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Economic recovery forecasts under impacts of COVID-19[☆]

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ABSTRACT

This paper proposes a joint model by combining the time-varying coefficient susceptible-infected-removal model with the hierarchical Bayesian vector autoregression model. This model establishes the relationship between several critical macroeconomic variables and pandemic transmission states and performs economic predictions under two predefined pandemic scenarios. The empirical part of the model predicts the economic recovery of several countries severely affected by COVID-19 (e.g., the United States and India, among others). Under the proposed pandemic scenarios, economies tend to recover rather than fall into prolonged recessions. The economy recovers faster in the scenario where the COVID-19 pandemic is controlled.

1. Introduction

COVID-19 has been classified as a Public Health Emergency of International Concern, and the pandemic has severely impacted the production, consumption, exports, and other economic aspects of countries worldwide. Hence, it is critical to study the economic changes of individual countries impacted by COVID-19.

Recent studies have estimated the pandemic's economic, social, and financial impacts. Zhang et al. (2020a) explored the impact of COVID-19 on stock market risks, noting that financial market risk is increasing globally in response to the pandemic. Malliet et al. (2020) examined the impact of COVID-19 on France's gross domestic product (GDP), unemployment, total investment, and CO_2 emissions, pointing out that COVID-19 would have a severe short-term macroeconomic impact. Sun et al. (2021) investigated the impact of COVID-19 on small and medium-sized firms in China and found that high-level digitization reduces the pandemic's negative impacts. Together with other studies, such as Sun et al. (2020b), Ftiti et al. (2021), Daehler et al. (2021), and Akhtaruzzaman et al. (2021), there is strong evidence of the pandemic's severe impact on the economy. For more empirical studies on the macroeconomic, social, financial, and environmental implications of the COVID-19 pandemic, we also refer to Altig et al. (2020), Ayittey et al. (2020), Caraka et al. (2020), Funke and Tsang (2020), Goodell (2020), Nicola et al. (2020), Umar et al. (2020), and Walmsley et al. (2021).

International Monetary Fund (2021) pointed out that global prospects remain highly uncertain one year into the pandemic. The different pandemic-induced disruptions and variations in policy support have caused economic recoveries to diverge across countries. From the academic research perspective, it is difficult to obtain reliable economic forecasts under high-level uncertainties even with complicated econometric models; see Foroni et al. (2022), An et al. (2018), Carriero et al. (2020), and others. For example, after considering various models, Carriero et al. (2020) showed that more information increased the accuracy of predictions on the tail risk to GDP growth. Making long-term predictions is more difficult due to unanticipated risk factors, such as random virus mutations.

As a result, a scenario analysis is one way to find practical solutions. Yan et al. (2021) designed scenario-based experiments to analyze the effects of government intervention measures in response to the

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COVID-19 pandemic in 25 countries. McKibbin and Fernando (2021) explored seven plausible COVID-19 scenarios and showed that even a contained outbreak could significantly impact the global economy in the short term. Both International Monetary Fund (2020a) and International Monetary Fund (2020b) adopted scenario analysis for global economy projections. International Monetary Fund (2020b) proposed the IMF's G-20 model and analyzed two specific scenarios: (i) a second COVID-19 outbreak in early 2021 and (ii) a faster recovery from the lockdown measures. The model's baseline projection is a gradual recovery in economic activity starting in the second half of 2020. This paper's framework is partly inspired by the ideas of International Monetary Fund (2020a) and International Monetary Fund (2020b).

This paper focuses on the resilience of economic indicators under pandemics, especially when the pandemic's outlook is uncertain. At the beginning of September 2020, some countries appeared to have passed the pandemic's peak. At that time, some analysts believed that the pandemic would gradually disappear, while others argued that it could return at any time due to increasing in-person interactions following the reemergence of economic and social activities. Therefore, it is difficult to accurately forecast economic recovery under the uncertainties of the global COVID-19 pandemic, and scenario assumptions are necessary under a forecasting framework.

