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The Impact of COVID-19 on Economic Growth: Evidence from a Bayesian Panel Vector Autoregressive (BPVAR) Model

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The Impact of COVID-19 on Economic Growth: Evidence from a Bayesian Panel Vector Autoregressive (BPVAR) Model

ABSTRACT

This paper explores the impact on the macroeconomy for certain OECD economies exposed to the COVID-19 pandemic shock. The analysis employs a panel of OECD countries, spanning the period March 2020 to January 2021. It also uses two proxies for the COVID-19 shocks: i) total confirmed incidences/cases and ii) total deaths while using the Bayesian Panel Vector Autoregressive (BPVAR) method. The findings document that the COVID-19 shock exerts a strong negative effect on industrial production. Considering how such epidemic shocks affect the expectations of economic participants, the paper questions their absence in accounting for forthcoming growth-related incidences.

KEYWORDS: COVID-19; industrial production; Bayesian PVAR model; OECD countries

JEL CLASSIFICATION: E32; E00; Q54; C33

I. Introduction

The COVID-19 pandemic event constitutes a severe threat to global health standards and has become one of the most economically costly pandemics in recent history. Moreover, it differs from previous pandemic episodes in specific ways. In particular, the globally synchronized lockdowns and the detrimental effects on specific financial markets, i.e., stock markets and commodity markets, reinforce one another into an unprecedented economic sudden stop. Although based on limited available data, this empirical work provides early formal documentation on the economic costs of epidemics regarding the impact on industrial production. The increasing spread of COVID-19 has prompted governments to introduce unprecedented measures to contain the pandemic. These measures have led many businesses to be shut down temporarily with widespread restrictions on travel and mobility. The present work aims to contribute to the economic growth literature by introducing epidemics, i.e. COVID-19 shocks, as
another supply shock to economic growth for the future course of industrial production. A rise of the COVID-19 case is articulated through a negative relation to economic performance. Therefore, the study econometrically attempts to quantify the potential global economic costs of COVID-19 in terms of the effect on industrial production. To this end, the analysis uses a Bayesian Panel Vector Autoregressive (BPVAR) model that facilitates the estimates due to the low number of the time span. Moreover, according to literature (Zellner and Hong, 1989; Canova and Ciccarelli, 2004; among others), the Bayesian panel VARs have the comparative advantage over regular and global panel VARs that employ a shrinkage prior to effectively reduce the dimensionality of the coefficient vector. Prior restrictions are superior to dogmatic restrictions used by the regular VARs. The findings could be of substantial importance for policymakers to get further insight into the economic benefits of globally coordinated policy responses to tame the pandemic.

COVID-19 can be considered part of the literature on supply shocks; such shocks in the literature have been the outcome of natural disasters and oil upstream provision, but little to no work has been done to consider an epidemic as another supply shock. Early research on natural disasters conveys that even though wealthier nations experience natural disasters as often as poorer nations, the former suffers less from such disasters. The implicit insurance against natural disasters has been economic growth (Anbarci et al., 2005; Kellenberg and Mobarak, 2008) and high-quality institutions (Kahn, 2005; Toya and Skidmore, 2007). Acemogly et al. (2003) pursue the hypothesis that economic growth is endogenously defined by internal forces, while Raddatz1 (2007) suggest that natural disasters have an adverse exogenous short-run impact on output. Noy (2009) and Cavallo et al. (2013) also observe exogenous adverse effects on the macro-economy in the short run, with disastrous events leading to more pronounced slowdowns in production.

It is not surprising to have items go out of stock in the days after a natural disaster, with demand for essential goods suddenly rising as retailers have limited time to adjust their stocks or prices (Cavallo et al., 2014). With retailers unable to restock due to supply disruptions and lack of transportation (in some instances, due to mandatory lockdown), inventories rise so fast that manufacturers have neither the

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1 Who uses a Panel Vector Autoregression (Panel VAR) framework.
human capital to produce them nor enough demand to sell their products. The disruptions have been documented as exogenous shocks propagated to upstream and downstream supply chains, affecting directly or indirectly suppliers and customers (Carvalho et al., 2016) and thereby labour demand.

