAR(3), and $\mathcal{M}_4$:BVAR(4) were estimated as 239.52, 232.99, 233.73, and 230.16, respectively; hence, the log of posterior ratios were found as $log_{10}(R_{12}) = 6.53$, $log_{10}(R_{13}) = 5.79$, and $log_{10}(R_{14}) = 9.37$. According to Jeffrey (1961)'s guideline, there is a decisive $\mathcal{M}_1$ model, thereby lag length is selected as $m = 1$. BVAR(2) and BVAR(3) models were also estimated, with robust results, as shown in Section 4. The total number of iterations of the Gibbs sampling algorithm was selected as 10,000, and 5,000 iterations were discarded as burn-in iterations.

To assess how different values of the overall tightness, λ_1, affect the model fit, we estimated four models with $m = 1$, such as benchmark $\mathcal{M}_b(\lambda_1 = 0.1, \lambda_3 = 2)$, data-dominant (OLS version) $\mathcal{M}_{ols}(\lambda_1 = 0.001, \lambda_3 = 2)$, prior-dominant $\mathcal{M}_p(\lambda_1 = 0.999, \lambda_3 = 2)$, and neutral $\mathcal{M}_n(\lambda_1 = 0.5, \lambda_3 = 2)$ models. Log marginal likelihoods for $\mathcal{M}_b$, $\mathcal{M}_{ols}$, $\mathcal{M}_p$, and $\mathcal{M}_n$ were estimated as 239.52, 113.20, 165.57, and 209.89, respectively. The results suggest that our choice of $\lambda_1 = 0.1$ improves the model fit compared to the three alternative choices (i.e., $\lambda_1 \to 0$, $\lambda_1 \to 1$ and $\lambda_1 = 0.5$).

3.3 Empirical Results

In this section, the following four questions are answered: 1) How did macroeconomic shocks in the economy move during the COVID-19 pandemic? 2) How does the economy respond to macroeconomic shocks? 3) How vital are the shocks in macroeconomic fluctuations? and 4) What shocks drive the economic recession during the pandemic?

As the triangular factorization scheme is utilized, structural shocks are identified using a simple recursive ordering. Regarding the ordering of variables in the VAR, most exogenous (endogenous) variables are placed first (last), and relationships among variables in New Keynesian structural models are used as the main criteria. The ordering is set as follows: P_{copper}, P_{oil}, GDP_{CH}, CPI_{CH}, FDI, $GEXP$, GDP, CPI, PR, DA, L, SP, EMP, W, and ER. The ordering is entirely in line with Jacobs and Rayner (2012), Kremer (2016), and Sznajderska and Kapuściński (2020). The identification helps to isolate demand and supply shocks in the global economy, domestic real sector, credit market, and labor market. Baqaee and Farhi (2021) highlighted that separating demand shortfalls from supply constraints is important since demand- and supply-constrained sectors respond differently to policies. Policies that boost demand by lowering interest rates or increasing government spending worsen problems of inadequate supply, leading to inflation. Likewise, policies that boost supply by relaxing lockdowns or providing liability exemptions are ineffective at restoring activity when applied to demand-constrained sectors.

To test the issue (i.e., a sequence of extreme observations such as recorded during the COVID-19 pandemic that is capable of severely distorting parameter estimates) raised by Lenza and Primiceri (2020), we compared impulse responses (parameters estimation) for the full sample including the pandemic period and pre-pandemic sample excluding the latest data. As shown in Section 4, results revealed no significant

smaller compared to the value of $\lambda_1 = 0.2$ selected by Sznajderska and Kapuściński (2020) for the Minnesota prior.

differences among the samples; hence we used the estimated parameters of the whole sample in the empirical analysis.

3.3.1 Time Series of Macroeconomic Shocks: How Did Macroeconomic Shocks in the Economy Move during the COVID-19 Pandemic?

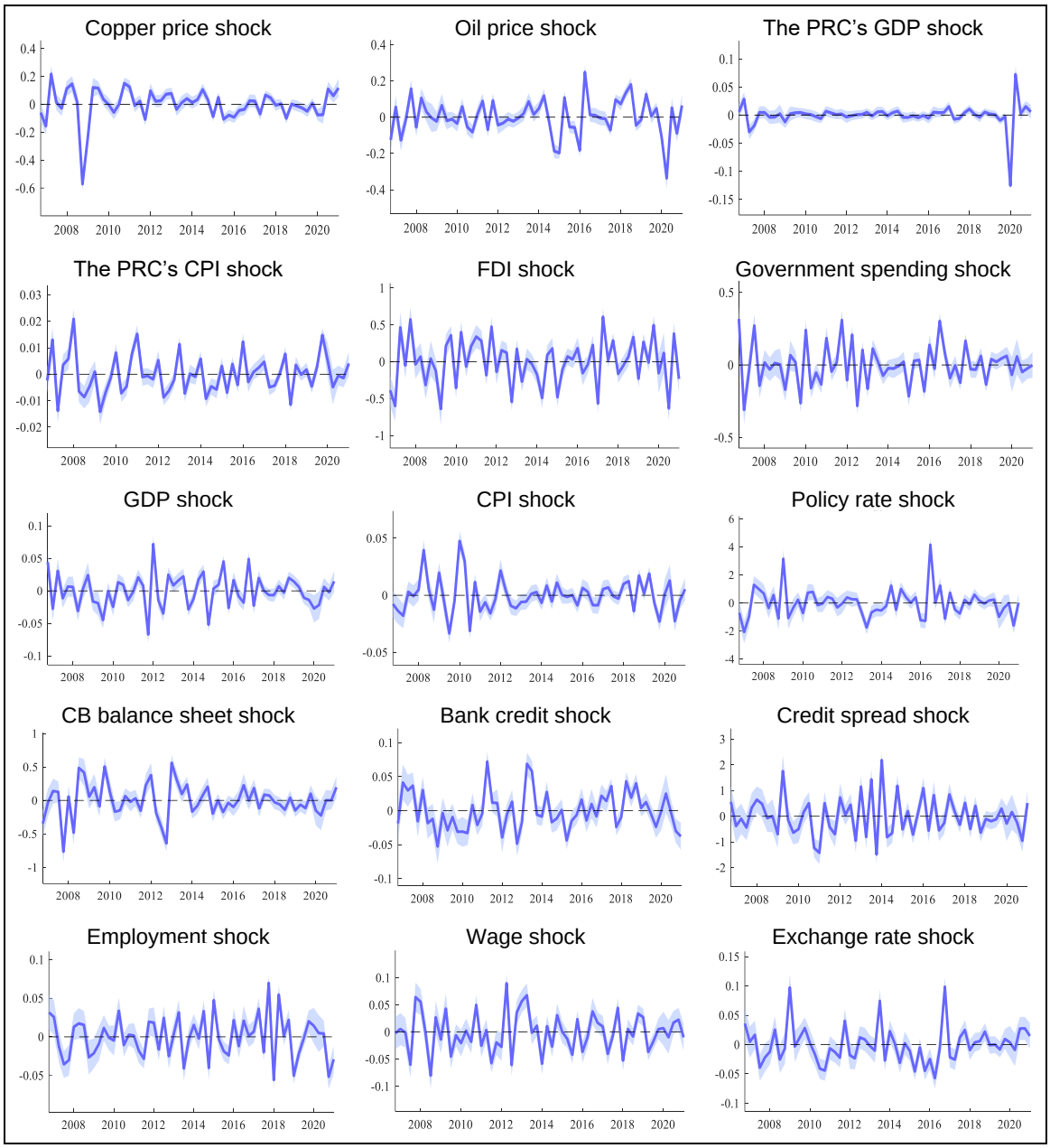
We first examined the time series of the identified structural shocks before discussing the dynamic effects and transmission mechanism of the macroeconomic shocks. Examining the shocks' time series should help interpret their exact source more carefully and assess whether the estimated innovations capture the significant changes in the global and domestic economy. Figure 1 presents the median time series of the shocks. In accordance with the aim of this paper, we focused more on the pandemic period (2020Q1–2021Q1).

The identified shocks capture the dates of critical events that happened during the pandemic. This implies that our identification strategy is plausible. The COVID-19 outbreak caused by the SARS-COV-2 virus was triggered in December 2019 in the PRC. Because of lockdowns and troubles in supply chains, COVID-19 severely disrupted the economy of the PRC in the first quarter of 2020. As the pandemic continued to spread globally, commodity markets were harshly affected in the first two quarters of 2020. For instance, copper price and oil price, respectively, fell by 10% and 70% in the first half of 2020. The shock in copper price was moderate compared to that observed during the Global Financial Crisis (GFC), while the shock in oil price is a historically large negative shock in the market. Copper and oil prices have increased by over 40% for the period 2020Q3–2021Q1. Thanks to effective lockdown measures and strong stimulus measures, the economy of the PRC quickly recovered, starting from the second quarter of 2020. However, inflation shock driven by supply factors has been mild in the PRC during the pandemic. As the global economy has started to recover, copper and oil prices have increased since the second quarter of 2020. In the case of Mongolia, the mining sector, particularly a few large projects, received the central portion of FDI inflows. FDI inflows on the ongoing projects shrank in the first three quarters of 2020. The developments are well reflected in the identified external shocks.

For the domestic variables, the economy has faced a sharp recession during the pandemic. The government implemented prompt measures to contain the spread of the virus, such as social distancing and border closures starting from February 2020. These have proven successful, as there was no reported community transmission until the middle of November 2020. However, the economic costs were significant. The fall in export and domestic demand led to a 9.7% contraction in GDP in the first half of 2020. As a result of no reported domestic transmission (i.e., weaker COVID-19 restrictions), the domestic economic activity recovered in the last three quarters of 2020.

COVID-19 restrictions on businesses, disruptions at the Mongolia–PRC border, changes in household consumption behavior, and decreases in young livestock are well captured in the dynamics of GDP shocks. Due to disrupted supply chains of local foods and imported goods, consumer prices have increased since 2020Q4, and the increases in prices driven by the supply factors are captured in the CPI shocks.