We aim to design a framework for quantitatively measuring future economic recovery, which could respond to any specific pandemic scenario forecast. To this end, we propose a joint model that combines hierarchical Bayesian vector autoregression (BVAR) and time-varying coefficient susceptible-infected-removal (vSIR) models; we then empirically analyze the recovery resilience of macroeconomic variables through a pandemic effect regression under two specific pandemic scenarios. The proposed framework can be briefly summarized as follows. First, we obtain baseline estimations under the pandemic-free scenario through BVAR. The deviation between the real economic trend after the COVID-19 outbreak and the baseline estimation can be regarded as a measure of the pandemic's economic impact. We then attempt to explain the economic impact through regression with the pandemic-related indicator estimated by vSIR. On this basis, the pandemic's impact on the economy can be evaluated under different pandemic scenarios.

The remainder of this paper is structured as follows. Section 2 presents the macroeconomic variable selection and the data sources, Section 3 describes the methodology in detail, Section 4 presents the empirical results of seven countries, and Section 5 discusses the limitations of the model and empirical results. Finally, Section 6 summarizes the main findings regarding economic recovery under the pandemic.

2. The data

2.1. Variable selection and data description

We analyze the economic recovery of seven countries: the United States (USA), India (IND), Russia (RUS), Mexico (MEX), Spain (ESP), Germany (DEU), and Indonesia (IDN). As of September 2020, these countries ranked in the top 20 worldwide regarding their number of COVID-19 cases.[1]

We selected eight macroeconomic variables: gross domestic product (GDP), consumer price index (CPI), broad money supply (M2), the value of imported and exported goods, unemployment rate, the exchange rate (USD to local currency), and international reserves. These variables are major economic indicators reflecting socioeconomic fluctuations after the pandemic.

2.2. Data sources

Macroeconomic data are taken from databases of the International Monetary Fund (IMF), the Organization for Economic Cooperation and Development (OECD), and the websites of the national central bank of each country.[2] These data started in January 2016 and ended in June 2020, measured monthly. Specifically, the raw GDP data, which are reported quarterly, are transformed into monthly data through quadratic interpolation.

COVID-19 case data are from Johns Hopkins University Center for Systems Science and Engineering (JHU CCSE), measured daily from January 22, 2020, to September 14, 2020.[3]

3. Methodology

This section presents the economic recovery model consisting of three components: a BVAR baseline estimation, a time-varying susceptible-infected-removal (vSIR) model for estimations of pandemic-related indicators, and a pandemic effects regression under different pandemic scenarios.

We divide each country's COVID-19 pandemic timeline into three segments. The first interval, $[0, T_0)$, is the period when no pandemic occurred. The second interval, $[T_0, T_1]$, is from the month when the country's first confirmed case appeared to the month when the latest economic data were disclosed or collected. The third interval, $(T_1, T_2]$, is the forecast interval in which the trends of economic variables have not been disclosed. This paper sets T_1 to June 2020 and T_2 to December 2021, the same for the seven countries. Since the month of first-case emergence varies for each country, we specify T_0 later in the data analysis.

3.1. Baseline estimation

Suppose y_t represents the monthly k-dimensional observed time series of macroeconomic indicators, as mentioned in Section 2.2. Consider $t \in [0, T_0)$, an interval in which the pandemic has not yet occurred, and build a hierarchical Bayesian vector autoregressive (BVAR) model unaffected by the pandemic:

$$\widetilde{y}_t = C + \sum_{j=1}^{p} A_j \widetilde{y}_{t-j} + e_t, \ \forall t \in [0, T_0), \tag{1}$$

where $\widetilde{y}_t$ is the stationarized variables of y_t, $\widetilde{y}_{t-j}$ represents the values j months ago, and e_t represents the random error (white noise).[4] The

[1] Limited by delays in releasing macroeconomic data and the reliability of the pandemic's statistical indicators, we selected seven representative countries from the top 20 countries ranked by their number of COVID-19 cases. Referring to the categorizations in International Monetary Fund (2020b), these seven countries belong to (i) Advanced Economies, including the United States, Euro Area (Germany, Spain), or (ii) Emerging Markets & Developing Economies, including Asia (India, Indonesia), Europe (Russia), Latin America and the Caribbean (Mexico).