Natural disasters include interruptions of economic activities, spillover effects attributed to production substitution, the demand for reconstruction, and any related economic path for recovery (Kousky, 2014). Typically, disasters are conceptualized as the sudden loss of production factors to which the economy adjusts, whether going back to the pre-disaster equilibrium or shifting to a new normality. The meta-analysis from Klomp and Valckx (2014) suggests a genuinely negative effect on economic growth, increasing over time.

Similar shocks are reported by the intertemporal global oil price shocks, with these shocks generally generating negative movements in GDP growth, in the case of China (Cross and Nguyen, 2017), the U.S. (Baumeister and Peersman, 2013), or oil supply disruption due to political events in oil-producing countries with unpredictable shifts in global production (Baumeister and Kilian, 2016). A supply-driven oil importer typically faces a long-lived fall in economic activity in response to a supply-driven surge in oil prices, often positive for energy-exporting countries with large oil reserves (Cashin et al., 2014). The negative effect of oil shocks on economic performance has been investigated early by Hamilton (1983; 2003). It often starts from a production function that requires energy produced from oil combustion as an input factor. Traditionally, the literature on the economic effects of oil price shocks has focused on oil-importing countries belonging to the OECD group (Killian, 2008a; 2008b).

This paper also touches on the literature on the role of epidemics in macroeconomic behaviour. The experience from swine-origin influenza (H1N1) supply shocks in Mexico can relate to tourist arrivals and airlines, which decide (or forced) to cut their flight frequencies (or destinations) and suspend flights (Rassy and Smith, 2013). McKibbin and Sidorenko (2006) explore different pandemic influenza scenarios. They consider a "mild" scenario, a "moderate" scenario, a "severe" scenario, and an "ultra" scenario. Their simulations identify the presence of costs to the global economy, running between SUS300 million and SUS4.4 trillion dollars for the scenarios considered. Carlsson et al. (2014) argue that the death toll from the 1918 Spanish flu
had major supply shocks in the Swedish economy. It was estimated that the 1918 pandemic curtailed manufacturing activity by around 20%, while containment measures had relatively higher medium-term growth (Correia et al. 2020). Barro et al. (2020) estimate the negative impact on GDP to be around 6-8%. By contrast, Lee and McKibbin (2004) estimate that in the SARS epidemic in 2003, the overall impact on global GDP was only 0.1% of this global output.

Moreover, Arnold et al. (2006) investigate the supply side channel in a 1918-like pandemic scenario by combining an estimated loss of employee workdays with an estimated productivity per worker. Their findings highlight that, in the first year, the pandemic reduces GDP by about 2.3%, while the demand-side channel, based on industries whose products required customers to congregate, reduces GDP by 2%. Certain studies conclude that pandemics can have long-lasting adverse effects on the economy. For instance, Fan et al. (2016) find that in the 1918 influenza pandemic, the most critical cost was mortality, reduced labour force, and GDP growth. In very recent work, McKibbin and Fernando (2020) explore the potential economic costs of COVID-19. Half of their light scenarios assume the epidemic would lead to a 0.3-2.2% loss in terms of global GDP, while severe pandemic scenarios, where fatality reaches 3% and risk premia spike globally, estimate expected losses to go up to 11%.

Finally, Eichengreen (2020) argues that there will possibly be long-term damages from a prolonged economic shutdown. Bankrupt firms could disrupt the supply chains of surviving firms, and unemployed workers could lose skills and long-term relationships with firms, which are costly and take time to re-establish (Apergis and Apergis, 2020). Thus, having further negative spillovers to labour productivity and output growth.

However, without capturing the country-specific idiosyncrasies, fatally, we fall into a vast generalization. Different countries follow the implementation of varying policy treatments. Hence, we need a panel context to capture more accurately the short-term effects of such a shock. As data gradually becomes available, we can estimate the impact left from the initial shock since households and governments need to reconstruct their damaged stock of goods and people.

Considering that the COVID-19 shock has hit multiple countries and not just one, this work offers, for the first time, a channel through which epidemics might
exercise a strong influence on GDP, leave it unaffected in the short-term or exert a positive impact assuming an immediate response. The results will help us uncover the proposed mechanism which works through and the opportunities offered to update the partially destroyed physical or human capital.