Figure 1: Time Series of Identified Macroeconomic Shocks



Note: Figures show median values of structural shocks, together with the % confidence interval of the posterior distributions.

Fiscal and monetary policies have been significantly loosened to maintain stability and protect the most vulnerable. On the fiscal policy front, the Ministry of Finance introduced a fiscal stimulus package, including reducing the social security contribution, increases in the universal transfer program (known as *child money*), health spending, one-off cash handout of 105 USD for each citizen, the one-off bonus of 18 USD for a fully vaccinated adult, and 6-month exceptions for all households and enterprises on electricity, water, and waste bills. The BOM has cut policy rates by 500 basis points, reduced the reserve requirement by 4.5 percentage points (reflected in a series of expansionary policy rate shocks in 2020), suspended the debt-service-to-income ceiling on consumer loans, and provided targeted long-term refinancing operations

(TLTRO) to the banking sector, engaging quasi-fiscal operations including providing liquidity for mortgage loans and loans to gold extraction companies as permitted under COVID-19 laws. The series of expansionary central bank balance sheet shocks in 2020 capture these unconventional monetary policy measures.

The BOM has taken temporary forbearance measures for the financial sector, softening asset classification requirements, extending maturities on consumer and mortgage loans, and restructuring business loans in the banking sector. These measures have reduced pressure on borrowers and banks. However, the credit crunch in the banking sector continued throughout 2020. It has been captured in both bank credit and credit spread shocks. The government has started to implement the "MNT 10 trillion Comprehensive Plan for Health Protection and Economic Recovery" since March 2021. As of the end of November 2021, MNT 4.1 trillion loans, equivalent to 20% of total loans outstanding, have been issued as part of the plan.

The domestic COVID-19 outbreak that began in November 2020 did disrupt the labor market. Employment fell by 8.4% between 2020Q3 and 2021Q1. The identified employment and wage shocks capture the recent changes in the market.

3.3.2 Impulse Responses: How Does the Economy Respond to the Macroeconomic Shocks?

Since impulse response functions are a nonlinear function of the reduced-form parameters, confidence bands for impulse responses fully reflect posterior distributions of the parameters (i.e., estimation uncertainty). As a standard in the VAR literature, we show the 68% confidence intervals of posterior distributions for impulse responses instead of providing graphical representations of posterior distributions for the reduced-form parameters.

Figure 2 reports impulse responses to a 1% shock in external variables. The solid lines are the median impulse responses of posterior distributions, while the dashed lines represent the 68% posterior probability interval of the estimated responses. The copper price shock seems a significant shock in the economy as all domestic variables significantly responded to the shock. For instance, a 1% increase in copper price led to a 0.1%–0.15% appreciation in nominal exchange rate, a 0.1% rise in real GDP, and a 0.2%–0.3% expansion in bank credit for the first four quarters. CPI increases gradually as demand-driven inflation builds up, and domestic demand and the rise in CPI increase the nominal wage. As a relatively small portion of employment is in the mining sector, employment response to the shock is insignificant.

The shock seems to have very persistent effects on the economy. As Mongolia is an exporter of crude oil and importer of final petroleum products, oil price shock has a hybrid characteristic of demand and supply shocks. For instance, in responding to a positive oil price shock, CPI, nominal wage, policy rate, and bank credit initially increase. Compared to the copper price, the effect of oil price in the economy is weak as most responses are insignificant.