[2] The IMF Data provide most of the monthly macroeconomic indicators for the selected countries (https://data.imf.org). The quarterly GDP data are also collected from the OECD National Accounts Statistics database (https://doi.org/10.1787/data-00017-en).

[3] The Github website of the COVID-19 data repository by JHU CCSE is https://github.com/CSSEGISandData/COVID-19. See Dong et al. (2020) for more details of the COVID-19 data repository.

[4] Logarithmization and seasonal differencing can be used to ensure stationarity, e.g., $\widetilde{y}_{it} = (1-B)(1-B^{12})\log y_{it}$ in which B is a lag operator and y_{it} represents the i-th element of vector y_t. The lag operator B operates on an element of a time series to produce the previous element, i.e., $B^j y_{it} = y_{i,t-j}$. Thus, for the above example, $\widetilde{y}_{it}$ is computed by

$$\begin{aligned}\widetilde{y}_{it} &= (1-B)(1-B^{12})\log y_{it} \\ &= (1-B)(\log y_{it} - \log y_{i,t-12}) \\ &= (\log y_{it} - \log y_{i,t-12}) - (\log y_{i,t-1} - \log y_{i,t-13}),\end{aligned}$$

where $1-B^{12}$ removes the seasonal effects of macroeconomic variables and $1-B$ is used to stationarize the series. The empirical analysis provides details for the criteria for determining whether differencing is required.

order p and posterior distribution of coefficients $\Theta = \{C, A_j; j = 1, \dots, p\}$ are fitted using the historical data in time interval $[0, T_0)$ up to the occurrence of the pandemic.[5] See more details about BVAR models and forecasts of macroeconomic variables in Sims (1980), Lütkepohl (2005), Kapetanios et al. (2012), Giannone et al. (2015), and Kuschnig and Vashold (2021).

According to the fitted posterior distribution of the BVAR(p) model, thousands of random paths $\mathcal{Y} := \{\hat{y}_t^{(n)}; t \in [T_0, T_1], n = 1, 2, \dots, N_{\text{path}}\}$ can be inferred effectively through the MCMC algorithm. More specifically, each forecast path, $\hat{y}_t^{(n)}, t \in [T_0, T_1]$, is inferred by the corresponding sampled coefficients $\widehat{\Theta}^{(n)}$ from the posterior distribution $P\left(\Theta \mid \tilde{y}_t, t \in [0, T_0)\right)$. The coefficient's posterior distribution is analogous to the probability of various economic conditions; thus, these random paths are the predictions under the corresponding economic conditions. Since the posterior distribution is estimated based on the data before the COVID-19 pandemic, none of the forecast paths of economic indicators are affected by the pandemic. We define the average forecast path as

$$\hat{y}_t = \frac{1}{N_{\text{path}}} \sum_{n=1}^{N_{\text{path}}} \hat{y}_t^{(n)}, \ \forall t \in [T_0, T_1]. \tag{2}$$

Throughout the paper, the average forecast path $\hat{y}_t$ is called the *baseline estimation*, and the paths mentioned above $\mathcal{Y}$ are called the paths of the baseline estimations.

The baseline estimation $\hat{y}_t$ ($t \in [T_0, T_1]$) represents the economic forecast unaffected by the pandemic. Although realized economic indicators y_t in $[T_0, T_1]$ are already disclosed, the baseline estimation does not consider any information after the COVID-19 outbreak. This is important in the later modeling process.