II. Theory and Hypothesis Development

COVID-19 has also been identified – like any other crises – for causing volatility in the stock exchange prices (Hong et al., 2021; Liu et al., 2020), energy commodities (Liu et al., 2020) and the tourism sector (Lee and Chen, 2020; Lee et al., 2021). While initial overreaction is attributed to investors' endemic fear, which will later correct itself (Phan and Narayan, 2020), the optimistic sentiment will revamp after an effective governmental intervention that will boost confidence (Sharif et al., 2020).

Reviewing the evolution of growth models, these were initially expressed as a function of labour and capital (Solow, 1956; Swan, 1956), when both rates are at a steady-state (same rate of growth). Then, Cass (1965) added the rate of savings in the steady-state. Later, Romer (1987) decided to include investment in innovation to extend the steady-state, where economies that keep their investment rate in line with the other rates will continuously enjoy above zero economic growth in the long run. Mankiw et al. (1992) realized that continuous investment in innovation requires human resources and training investment. The rate of human capital accumulation (investment in education) adds to the steady-state. Pagano (1993) and Levine (1997) identify the financial development of the banking system as an innovation that contributes to growth. According to King and Levine (1993), as well as McCraig and Stengos (2005) and Geortzopoulos and Tsiamis (2012), the actual economy benefits as the money supply grows. Even though in the literature we have attempted to identify other variables that directly affect economic growth\(^2\) or indirectly\(^3\), many authors have considered money supply as the first tool at the hands of policymakers to mitigate the effects of COVID-19 and subsequent lockdowns.

\(^2\) Apergis and Apergis (2018)
\(^3\) Apergis and Apergis (2017), Apergis and Apergis (2020)
Hypothesis 1: *Explanatory power of money supply is significant to economic growth during COVID-19.*

Growth theory, however, has been inconclusive in the relationship between natural disasters and income, with many studies supporting the positive hypothesis (Albala-Bertrand, 1993; Skidmore and Toya, 2002; Strulik and Trimborn, 2019), the naturally damaging effect hypothesis (Tol, 1995; Strobl, 2011; Felbermayr and Gröschl, 2014), and mixed results based on natural disasters (Loayza et al., 2012; Fomby et al., 2013). The empirical observations seem puzzling, and once we acknowledge that disasters severely damage the productive inputs and harm economic performance, this effect generates exogenous losses of capital (i.e., physical for climate change and human in an epidemic context). In addition, the short-run theoretical model on natural disasters by Hallegate-Dumas (2009) states that disasters do not influence growth in a Solow-like model; thus, they can never positively impact economic growth. Reconstruction, if any, can merely mitigate negative shocks and, if bifurcation exists with damages exceeding the reconstruction capacity, it can potentially lead to a poverty trap (Hallegate and Dumas, 2009).

Many studies have initially stirred their attention to the consumption-led growth effects (Baker et al., 2020; Hassan et al., 2020). However, certain occupations become riskier than others (Baker et al., 2020) and are forced to stop as wage premia are not enough to compensate for the increased risk (Smith, 1979; Garen, 1988). Growing evidence has demonstrated that climatic conditions can also profoundly impact the functioning of modern human societies (Tol, 2009; Dell et al., 2014; Burke et al., 2015). Although some readers might question why we consider epidemics similar to natural disasters or climate change, pandemics can have long-lasting effects and have a longer duration (Keogh-Brown et al., 2010) or cyclical re-emergence.

Hypothesis 2: *COVID-19 death and cases have significant explanatory power on economic growth in the short-term*

Hypothesis 3: *COVID-19 deaths and cases have significant explanatory power on economic growth in the medium term.*
Hypothesis 4: COVID-19 deaths and cases have a causal impact on economic growth.

The increasing spread of COVID-19 has prompted governments to introduce unprecedented measures to contain the pandemic. These measures have led many businesses to be shut down temporarily with widespread restrictions on travel and mobility. The present work contributes to the economic growth literature by introducing epidemics as another supply shock to economic growth and natural calamities, and oil supply shocks. A rise in the COVID-19 case is articulated negatively related to economic performance (Hong et al., 2021).