Figure 2: Selected Impulse Responses to External Shocks

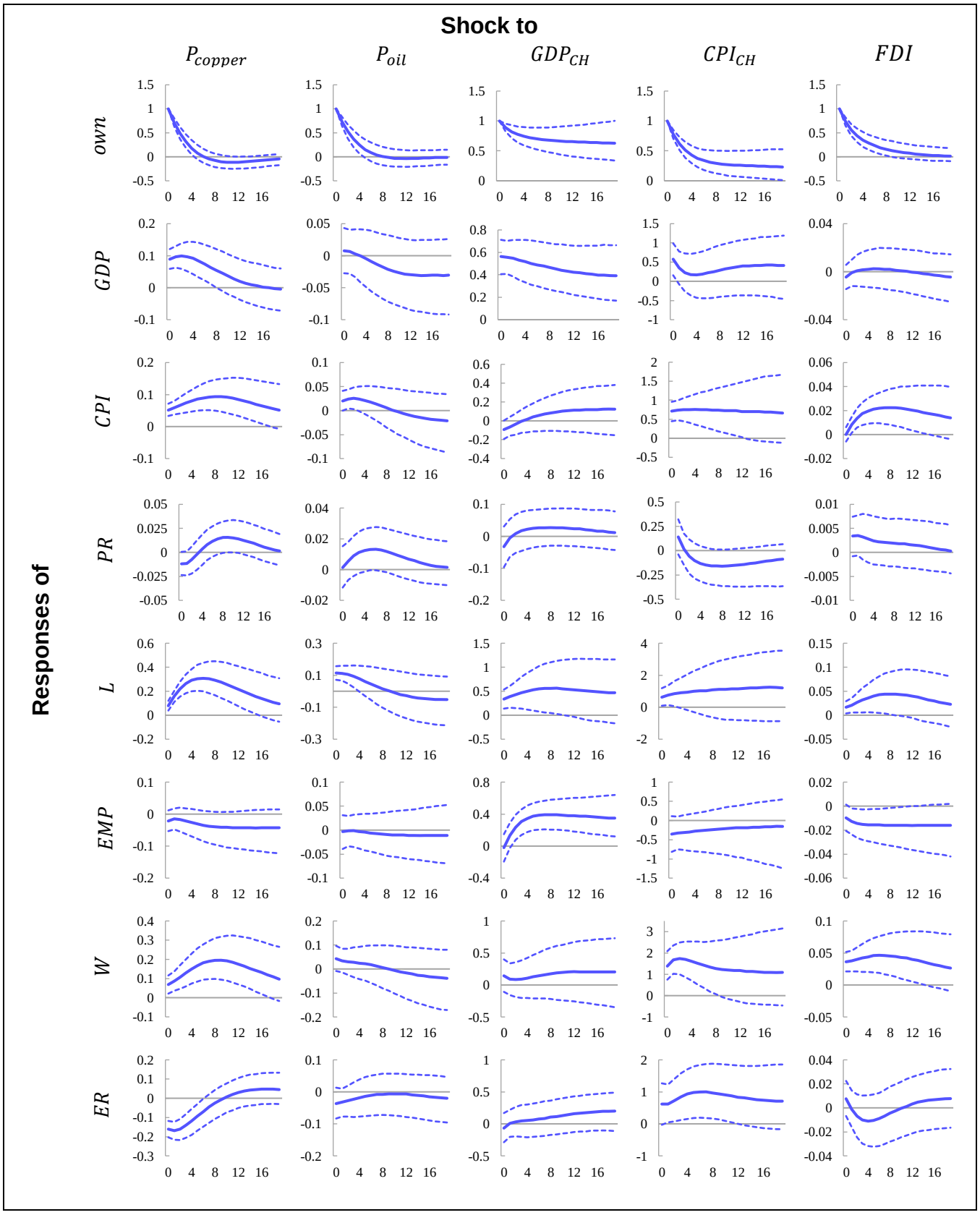


Figure 3: Selected Impulse Responses to Real Sector and Policy Shocks

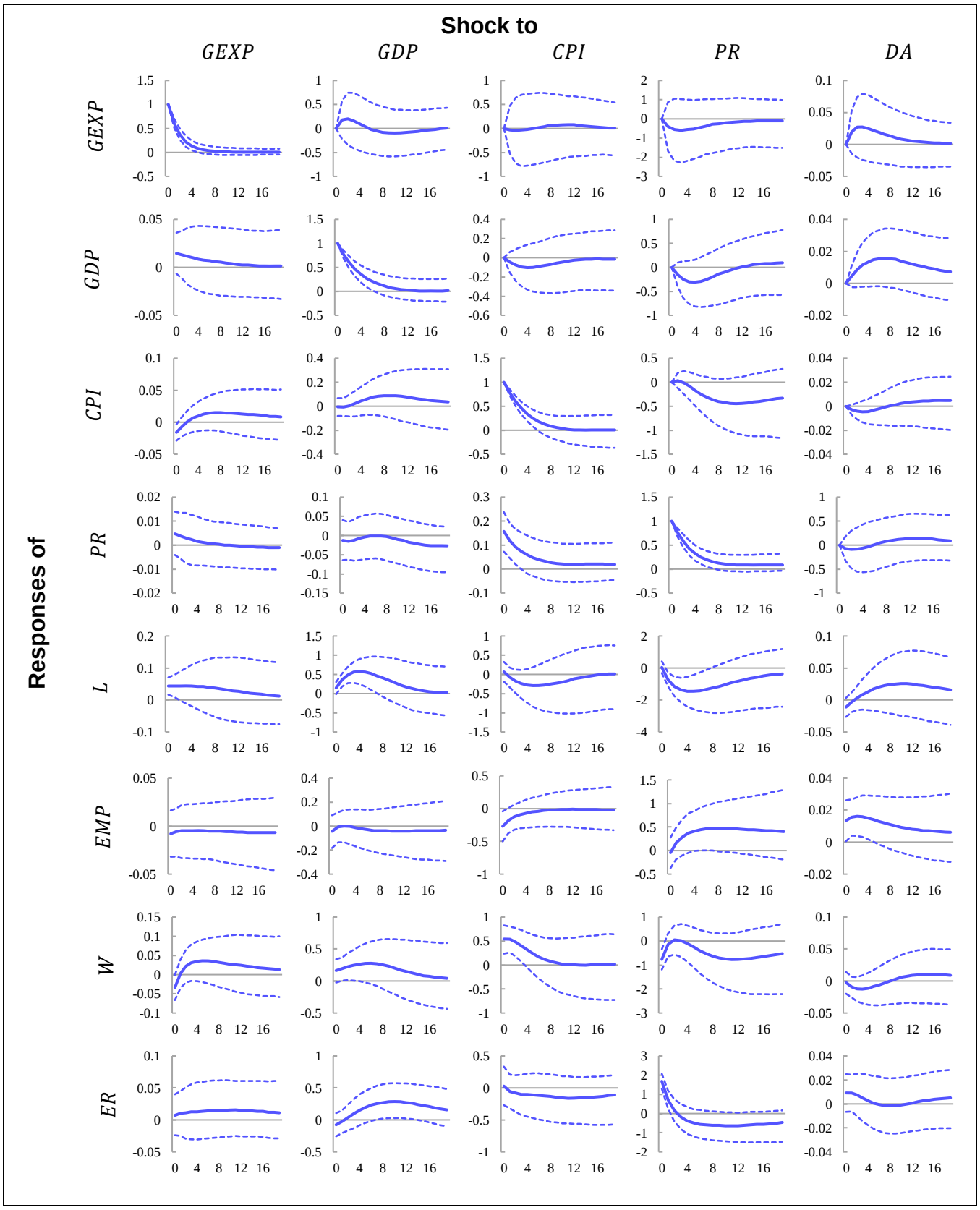
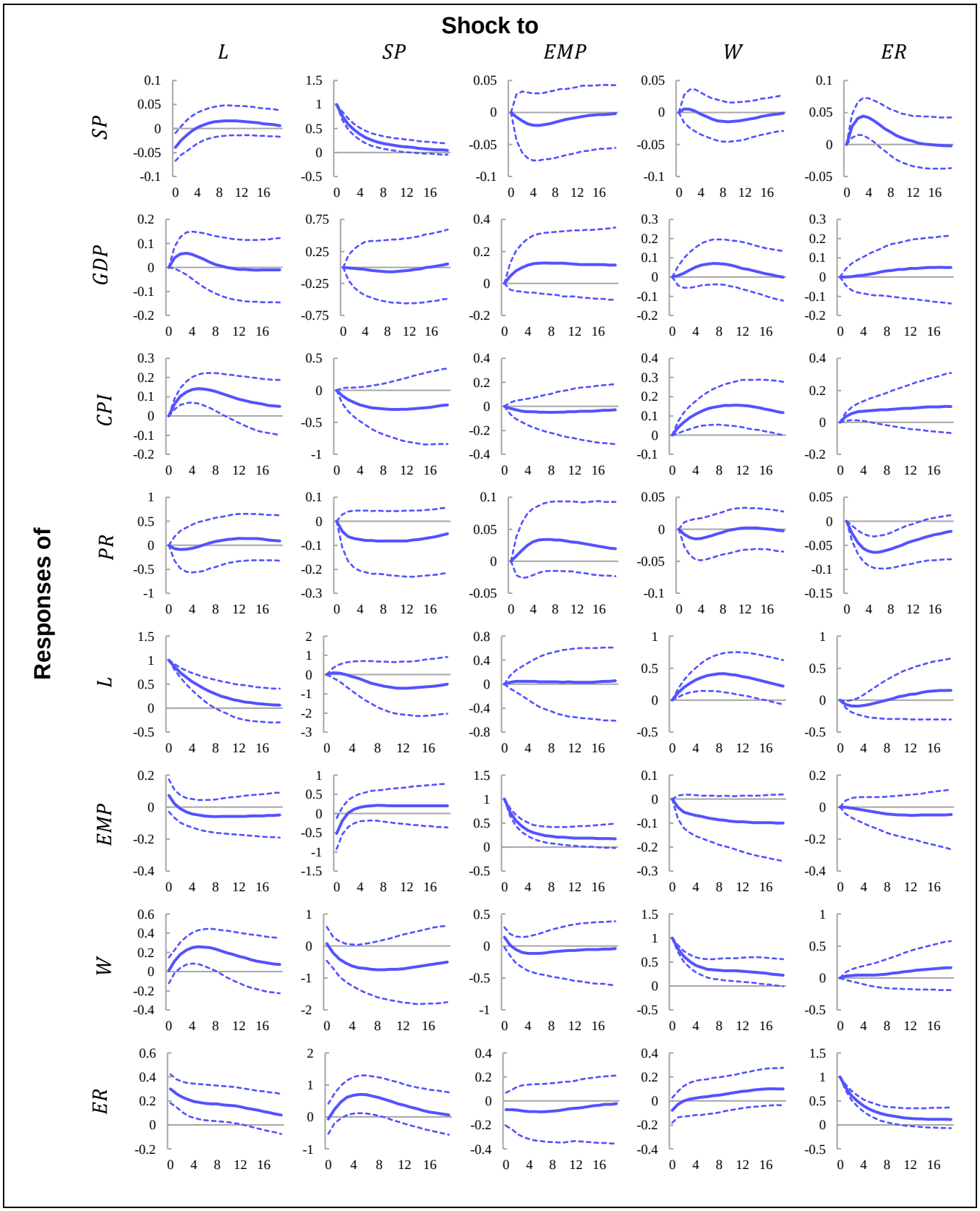


Figure 4: Selected Impulse Responses to Financial and Labor Market Shocks



Another critical external shock is the PRC's GDP shock, which fully reflects the global demand shock in the model. An interesting result is that a 1% growth in the PRC's GDP leads to 0.55% increases in the domestic GDP for the first four quarters. As the shock has strong cross-border spillover effects on domestic demand, it also increases employment and bank credit. However, the PRC's CPI shock has characteristics of the global supply shock. A 1% rise in the PRC's CPI leads to 0.70% increase in the domestic CPI for the first four quarters, thereby raising nominal wages. As import prices increase, the nominal exchange rate needs to depreciate to adjust in the real exchange rate and the current account. Responses to the FDI shock are like copper price shock; however, the impacts on GDP and the nominal exchange rate are insignificant.

Figure 3 shows impulse responses to the domestic real sector and policy shocks. Responses to government spending shock are quantitatively in line with the literature, but effects are weak and insignificant. A rise in policy rate reduces bank credit, leading to a fall in GDP and CPI with lags. The depreciation response of the nominal exchange rate was also found by Hnatkovska, Lahiri, and Vegh et al. (2016) for developing countries. The central bank balance sheet shock is characterized by increased BOM domestic assets (excluding other assets), thereby capturing unconventional monetary policy measures. An expansionary balance sheet shock leads to increases in bank credit, GDP, and employment.

The GDP shock has the complete characteristics of domestic demand shock in the real sector. The shocks lead to rises in GDP and CPI, and the financial accelerator is operative in the economy. The presence of a financial accelerator tends to amplify the economic effects of any shock that has a pro-cyclical impact on economic activity. In our case, domestic GDP, copper price, and the PRC's GDP shocks move output and bank credit in the same direction. Therefore, the accelerator channel works to propagate and amplify the effects of these shocks on the macroeconomy. However, CPI shock captures domestic supply shock in the real sector. The positive shock increases the price level and nominal wage and reduces output. There is also evidence that financial friction amplifies the effects of supply shock on the economy. For instance, the negative shock reduces output and raises policy rates, while the lower output and higher interest rate can weaken borrowers' balance sheets, impeding their ability to obtain financing.

Figure 4 displays impulse responses to financial and labor market shocks. Bank credit shock in the model is more like credit demand shock. In responding to the positive shock, output, consumer price, and nominal wage increases, while nominal exchange rate depreciates. Credit spread shock is a credit supply shock as the shock increases the lending rate and reduces bank credit at the same time, and the fall in bank credit leads to decreases in employment, GDP, CPI, and nominal wage. The policy rate declines to stabilize the economy, and it leads to nominal exchange rate depreciation. As stressed by Brinca, Duarte, and Castro (2020), disentangling labor supply and demand shocks is helpful to design public policies aimed at minimizing the long-term effects of COVID-19.[7] In our model, employment shock is more like labor demand shock since this shock initially increases both employment and wages. The shock has

[7] Labor supply shock is related to the state of the public health crisis: once this pandemic is brought under control, negative supply shocks should disappear as workers no longer reluctant to go to work and lockdowns are lifted. Demand shocks may be more related to the general stare of the economy, while they may also have a public health-related component. The fall in employment and aggregate expenditure that are caused by the demand shock can lead to a reduction in activity that is not explicitly subject to the lockdown. In this case, the reduction in activity can be addressed via targeted stabilization policies, such as fiscal or credit policies.

a positive effect on output. However, the wage shock has characteristics of a labor supply shock because the shock increases wages but reduces employment. The surge in wages also leads to a rise in consumer prices, and bank credit also rises because collateral for the credit increases. In the Mongolian economy, household loans account for almost half of total bank loans, and a salary collateral loan is a primary product for households.

Exchange rate shock is another significant shock in small, open, and developing economies like Mongolia. Here we find a novel empirical in the fact that exchange rate depreciation increases private credit spread in Mongolia. As highlighted by Adrian et al. (2020), this relationship captures a balance sheet channel of the exchange rate. Exchange rate depreciation causes debt and debt-servicing costs to jump and financial conditions to tighten, mainly when a substantial part of borrowing represents unhedged foreign currency debt. In the case of Mongolia, the total external debt-to-GDP ratio is about 220%. As financial conditions tighten, both bank credit and employment fall, and the central bank decreases its policy rate to ease financial conditions. However, this may not be a good policy response as it may also lead to exchange rate depreciation. Therefore, the Integrated Policy Framework is essential in economies like Mongolia. Another interesting result here is that exchange rate pass-through to consumer price is estimated at a relatively lower level. For example, 1% depreciation leads to a 0.1% increase in CPI after four quarters. However, this result is in line with the fact that exchange rate pass-through is declining over time. The increase in CPI also leads to a rise in nominal wage, and effects on output are neutral in the short term as the financial channel of exchange rate offsets its trade channel effect on output.

3.3.3 Variance Decomposition: How Vital are the Shocks in Macroeconomic Fluctuations?

Though impulse responses show the transmission mechanism and effect of structural shocks, they do not provide evidence regarding their importance in macroeconomic fluctuations. Therefore, this section examines the forecast error variance decomposition (FEVD) to investigate the role of identified shocks in driving fluctuations in domestic variables. The FEVD analysis can assess the contribution of each shock “relative” to other shocks. Table 1 presents the variance decomposition of key domestic variables at the posterior median.

Results in Table 1 reconfirm that those external shocks play essential roles in the Mongolian economic fluctuations. External shocks account for 42% and 44% of the 6-quarter ahead fluctuations in GDP and CPI, respectively. Notably, copper price (18%) and PRC GDP shock (19%) are key drivers of GDP fluctuations, while copper price (22%), PRC CPI shock (10%), and FDI (8%) explain the main component of movements in CPI. The external shocks also account for 33% of exchange rate fluctuations, about 40% of wage fluctuations, and 45% of bank credit fluctuations. For these variables, copper price is a key leading indicator. For example, the shock explains 30% of bank credit fluctuations, 24% of exchange rate fluctuations, and about 15% of wage fluctuations. FDI shock is vital for credit spread, employment, and nominal wage fluctuations. However, oil price shock plays a critical role in bank credit and government spending fluctuations. These results imply that copper price, oil price, and the PRC GDP are vital channels for the cross-border spillover effects of COVID-19.

Among the domestic shocks, own exogenous shocks explain a high portion of the variables' fluctuations in the short term. Real sector shocks mainly account for fluctuations in GDP and CPI, and they explain about 7% of the policy rate, bank credit, credit spread, and nominal exchange rate at the 20-quarter ahead. Policy shocks explain around 9% of GDP and CPI fluctuations and account for about 10% of other variable fluctuations. The variance decomposition results show that financial shocks are less important in explaining GDP and CPI fluctuations as compared to labor market shocks. These findings suggest that i) macroeconomic effects of COVID-19 pass-through shocks that originate in the real sector and labor market are domestic channels and ii) fiscal and monetary policy measures can mitigate risks of economic and financial instability due to the pandemic.

3.3.4 Historical Decomposition: What Shocks Drive the Economic Recession during the Pandemic?

In this section, we analyze the evaluation and drivers of GDP, consumer prices, bank credit, and employment during the pandemic using historical decomposition analysis, which breaks down variations of key variables over time in terms of structural shocks. Shock decomposition allows policymakers to identify the markets that are mainly affected by external shocks or lack of demand and adequately design and target policies to minimize the effects of the pandemic.

Historically, external shocks in copper price and the PRC's GDP shock have driven business cycle fluctuations in Mongolia (Figure 4.A). Since this paper is focused on the macroeconomic effects of COVID-19, we have concentrated on the period 2020Q1–2021Q1. The PRC GDP, copper price, and oil shocks caused a sharp fall in domestic output in 2020Q1 when real GDP fell by -10.7%. In addition to external demand from the PRC, the shock might also reflect the suspension of coal and crude oil exports.

As the economy of the PRC has recovered and border restrictions have been lifted, the adverse effects of the shock on domestic GDP have declined, starting from 2020Q2. However, continued sharp falls in copper and crude oil prices in 2020Q2 slowed the domestic recovery. The recent rises in commodity prices and positive developments in the Chinese economy have contributed to the recovery of the domestic economy. These results suggest that the international spillover effects of COVID-19 passing through changes in the commodity market and the Chinese economy have been vital in the case of Mongolia.

Among the domestic shocks, the demand shock in the real sector significantly affected the sharp fall of GDP in 2020Q1 (Figure 4.B). The shock reflects the loss of income during the pandemic, cancellation of national holidays, school closures, a domestic travel ban, cancellation of flights to and from overseas (i.e., disruption in tourism sector), restriction of services and community activities, and heightened uncertainty that reduced spending. Negative contributions of the shock remained at a higher level for the first four quarters of COVID-19 but were reduced in 2021Q1. Contributions from other shocks have been minor, and policy rate shock has positively contributed to the GDP since 2020Q2. Therefore, the recent economic recovery reflects rising demand for coal and copper from the PRC, higher copper prices, and the loosening of conventional monetary and fiscal policies. However, there is no solid evidence that unconventional monetary policy measures have significant effects on the real GDP.

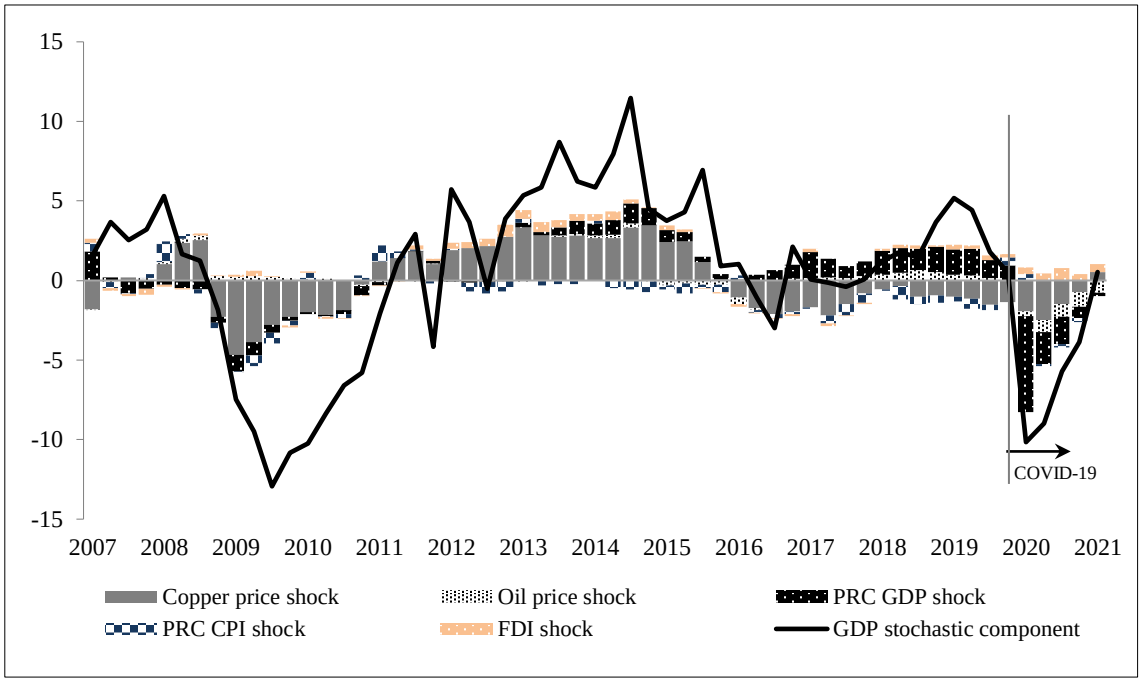
Table 1: Forecast Error Variance Decomposition for the Benchmark VAR

		Contribution of Shocks, in percent														
		External Shocks					Real Sector Shocks		Policy Shocks			Financial Market Shocks			Labor Market Shocks	
Variable	Horizon	P_{copper}	P_{oil}	GDP_{CH}	CPI_{CH}	FDI	GDP	CPI	$GEXP$	PR	DA	L	SP	ER	EMP	W
GDP	1	11.6	0.7	15.0	2.0	0.6	64.7	0.0	0.7	0.0	0.0	0.0	0.0	0.0	0.0	0.0
	6	18.0	1.5	19.2	1.9	1.6	35.5	0.6	1.7	1.6	1.1	0.6	0.4	0.4	1.3	0.7
	12	15.0	2.6	19.4	2.6	2.3	22.7	1.2	2.1	2.7	2.3	1.0	0.8	1.0	2.5	1.3
	20	12.7	3.5	18.4	3.5	3.1	16.5	1.6	2.5	3.6	2.6	1.3	1.2	1.6	3.3	1.6
CPI	1	11.7	1.5	1.4	8.9	0.5	0.5	67.7	1.6	0.0	0.0	0.0	0.0	0.0	0.0	0.0
	6	22.0	2.5	1.7	10.3	7.6	1.3	27.2	2.0	1.5	0.7	3.4	0.7	0.9	0.9	2.6
	12	23.1	2.5	2.1	8.2	9.2	2.1	11.7	2.3	3.4	1.3	3.2	1.2	1.4	1.6	4.4
	20	18.6	3.1	2.6	7.5	8.1	2.6	7.4	2.5	4.4	1.8	2.7	1.6	2.1	2.3	4.5
$GEXP$	1	0.7	7.9	0.8	1.5	1.1	0.7	0.0	83.5	0.0	0.0	0.0	0.0	0.0	0.0	0.0
	6	3.5	7.6	1.8	3.7	2.8	1.7	0.6	61.4	1.4	0.8	0.5	0.4	1.5	1.0	0.6
	12	4.9	7.5	2.3	4.5	3.6	2.1	1.1	49.8	2.4	1.5	0.9	0.8	3.2	1.6	1.1
	20	5.8	7.4	2.8	5.0	4.0	2.5	1.6	42.6	3.1	1.8	1.1	1.1	1.6	2.1	1.4
PR	1	1.8	0.7	0.9	1.2	1.1	0.7	4.3	0.8	81.4	0.0	0.0	0.0	0.0	0.0	0.0
	6	4.0	2.7	1.8	2.6	2.7	1.7	3.7	1.9	57.6	0.7	0.7	0.6	3.1	1.1	2.1
	12	7.2	3.8	2.3	3.7	3.4	2.4	3.3	2.4	40.6	1.4	1.1	1.1	4.7	2.2	3.2
	20	8.0	4.2	2.7	4.4	3.9	3.2	3.3	2.7	32.3	1.9	1.5	1.5	4.9	2.7	3.5
L	1	5.8	9.5	3.5	1.6	1.9	1.0	0.5	2.6	0.4	0.7	63.2	0.1	0.0	0.0	0.0
	6	30.4	4.4	3.9	2.2	3.8	5.7	0.9	2.2	5.7	1.0	20.0	0.4	0.4	0.8	2.7
	12	29.0	3.4	4.1	2.9	5.0	4.4	1.2	2.4	5.3	1.6	9.3	0.9	0.9	1.5	4.1
	20	22.7	3.8	4.4	4.0	5.5	4.3	1.7	2.7	5.4	2.2	6.4	1.4	1.6	2.3	4.1
SP	1	3.2	0.7	0.8	1.5	5.6	0.6	0.9	1.3	42.8	0.3	0.8	32.2	0.0	0.0	0.0
	6	6.4	1.9	1.7	2.4	7.8	1.8	2.0	2.4	25.2	1.1	1.1	29.4	1.6	0.9	0.6
	12	8.4	2.6	2.0	3.0	7.8	2.9	2.6	2.8	19.5	1.6	1.6	22.8	2.0	1.8	1.2
	20	8.8	3.2	2.5	3.5	7.5	3.8	2.8	3.0	17.2	2.0	1.8	18.8	2.4	2.3	1.5
ER	1	18.3	1.0	0.6	1.3	0.6	0.6	0.5	0.5	15.1	0.5	4.2	0.3	46.2	0.4	0.5
	6	24.1	1.9	1.4	3.6	2.1	1.9	1.1	1.7	7.5	1.2	4.5	1.6	30.4	1.4	1.1
	12	18.0	2.6	2.1	5.4	2.9	4.0	1.6	2.3	7.7	1.7	4.4	2.2	20.8	2.2	1.5
	20	16.1	3.2	2.8	5.9	3.7	5.0	2.0	2.7	7.8	2.1	4.0	2.2	15.2	2.7	2.0
EMP	1	1.1	0.7	0.7	1.1	1.3	0.7	1.9	0.7	0.6	1.4	0.8	1.8	0.0	76.8	0.0
	6	3.2	1.7	7.0	2.2	4.5	1.5	1.9	1.8	3.3	3.1	1.3	1.6	0.4	49.3	0.9
	12	5.3	2.3	11.2	2.5	5.8	2.2	2.0	2.2	5.0	3.1	1.5	1.7	0.9	30.7	1.8
	20	6.5	2.8	11.6	2.9	6.2	2.6	2.0	2.3	5.6	2.9	1.7	1.7	1.5	20.7	2.4
W	1	3.4	1.3	0.9	5.8	7.0	1.0	3.3	1.3	3.1	0.4	0.4	0.4	0.0	0.8	60.0
	6	13.3	1.8	1.5	9.6	10.7	2.5	2.8	2.2	2.2	1.1	2.3	1.2	0.4	1.5	30.1
	12	19.5	2.1	1.9	7.1	10.3	2.9	2.2	2.5	3.1	1.5	2.6	1.6	0.9	1.9	16.7
	20	17.2	2.8	2.4	6.5	8.9	3.2	2.3	2.6	4.0	2.0	2.4	1.9	1.6	2.4	11.6