III. Methodology

The empirical analysis employs Bayesian Panel Vector Autoregression (BPVAR) methods. This method estimates a Panel VAR (PVAR) model developed by Canova and Ciccarelli (2004), based on the Bayesian shrinkage estimators and predictors recommended by Zellner and Hong (1989) and Zellner et al. (1991). This estimation framework allows for variation in both the time and the cross-sectional dimensions of the data. It infers dynamic relationships among variables, allowing for fully endogenous covariates in contrast to conventional panel data methods. The interactions between those shocks and macroeconomic variables are analyzed using this panel VAR framework, which accounts for individual country heterogeneity while allowing for dynamic relationships between multiple endogenous and exogenous variables. Therefore, when setting up our model, we limit the focus to a small number of variables conveying the dynamics of key macroeconomic variables. Also, we opt for a joint estimation pooling all countries in the sample via a PVAR framework, which also generally improves estimation quality by increasing the cross-sectional dimension.

Over the recent years, several theoretical and applied models have been developed to infer and evaluate idiosyncratic shocks across units and periods by accounting for several additional transmitted shocks and additional spillover effects within the PVAR framework (Lane and Milesi-Ferretti, 2007; Mastrogiacomo et al., 2017; Facchini et al., 2017; Degiannakis et al., 2016; Crespo-Cuaresma and Fernandez-Amadorb, 2013; Reinhart and Rogoff, 2009; Ciccarelli and Rebuscicelli, 2007). The PVAR approach combines the traditional VAR approach, treating all the variables in the
system as endogenous. The panel-data approach allows for unobserved individual heterogeneity by introducing fixed effects, resulting in improved estimation consistency (Love and Zicchino, 2006).

Formalizing, given N countries indexed \( i = 1, 2, \ldots, N \) and time \( t = 1, 2, \ldots, T \), the model is defined as follows:

\[
X_{it} = \mu_i + \Theta(L)X_{it} + u_{it}
\]  

where the vector \( X_{it} \) consists of two endogenous variables, i.e. real output and money supply, plus one exogenous variable, i.e. COVID-19 incidences or deaths, \( \Theta(L) \) is a matrix polynomial in the lag operator \( L \), \( \mu_i \) is the vector of time-invariant country fixed effects, and \( u_{it} \) is the error term. The specified variable setup represents a most parsimonious model allowing for efficient estimation in light of the relatively small number of observations.

Next, the analysis will consider the Bayesian PVAR estimator in line with Dieppe et al. (2016). It uses Bayesian methods to address potential over-parametrization issues; moreover, given that the sample size is particularly limiting, these methods necessitate the use of Bayesian shrinkage. The estimation procedure uses the MATLAB version of the Bayesian Estimation, Analysis and Regression (BEAR) toolbox developed by the ECB and documented in Dieppe et al. (2016). Under the Bayesian VAR approach (Doan et al., 1984), the model parameters are treated as random variables, characterized by some underlying probability distribution. This methodological approach provides a framework for incorporating prior information about the model parameters and updating these probability distributions conditional on the observed data. The analysis uses the standard normal-Wishart prior with default hyperparameter values. The prior belongs to the Normal-Wishart family, so the analysis can draw all recursive-form parameters jointly from this using Monte Carlo integration methods (Uhlig, 2005; Koop and Korobilis, 2010), while the prior ensures that responses are non-explosive (Cogley and Sargent, 2005; S'a et al., 2014). This prior assumes that the model parameters, i.e. panel VAR coefficients and the residual covariance matrix in Equation (1), are unknown, and in this respect, it is superior to another choice. As the objective of the empirical analysis is to infer dynamic responses to shocks of interest, the Bayesian PVAR pooled estimator is used, which is the
Bayesian counterpart of the mean-group estimator and implies that the coefficients are homogeneous across countries.

The modelling approach assumes that the vector of residuals \((u_t)\) is independent and identically distributed. However, this assumption fails typically in practice, as the concrete variance-covariance matrix of the errors is unlikely to be diagonal. Thus, to isolate shocks to one of the VAR errors, it is necessary to decompose the residuals to become orthogonal. According to Sims (1980), the variables in the VAR model should have a recursive causal ordering based on their degree of exogeneity. This procedure is also known as the Cholesky decomposition of the variance-covariance matrix of residuals and ensures the orthogonalization of shocks. The variables that come earlier in order affect the following variables simultaneously and with a lag, while the variables that come later only affect previous variables with a lag (Love and Zicchino, 2006). In our case, COVID-19 is ordered before the two endogenous variables. The pandemic COVID-19 variable is assumed to be exogenous among the variables included in the \(X_{it}\) vector, as self-reinforcing dynamics, heavily drive them.