Note: Numbers in the table indicate median contributions of the posterior distributions. Horizon is quarterly.

Figure 4: Historical Decomposition of Stochastic Component of GDP, in percent

A) Contribution of external shocks



B) Contribution of domestic shocks

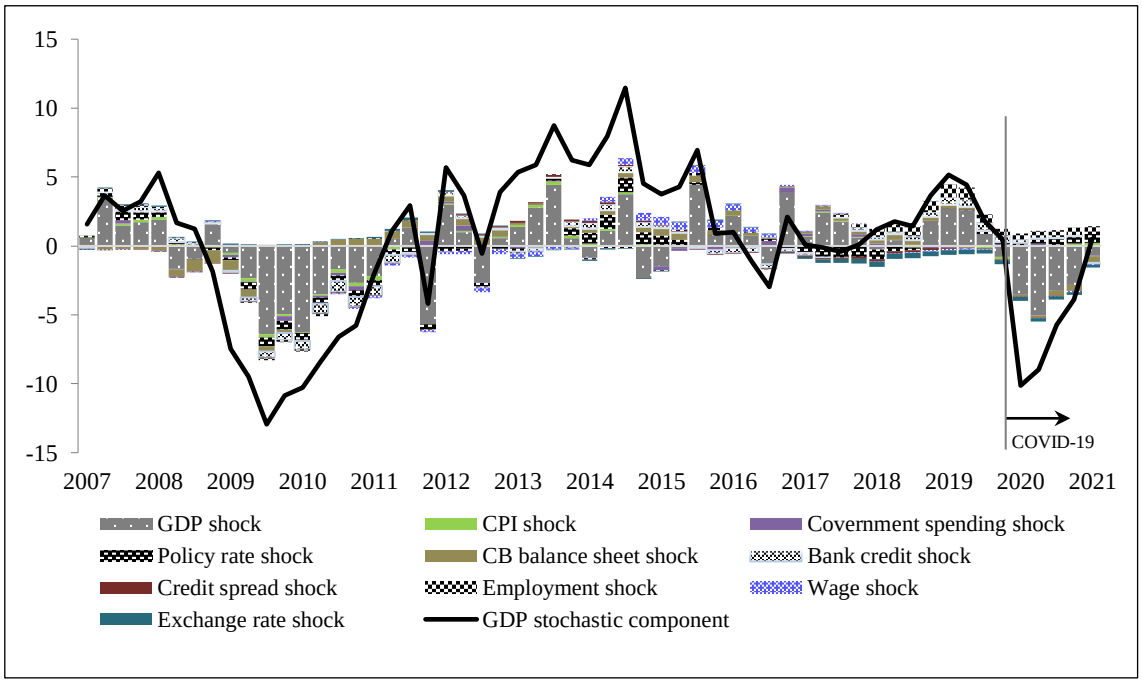
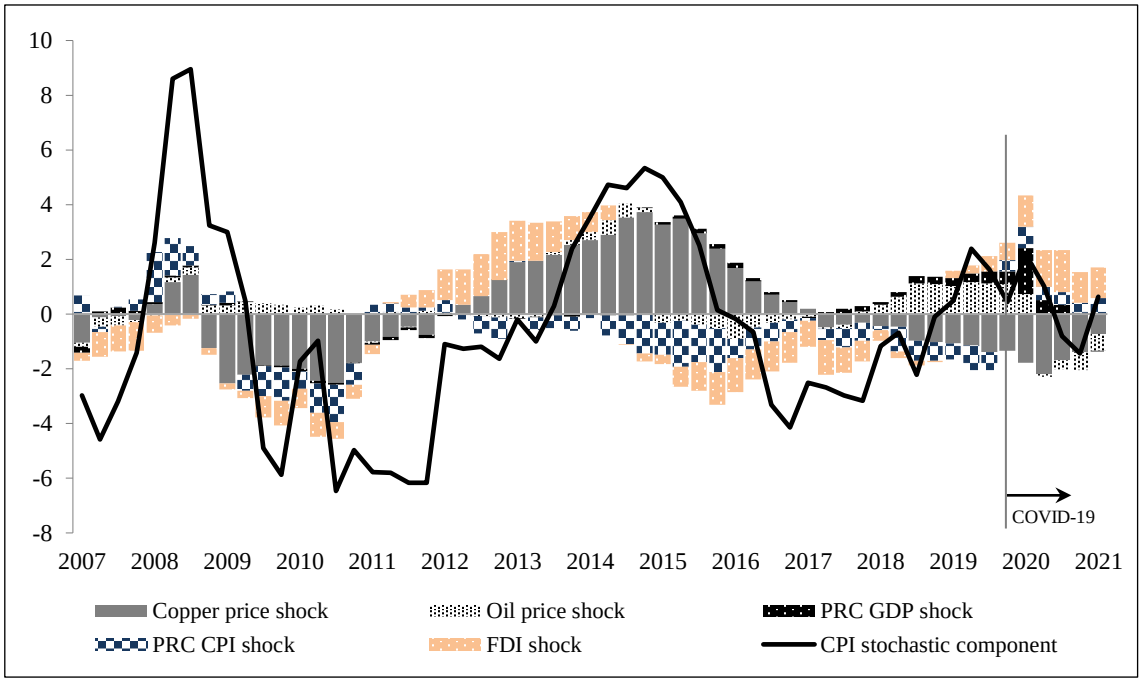


Figure 5: Historical Decomposition of Stochastic Component of CPI, in percent

A) Contribution of external shocks



B) Contribution of domestic shocks

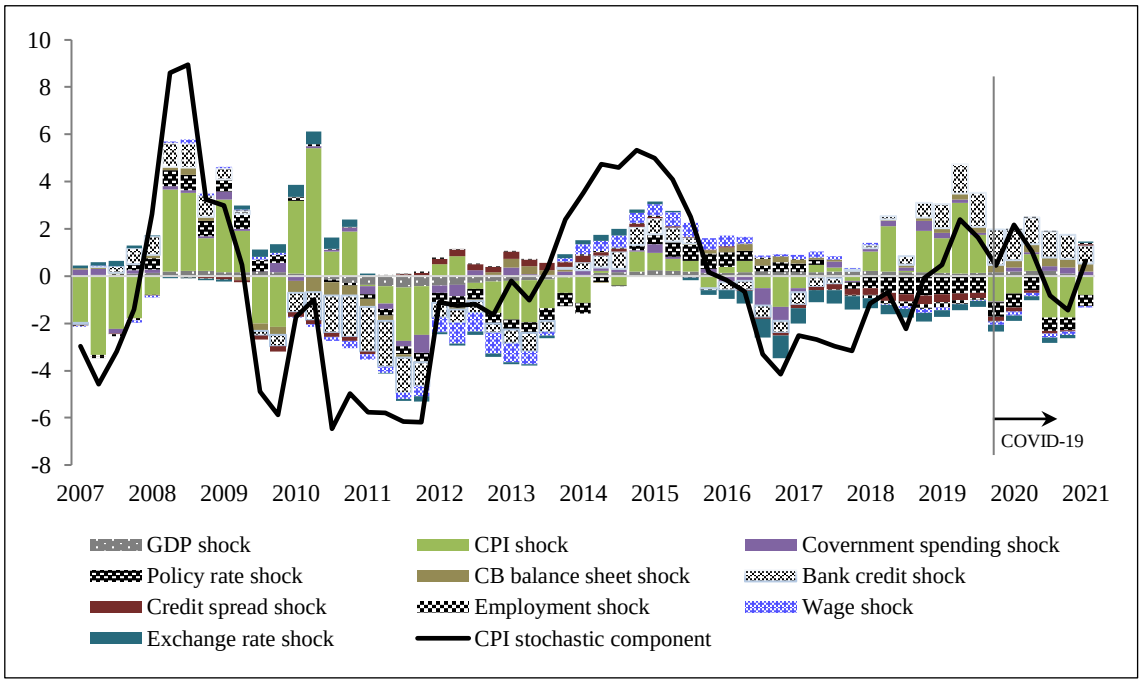
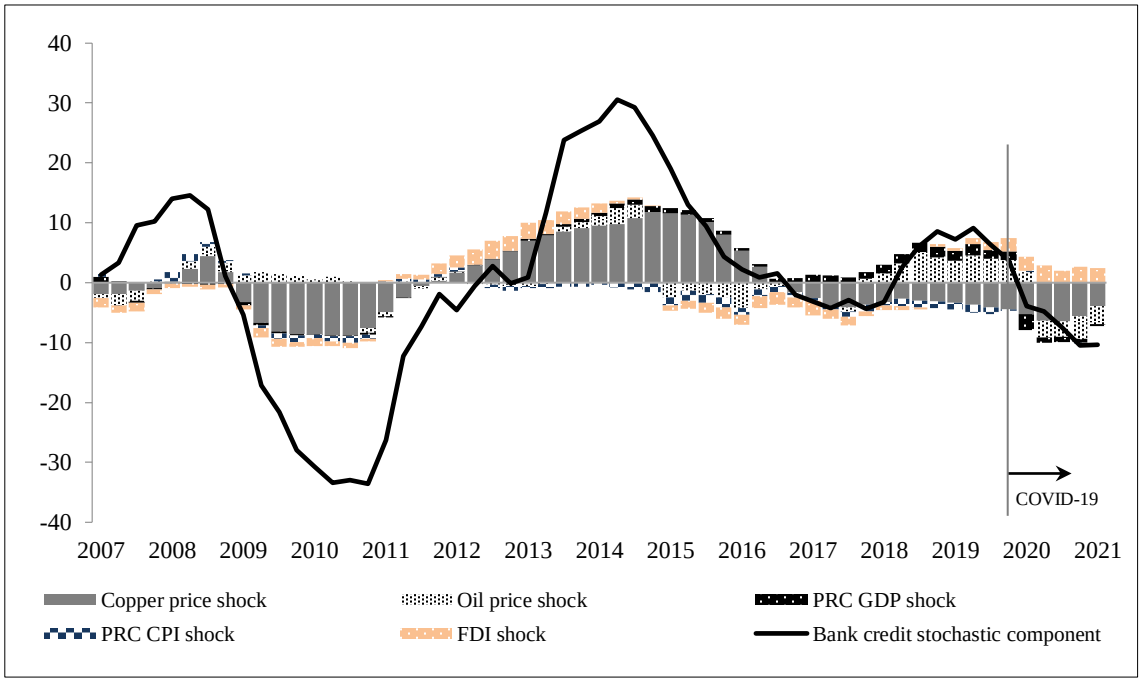


Figure 6: Historical Decomposition of Stochastic Component of Bank Credit, in percent

A) Contribution of external shocks



B) Contribution of domestic shocks

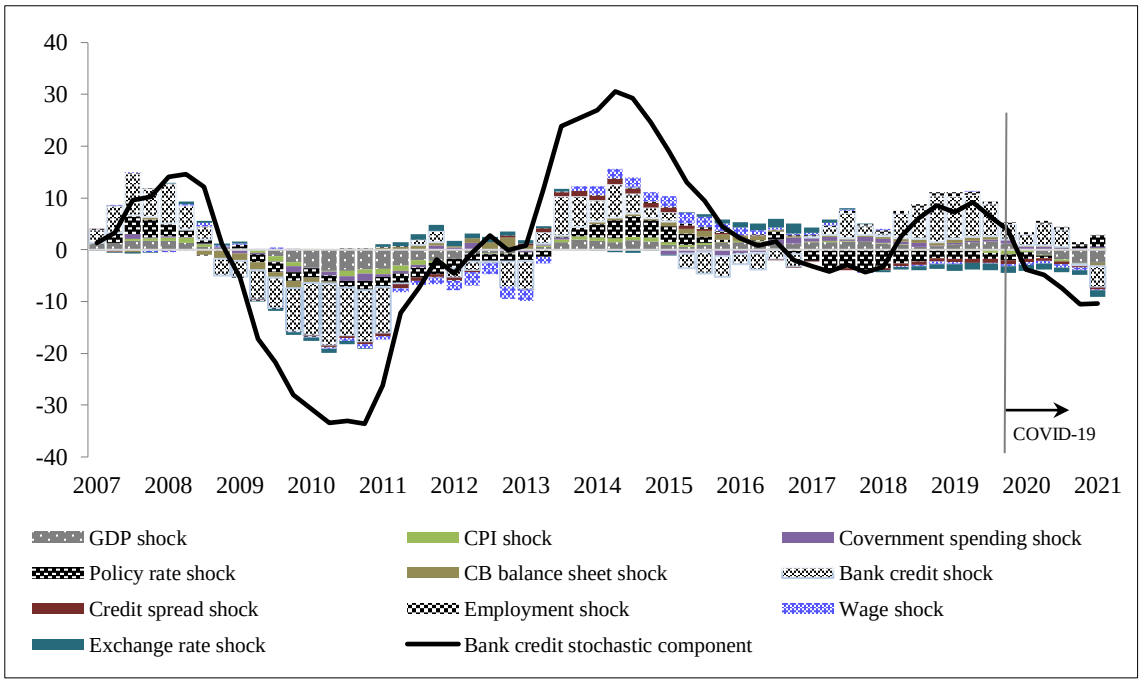
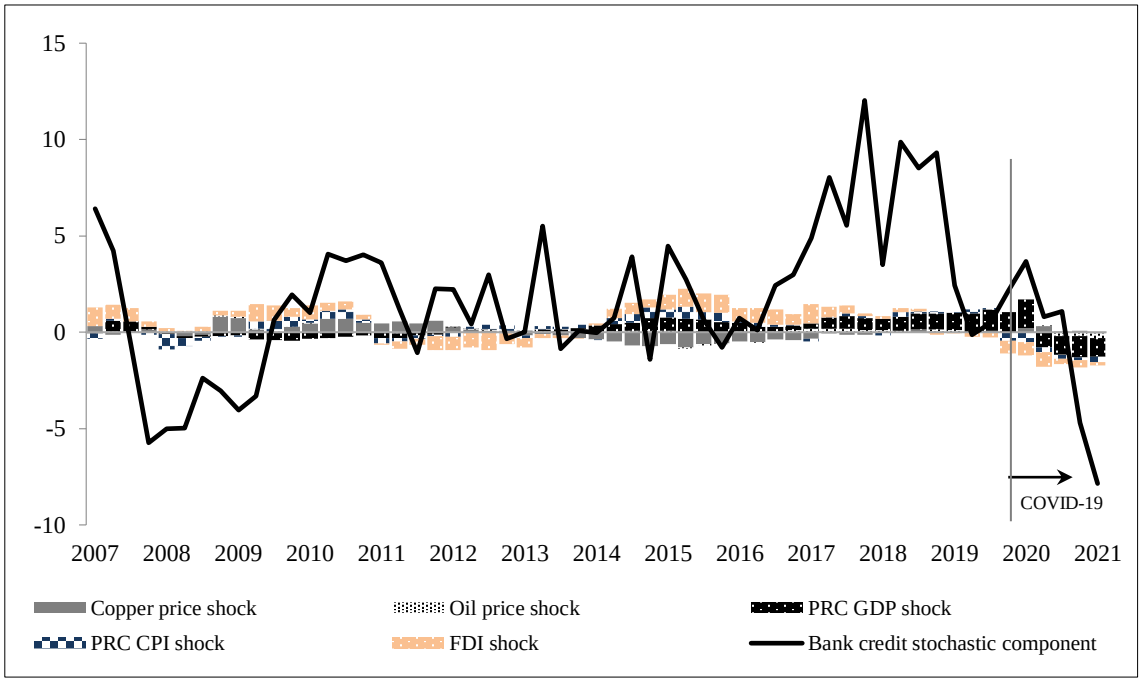
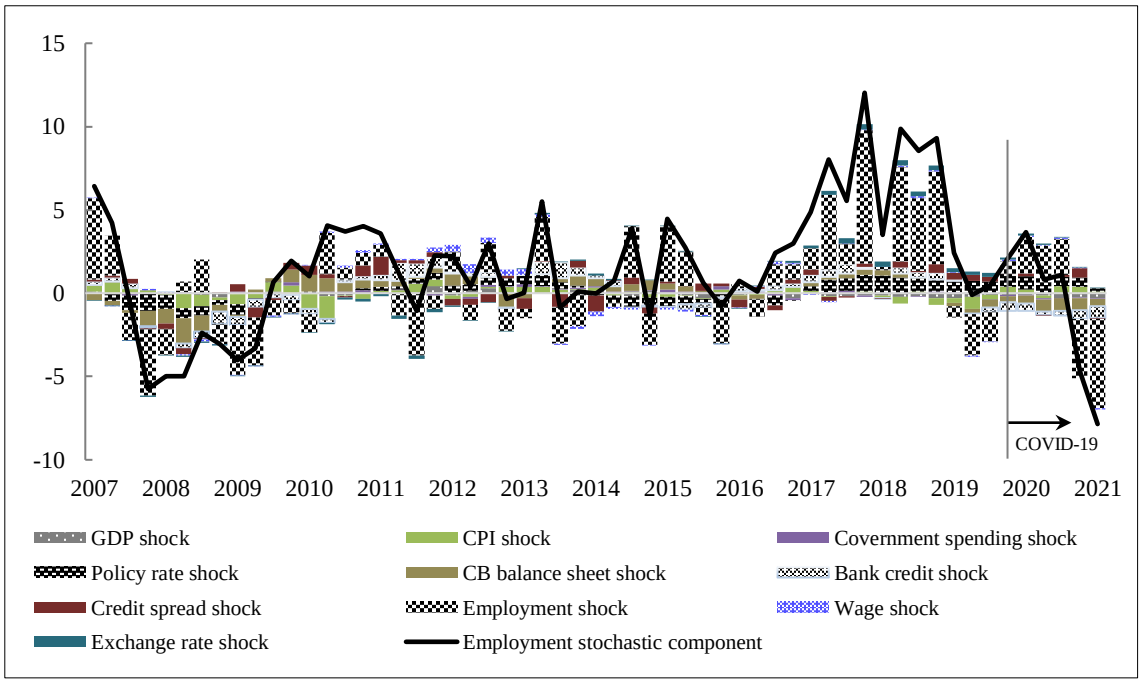


Figure 7: Historical Decomposition of Stochastic Component of Total Employment, in percent

A) Contribution of external shocks



B) Contribution of domestic shocks



The decline in the cyclical component of CPI during the 2020 recession was the most muted and shortest-lived of any of the three recessions over the past 15 years, and the increase in CPI since 2021Q1 has been one of the fastest (Figure 5). Both external and domestic shocks have played a critical role in CPI dynamics during the pandemic. The PRC GDP, PRC CPI, and FDI shocks have led to the rise of CPI in 2020Q1. Since the PRC GDP shock partially reflects the closure of PRC–Mongolia borders, the negative shock in 2020Q1 has significantly contributed to the increase in consumer prices. The decline in the cyclical component of CPI from 2020Q2–2020Q4 was mainly driven by plugging oil and copper prices.