Following the estimation of the Bayesian PVAR model, the analysis computes orthogonalized impulse response functions (IRFs) and forecast error variance decomposition (FEVD) to track the impact of the COVID-19 shocks on real output. Orthogonal IRFs are obtained via the Cholesky factorization scheme. The ordering of the variables for Cholesky decomposition is the same as appears in the PVAR specification, that is, \(X_{it} = [\text{COVID-19, liquidity, real output}]\). This ordering implies that the variables lower in the ordering may affect the variables of higher order.

IV. Data

The analysis considers 35 countries in the model, with these countries covering over 90% of world PPP-adjusted income according to the World Bank database (the countries included in the empirical analysis are provided in the Appendix). Each individual country model includes two variables:

1. Real output (measured as seasonally adjusted industrial production) and
2. Liquidity (measured as M1 money supply).
The analysis, based on the availability of data, spans the period March 2020 to January 2021. The time span of 11 months provides 385 observations, with data being end-of-month observations. All data come from Datastream. Finally, the analysis uses interchangeably two potential proxies for the COVID-19 shocks: i) total confirmed incidences and ii) death incidences. COVID-19 data also come from Datastream. Table 1 offers specific descriptive statistics.

V. Empirical analysis

We start the empirical part by concluding on the panel unit root analysis. The unit root testing procedure considers first the Pesaran (2007) panel unit root test, which is not set as a requirement for cross-sectional independence across the variables under investigation. The null hypothesis considers the presence of a unit root. Moreover, the analysis reports panel unit root findings through the panel unit root tests, recommended by Smith et al. (2004). All four versions of this testing procedure adopt the presence of a unit root as the null hypothesis. The empirical findings are provided in Table 2. According to these findings, the presence of a unit root across all three variables is receiving statistical support while they turn stationary at their first differences.

[Insert Table 1 about here]

Next, to infer the relationship between industrial output and the COVID-19 shock, the analysis estimates the model using the global sample of countries as a baseline case. To this end, it estimates the Bayesian PVAR model and the analysis computes orthogonalized impulse response functions (IRFs) and forecast error variance decompositions (FEVD) to track the impact of COVID-19 on industrial production. In the first step, Tables 3 and 4 report the forecast error variance decomposition for industrial production when the COVID-19 variable is measured as a number of incidences and deaths, respectively. These decompositions measure the proportion of forecast error variance explained by innovations in themselves (industrial production) and the other model variables (M1 and COVID-19). Both tables show the relative importance of the variable under study (industrial production) at selected time horizons (1, 2, 5, 10 and 24 months) following the initial shock. In both cases, the findings
document that most of the forecast error variance of industrial production is attributed to COVID-19 shock innovations, with money supply not having notable explanatory power (thus rejecting Hypothesis 1). More specifically, in terms of the number of incidences, the COVID-19 shock starts explaining industrial production in the 2nd month after the initial shock with 24.06% of its total variance explained and remains persistent, gradually increasing over the following 22 months, eventually reaching 61.06%. When it comes to the COVID-19 shocks measured as the number of deaths, the variable starts explaining the forecasting variance of industrial production even from the first month (thus supporting Hypothesis 2), that is 7.86%, when its contribution reaches 72.42% after 24 months (thus supporting Hypothesis 3).

[Insert Tables 3 and 4 about here]

In the second part of the empirical analysis, Figures 1 and 2 illustrate impulse response functions of industrial production when the COVID-19 shock hits it. The results show that, notably, a positive COVID-19 shock (in both Figures) does have a strong (negative) impact on industrial production, constituting an essential driver of the industrial output. Moreover, both figures show that the impulse response estimates are statistically significant because they remain inside the confidence intervals generated by Monte-Carlo simulations with 1000 iterations for the horizon of 24 months. The economic significance of the effects is also non-trivial: a shock of one standard deviation in the COVID-19 variable induces a strong negative effect on industrial production. More specifically, a 1% increase in incidences leads to an initial 1.8% decline in output growth. The global income reaches its trough point at around 2.4% in about 12 months, when it starts experiencing lower growth declines, probably due to the impact of certain positive events, such as supportive monetary and fiscal measures and vaccination processes. The figures in the case of deaths are correspondingly -2.1% initial decline, and -2.8% the trough point in 11 months.

[Insert Figures 1 and 2 about here]

Finally, complementing the impulse response functions analysis, this part examines potential causal linkages across the three variables via Granger causality tests. The analysis carries out Granger causality tests based on the Dumistrescu and Hurlin (2012) causality tests for heterogeneous panels, yielding substantially statistically significant results. The test has been developed for heterogeneous panels based on individual Wald
statistics of Granger non-causality. On top of its computational simplicity and allowing for cross-country heterogeneity, the method also carries other instrumental advantages. The power of the test is preserved even for small \( N \) and \( T \) (which is our case here), and it can be implemented in unbalanced panels. The causality results are outlined in Table 5. They highlight a causal link, running from both types of the COVID-19 to industrial production (in both cases, the hypothesis of Granger non-causality is rejected at 1%), thus supporting **Hypothesis 4**.

[Insert Table 5 about here]

VI. Conclusion

Natural disasters can be responsible for supply shocks that originate in the destruction of production capacity and the disruption of supply chains. Growth can be the outcome of technological progress, even if the disruption of human capital (due to a recession), assuming production supply embodies product innovation and the newest methods to accommodate change (Caballero and Hammour, 1994). A natural disaster can seriously impact human health (Kousky, 2016) and life satisfaction (Hudson et al., 2019). Barro et al. (2020) draw the example of the Spanish flu to support a direction towards the long-term effects of the pandemics. Nothing can be done to prevent new viruses from evolving and infecting humans (Martin and Pindyck, 2015).

Based on this discussion, this current study explored the significance of the COVID-19 shock as a driver of economic growth and its strong implications for shaping the future course of the macroeconomy empirically. Using monthly data and a simple PVAR model with three variables, spanning the period March 2020 to January 2021, and a battery of empirical tests, the findings documented that shocks like the COVID-19 pandemic can generate a significant drop in industrial production. These shocks can have potentially further negative spillovers to other parts of the real economy.

Our results also justify the massive responses from different policymakers on a world scale. Such policy responses seem to be required both in the short term and in the coming years. In the short run, both monetary and fiscal policymakers need to ensure that disrupted economies continue to function during the disease outbreak. Overall, there is a critical role for both central banks and governments in the face of
such a global natural disaster event. Cutting interest rates is a satisfying response for central banks. However, given that the COVID-19 shock is not only a demand management problem but primarily a multifaceted crisis that requires monetary, fiscal and health policy responses, other policymakers should also have an important role to play. Such a range of policymakers goes beyond central banks and fiscal authorities. It could also include health authorities and regulators since wide dissemination of good hygiene practices (Levine and McKibbin, 2020) can be a low cost and highly effective response that could also mitigate potential contagion. Moreover, countries could start seriously investing sufficiently in their health care systems, while global cooperation within the public health domain seems to be more than necessary.

As potential future research avenues, the theoretical literature could attempt to endogenize natural disasters (including pandemics, climate change, and other disruptions) with the rate of investment on mitigating them as having a positive effect to economic growth. As we have explored above the shocks from pandemic here has a serious negative and causal effect (investigated in our hypotheses above) in the short-, medium-term (even more important than money supply as we rejected our first hypothesis above). The exploration of longer-term shocks is a possible avenue on the paths of Garrett (2009), who views influenza in the U.S. as a significant shock in the economy. As potential solutions, Lee and Lin (2018) advise enhancing the insurance sector to mitigate the crisis (in our case, the crisis is COVID-19). Chiu and Lee (2017) recommend lenient borrowing depending on the country's needs for risk. Therefore, government intervention is deemed essential to reduce the transmission of the negative consequences to the economy (Eichenbaum et al., 2020) or help pandemic-inflicted companies access funding from natural disasters relief programmes (Garrett, 2003).

References


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### Table 1. Descriptive statistics.

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<th>Mean</th>
<th>SD</th>
<th>Minimum</th>
<th>Maximum</th>
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<tr>
<td>Industrial production</td>
<td>108.95</td>
<td>21.67</td>
<td>55.67</td>
<td>202.25</td>
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<tr>
<td>Money supply (trillion $)</td>
<td>2,901.78</td>
<td>8,651.34</td>
<td>16.19</td>
<td>52,947.91</td>
</tr>
<tr>
<td>COVID-19-1</td>
<td>648,317.91</td>
<td>1,902,522.00</td>
<td>579.00</td>
<td>18,699,055.00</td>
</tr>
<tr>
<td>COVID-19-2</td>
<td>18,789.72</td>
<td>41,541.81</td>
<td>119.00</td>
<td>320,180.00</td>
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Table 2. Panel unit root tests.