As crude oil prices fell in the first half of 2020, the oil shock contributed to lower inflation for 2020Q2–2021Q1. The negative contributions of copper price shock on CPI dynamics increased over the period 2017Q2–2020Q2, while its effects weakened as of 2020Q3 as copper prices increased. Among the domestic shocks, bank credit shock positively affected CPI during the period, while supply shocks in the real sector contributed to higher CPI for 2020Q2. The policy rate shocks decreased the CPI, while the unconventional monetary policy measures positively contributed to the CPI over the period.

Though GDP has recovered since 2020Q2, disruptions in credit and labor markets have continued in the domestic economy. A phenomenon observed during COVID-19 in the domestic economy is a disruption in bank credit (Figure 6). Hence, it is important to study which shocks affected the bank credit dynamics for the period. Negative copper price, crude oil price, and the PRC GDP shocks initially led to the bank credit crunch. Credit supply shock had no significance on bank credit over the period, while credit demand shock negatively affected bank credit in 2021Q1. This result is in line with the fact that banks had excess liquidity; however, their risk aversion was heightened by the uncertainty due to COVID-19. As a policy response to the disruption in the credit market, the government and Bank of Mongolia jointly implemented the economic recovery plan in March 2021, primarily based on subsidized loans. In addition, the loosening of conventional monetary policy has positively contributed to bank credit since 2020Q4.

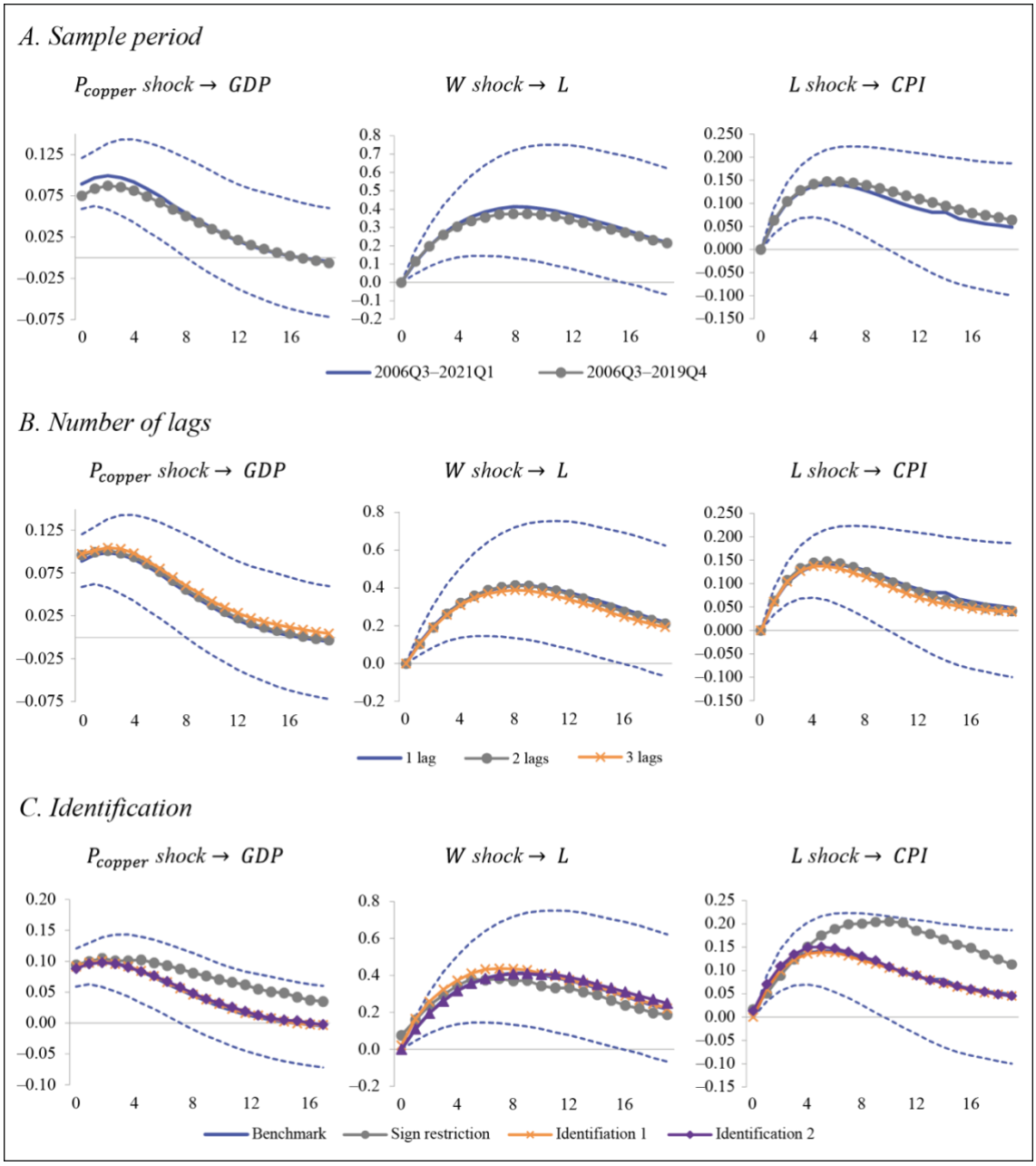
External shocks negatively affected employment during the pandemic (Figure 7.A). Domestic shocks, including generous support from the government to the private sector and policy measures, contributed to the moderate impact of the pandemic on the labor market in the first three quarters of 2020. Strict lockdowns and restrictions following the first domestic contagion recorded on 11 November 2020 led to the sharp fall in employment in 2020Q4–2021Q2, and the labor market recession has mainly been driven by labor demand shocks (Figure 7.B).

4. ROBUSTNESS

The results of structural VAR estimation can be sensitive to the model's specifications. Our findings changed little in response to three different types of alternative specifications: i) sample period, ii) the number of lags, and iii) identification. The impulse response of GDP to copper price shock, responses of bank credit to wage shock, and the response of CPI to bank credit shock were chosen for the comparison of alternative specifications. Results are also robust for other impulse responses, and the selection is based on the novel findings of this paper.

The benchmark model was estimated using one lag for the period 2006Q3–2021Q1. Given the significant movements in real, financial, and labor market variables during the COVID-19 pandemic, we also estimated the benchmark specification over a shorter sample ending before the pandemic in 2019Q4 (Figure 8.A). The benchmark specification was also estimated using two and three lags (Figure 8.B).

Figure 8: Robustness Exercises



Note: Dashed lines in the Figures are 68% confidence intervals of the posterior distributions for the benchmark specifications.

Two alternative methods are employed in terms of shock identification: 1) different ordering of variables in the system and 2) sign restrictions to identify the selected shocks. Alternative ordering of variables is i) GDP, CPI, and financial variables are assumed to respond contemporaneously to labor market variables, reflecting quick

pass-through of wage growth to CPI and employment to GDP. The ordering is set as P_{copper}, P_{oil}, GDP_{CH}, CPI_{CH}, FDI, $GEXP$, EMP, W, GDP, CPI, PR, DA, L, SP, and ER (Identification 1) and ii) GDP, CPI, and financial variables are assumed to respond contemporaneously to credit market variables and unconventional monetary policy measures, reflecting quick pass-through of bank credit to aggregate demand. Ordering is set as P_{copper}, P_{oil}, GDP_{CH}, CPI_{CH}, FDI, $GEXP$, DA, L, SP, GDP, CPI, PR, EMP, W, and ER (Identification 2).

Based on sign restrictions, copper price shock, wage shock (labor supply shock), and bank credit shock (credit demand shock) are identified as follows: i) copper price shock is identified using an approach similar to the identification scheme employed by Pedersen (2019)—a copper price shock is positively associated with global demand (i.e., the PRC's GDP), ii) labor supply shock is identified using the scheme used by Brinca, Duarte, and Castro (2020)—a negative labor supply shock does not lead to a rise in employment and a fall in wages, and iii) credit demand shock is identified using the scheme utilized by Barnett and Thomes (2014)—a positive credit demand shock does not reduce bank credit and credit spread. Impulse responses of alternative identification schemes are shown in Figure 8.C; the results are robust as the median responses are within the 68% intervals.

5. CONCLUSION

This paper has examined the macroeconomic effects and transmission mechanisms of COVID-19 in a developing and commodity-exporting economy. Using Mongolia as a representative case study, the paper estimates Bayesian structural VARs with normal-Wishart prior including key domestic macroeconomic variables (i.e., variables of the real sector, financial market, and labor markets) and global economic activity, commodity prices, and FDI.