<table>
<thead>
<tr>
<th>Variables</th>
<th>CIPS</th>
<th>CIPS*</th>
<th>t-test</th>
<th>LM-test</th>
<th>max-test</th>
<th>min-test</th>
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<tr>
<td>IP</td>
<td>-1.18</td>
<td>-1.29</td>
<td>-1.35</td>
<td>3.16</td>
<td>-1.22</td>
<td>1.34</td>
</tr>
<tr>
<td>ΔIP</td>
<td>-5.96***</td>
<td>-6.19***</td>
<td>-5.74***</td>
<td>22.48***</td>
<td>-7.19***</td>
<td>7.33***</td>
</tr>
<tr>
<td>M1</td>
<td>-1.27</td>
<td>-1.38</td>
<td>-1.49</td>
<td>3.68</td>
<td>-1.46</td>
<td>1.68</td>
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<tr>
<td>ΔM1</td>
<td>-5.94***</td>
<td>-6.12***</td>
<td>-6.91***</td>
<td>21.75***</td>
<td>-7.98***</td>
<td>8.29***</td>
</tr>
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</table>
Cov19-1 is the number of COVID-19 incidences, while Cov19-2 is the number of COVID-19 deaths. A constant is included in the Pesaran (2007) tests, Δ denotes first differences. CIPS* = truncated CIPS test. Critical values for the Pesaran (2007) test are -2.40 at 1%, -2.22 at 5%, and -2.14 at 10%, respectively. ***: p≤0.01. Both a constant and a time trend are included in the Smith et al. (2004) tests. Rejection of the null hypothesis indicates stationarity in at least one country. For both tests, the results are reported at lag = 4. The null hypothesis is that of a unit root.

Table 3. Forecast error variance decompositions (cases).

<table>
<thead>
<tr>
<th>Steps</th>
<th>Industrial production</th>
<th>Money supply</th>
<th>COVID-19</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>100.00 (2.48)</td>
<td>0.00 (2.25)</td>
<td>0.00 (2.06)</td>
</tr>
<tr>
<td>2</td>
<td>65.52 (3.52)</td>
<td>10.42 (2.31)</td>
<td>24.06 (4.29)</td>
</tr>
<tr>
<td>5</td>
<td>46.83 (3.58)</td>
<td>11.34 (2.09)</td>
<td>41.83 (4.17)</td>
</tr>
</tbody>
</table>
Figures in parentheses denote standard errors generated by Monte-Carlo simulations with 1000 iterations for the horizon of 24 months.

<table>
<thead>
<tr>
<th>Steps</th>
<th>Industrial production</th>
<th>Money supply</th>
<th>COVID-19</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>92.14 (4.09)</td>
<td>0.00 (3.71)</td>
<td>7.86 (2.62)</td>
</tr>
<tr>
<td>2</td>
<td>61.38 (4.19)</td>
<td>4.02 (3.75)</td>
<td>34.60 (3.09)</td>
</tr>
</tbody>
</table>
Figures in parentheses denote standard errors generated by Monte-Carlo simulations with 1000 iterations for the horizon of 24 months.

### Table 5. Dumitrescu and Hurlin Granger causality.

<table>
<thead>
<tr>
<th></th>
<th>Industrial production</th>
<th>COVID-19 (incidences)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Industrial production</td>
<td>______</td>
<td>[0.79]</td>
</tr>
<tr>
<td>COVID-19 (incidences)</td>
<td>[0.00]</td>
<td>______</td>
</tr>
</tbody>
</table>
The dashed lines above and below the impulse line are 95% confidence intervals (bootstrapped with 1000 iterations)

Figure 1. Impulse responses (cases).
Figure 2. Impulse responses (deaths)
Appendix

Country list

Austria, Brazil, Bulgaria, Canada, Chile, China, Czech Republic, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, India, Indonesia, Ireland, Israel, Italy, Japan, Korea, Mexico, Netherlands, Norway, Poland, Portugal, Russia, Slovakia, Slovenia, South Africa, Spain, Sweden, Turkey, U.K., and the U.S.