We find strong cross-border spillover effects of COVID-. Our results show that the recession (i.e., drop in real GDP) in the beginning of the pandemic was mainly driven by the PRC's GDP, copper prices, and oil shocks. For example, the PRC's GDP and copper price shocks accounted for three-fifths and one-fifth, respectively, of the drop in real GDP (i.e., output deviation from its trend) in 2020Q1. The real sector recovery observed for 2020Q2–2021Q1 was also primarily driven by positive shocks to commodity prices and the PRC's GDP. Our estimates confirm that external shocks account for over 40% of fluctuations in output, consumer price, bank credit, and nominal wage in the economy. Among the external shocks, changes in the PRC's GDP and copper price significantly affected the domestic GDP, while the PRC's CPI and copper price were relevant for the domestic CPI dynamics. As a novel result, we find that a 1% increase in the PRC's GDP and the PRC's CPI leads to 0.55% and 0.7% increases, respectively, in the domestic GDP and CPI within the first four quarters. The decline in the cyclical component of CPI during the 2020 recession was the most muted and shortest-lived of any of the three recessions over the past 15 years, and the increase in CPI since 2021Q1 has been one of the fastest.

Disruptions in credit and labor markets have been sustained, while there is a sign of recovery in the real sector. Our estimates suggest that two-thirds of the fall in employment (i.e., deviation from its trend) for 2020Q4–2021Q1 could be attributed to adverse labor demand shocks. The drop in bank credit observed during COVID-19 was initially led by negative copper prices, crude oil prices, and the PRC GDP shocks, and domestic credit demand shock negatively affected bank credit in 2021Q1. Overall, economic turmoil and labor market dislocations from the COVID-19 pandemic continue in the Mongolian economy, despite extraordinary policy support. The economy remains vulnerable to shocks caused by COVID-19. The continued uncertainty about the

duration of the health crisis affects all aspects of the recovery path. Policy measures should be guided by the principles of timeliness and fiscal sustainability, targeted to those who need them, and proportionate to the level of the shock.

This paper has also revealed novel empirical evidence. First, the balance sheet channel of the exchange rate is operative in the economy because exchange rate depreciation increases private credit spread, leading to tight financial conditions. This finding indicates that policymakers need to reconsider whether excessive depreciation in response to adverse external shocks is optimal or not, particularly when the credit condition is tightening in the economy. Second, the financial accelerator is operative in the economy since GDP, copper price, and the PRC's GDP shocks move output and bank credit in the same direction. The accelerator channel works to propagate and amplify the effects of these shocks on the macroeconomy. There is also evidence that financial friction amplifies the effects of a domestic supply shock. Third, there is an indirect channel of wage shock passing to consumer price. Our results reveal that an increase in wage leads to a rise in bank credit, and bank credit growth causes higher consumer prices. This finding is in line with the fact that a wage collateral loan is a highly demanded product for households, and the borrowed funds are mainly spent on non-durable consumer goods in the economy. Fourth, the dynamics of copper price and the PRC's GDP can be good leading indicators of domestic business cycle fluctuations as domestic variables significantly respond to exogenous changes in the variables. These novel results remain robust to variations in alternative model specifications.

REFERENCES

Adam, C., Hensridge, M., and Lee, S. 2020. After the Lockdown: Macroeconomic Adjustments to the COVID-19 Pandemic in Sub-Saharan Africa. *Oxford Review of Economic Policy* 36(S1): 338–358.

Adrian, T., Erceg, C., Lindé, J., Zabczyk, P., and Zhou, J. 2020. A Quantitative Model for the Integrated Policy Framework. IMF Working Paper. WP/20/122. International Monetary Fund, Washington, DC. Baqaee, D. and Farhi, E. 2021. Supply and Demand in Disaggregated Keynesian Economies with an Application to the COVID-19 Crisis, NBER Working Paper Series. No. 27152. National Bureau of Economic Research (NBER), Cambridge, MA.

Barnett, A. and Thomes, R. 2014. Has Weak Lending and Activity in the UK been Driven by Credit Supply Shocks?. *The Manchester School,* Supplement 2014: 60–89.

Barrett, P., Das, S., Magistretti, G., Pugacheva, E., and Wingender, P. 2021. After-Effects of the COVID-19 Pandemic: Prospects for Medium-Term Economic Damage. IMF Working Paper WP/21/203, International Monetary Fund, Washington, DC.

Barrot, J., Grassi, B., and Sauvagnat, J. 2021. Sectoral Effects of Social Distancing.*AEA Papers and Proceedings* 111: 277–281.

Bekaert, G., Engstrom, E., and Ermolov, A. 2020. Aggregate Demand and Aggregate Supply Effects of Covid-19: A Real-Time Analysis. Finance and Economics Discussion Series. 2020-049. Washington: Board of Governors of the Federal Reserve System.

Bobeica, E. and Hartwig, B. 2021. The COVID-19 Shock and Challenges for Time Series Models. Working Paper Series. No 2558/May 2021. European Central Bank, Frankfurt.

Brinca, P., Duarte, J., and Castro, M. 2020. Measuring Labor Supply and Demand Shocks During COVID-19. Working Paper Series. 2020-011F. Economic Research. Federal Reserve Bank of St. Louis.

Coulibaly, S. 2021. COVID-19 Policy Responses, Inflation and Spillover Effects in the West African Economic and Monetary Union. *African Development Review* Special Issue Article: 1–13.

Dieppe, A., Legrand, R., and Roye, B. 2018. The Bayesian Estimation, Analysis and Regression (BEAR) Toolbox: Technical Guide. Version 4.2. European Central Bank, Frankfurt.

Djurovic, G., Djurovic, V., and Bojaj, M. 2020. The Macroeconomic Effects of COVID-19 in Montenegro: a Bayesian VARX approach. *Financial Innovation*6(40): 1–16.

Gan-Ochir, D. and Davaajargal, L. 2019. External Shocks and Business Cycle Fluctuations in Mongolia: Evidence from a Large Bayesian VAR', *International Economic Journal* 33(1): 42–64.

Gharehgozli, O., Nayebvali, P., Gharehgozli, A., and Zamanian, Z. 2020. Impact of COVID-19 on the Economic Output of the US Outbreak's Epicenter. *Economics of Disasters and Climate Change* 4: 561–573.

Guerrieri, V., Lorenzoni, G., Straub, L., and Werning, I. 2020. Macroeconomic Implications of COVID-19: Can Negative Supply Shocks Cause Demand Shortages?. NBER Working Paper. Series No. 26918. National Bureau of Economic Research (NBER), Cambridge, MA.

Ha, J., Kose, A., and Ohnsorge, F. 2021. Inflation During the Pandemic: What Happened? What is Next?', Working Paper. No. 2108. Koç University-Tüsiad Economic Research Forum, Istanbul.

Harjes, T., Hofman, D., Nier, E., and Olafsson, T. 2020. Monetary and Financial Policy Responses for Emerging Market and Developing Economies. Special Series on COVID-19.International Monetary Fund, Washington, DC.

Hnatkovska, V., Lahiri, A., and Vegh, C. 2016. The Exchange Rate Response to Monetary Policy Innovations. *American Economic Journal: Macroeconomics* 8(2): 137–181.

IMF. 2020. Assessing Stress from Oil Price Shocks. Special Series on COVID-19. International Monetary Fund, Washington, DC.

Jacobs, D. and Rayner, V. 2012. The Role of Credit Supply in the Australian Economy. Research Discussion Paper. RDP 2012-02. The Reserve Bank of Australia, Sydney.

Jeffreys, H. 1961. *Theory of Probability.* Third edition. Oxford, UK: Oxford University Press.

Kadiyala, KR. and Karlsson, S. 1997. Numerical Methods for Estimation and Inference in Bayesian VAR models. *Journal of Applied Econometrics* 12: 99–132.

Kohlscheen, E., Mojon, B., and Rees, D. 2020. The Macroeconomic Spillover Effects of the Pandemic on the Global Economy', BIS Bulletin. No.4. Bank for International Settlements (BIS), Basel.

Kremer, M. 2016. Macroeconomic Effects of Financial Stress and the Role of Monetary Policy: A VAR Analysis for the Euro Area. *International Economics and Economic Policy* 13(1): 105–138.

Kuschnig, N. and Vashold, L. 2021. BVAR: Bayesian Vector Autoregressions with Hierarchical Prior Selection in R. *Journal of Statistical Software* 100(14): 1–27.

Lenza, M. and Primiceri, G. 2020. How to Estimate a VAR after March 2020. Working Paper Series. No. 2461. European Central Bank, Frankfurt.

Litterman, R. 1980. Bayesian Procedure for Forecasting with Vector Autoregressions. Mimeo. Massachusetts Institute of Technology, Cambridge, MA.

———. 1986. Forecasting with Bayesian Vector Autoregressions: Five Years of Experience. *Journal of Business and Economic Statistics* 4(1): 25–38.

Ludvingson, S., Ma, S., and Ng, S. 2020. COVID-19 and the Macroeconomic Effects of Costly Disasters. NBER Working Paper. No. 26987. National Bureau of Economic Research (NBER), Cambridge, MA.

McKibben, W. and Fernando, R. 2020. The Global Macroeconomic Impacts of COVID-19: Seven Scenarios. *Asian Economic Papers* 20(2): 1–28.

Mihailov, A. 2020. Quantifying the Macroeconomic Effects of the COVID-19 Lockdown: Comparative Simulations of the Estimated Galí-Smets-Wouters Model. Discussion Paper. No. 2020-07. University of Reading, Reading.

Pedersen, M. 2019. The Impact of Commodity Price Shocks in a Copper-Rich Economy: The Case of Chile. *Empirical Economics*57: 1291–1318.

Sawada, Y. and Sumulong, L. 2021. Macroeconomic Impact of COVID-19 in Developing Asia. ADBI Working Paper Series. No. 1215, Asian Development Bank Institute, Tokyo.

Sznajderska, A. and Kapuściński, M. 2020. Macroeconomic Spillover Effects of the Chinese Economy. *Review of International Economics* 28(4): 992–1019.

Wang, Q. and Han, X. 2021. Spillover Effects of the United States Economic Slowdown Induced by COVID-19 Pandemic on Energy, Economy, and Environment in Other Countries. *Environmental Research,* 196: 1–10.

World Bank Group. 2021. *Mongolia Economic Update: From Relief to Recovery*. World Bank Group, Washington, DC.