The diffusion patterns of the paths $\{\hat{y}_t^{(n)}\}$ through the BVAR model are similar to the prediction confidence interval of the VAR/VARMA model; see Figs. F.7–F.13 in Appendix F. However, in Section 3.3, we must compare each path with the actual economic data during the pandemic, which is difficult to achieve with confidence intervals. This is one of the reasons why we use BVAR instead of VAR/VARMA.

The gradual diffusion of the simulated paths $\{\hat{y}_t^{(n)}\}$ over time implies increasing uncertainty. Thus, in the subsequent modeling, we assume that the interval $[T_0, T_1]$ is relatively short, which guarantees the reliability of $\hat{y}_t, t \in [T_0, T_1]$.

3.2. Estimates and scenario assumptions of COVID-19 via a vSIR model

The SIR model is a classical model of infectious disease proposed by Kermack and Mckendrick (1927). The SIR model's coefficients β and γ represent infectious and removal rates, respectively. A variety of factors, such as virus mutation, implementation of pandemic prevention and control interventions, increased awareness of individual self-protection, and resumption of work, may make the infectious rate β vary over time. This time-varying infection rate is a reasonable indicator for characterizing the real-time status of the pandemic. Therefore, we introduce the following time-varying coefficient SIR model (vSIR) derived by Sun et al. (2020a):

$$\frac{\mathrm{d}S_t}{\mathrm{d}t} = -\beta_t \frac{S_t I_t}{N}, \tag{3a}$$

$$\frac{\mathrm{d}I_t}{\mathrm{d}t} = -\beta_t \frac{S_t I_t}{N} - \gamma_t T_t, \tag{3b}$$

$$\frac{\mathrm{d}R_t}{\mathrm{d}t} = \gamma_t I_t, \tag{3c}$$

where S_t, I_t and R_t are the number of susceptible, infected, and recovered (or dead). N is the country's total population, and $N = S_t + I_t + R_t$. β_t and γ_t are the time-varying infection and removal rates, respectively.[6]

In the following, we need to obtain two vSIR results during the pandemic period $t \in [T_0, T_1] \cup (T_1, T_2]$: (i) monthly estimates $\{\hat{\beta}_t, \hat{\gamma}_t; t \in [T_0, T_1]\}$ given daily observed data $S_u^{\mathrm{D}}, I_u^{\mathrm{D}}, R_u^{\mathrm{D}}$, $u \in [T_0, T_1]$; and (ii) monthly forecasts $\{\hat{I}_t; t \in (T_1, T_2]\}$ given daily future scenarios $\{\hat{\beta}_u^{\mathrm{D}}, \hat{\gamma}_u^{\mathrm{D}}; u \in (T_1, T_2]\}$. To avoid confusion between monthly and daily frequencies, we use u, z as subscripts to denote the time index of the daily frequency variable and add a superscript, D, which stands for "Daily".[7]

To determine (i), given daily observed data $S_u^{\mathrm{D}}, I_u^{\mathrm{D}}, R_u^{\mathrm{D}}$ during the time interval $[T_0, T_1]$, the daily frequency estimates $\hat{\beta}_u^{\mathrm{D}}, \hat{\gamma}_u^{\mathrm{D}}$ can be obtained via equations (3b) and (3c) as

$$\hat{\beta}_u^{\mathrm{D}} = \frac{\sum_{z=u-m+1}^{u+m} (I_z^{\mathrm{D}} - I_{z-1}^{\mathrm{D}} + R_z^{\mathrm{D}} - R_{z-1}^{\mathrm{D}})N}{\sum_{z=u-m+1}^{u+m} S_z^{\mathrm{D}} I_z^{\mathrm{D}}}, \ \forall u \in [T_0, T_1], \tag{4}$$

$$\hat{\gamma}_u^{\mathrm{D}} = \frac{\sum_{z=u-m+1}^{u+m} (R_z^{\mathrm{D}} - R_{z-1}^{\mathrm{D}})}{\sum_{z=u-m+1}^{u+m} I_z^{\mathrm{D}}}, \ \forall u \in [T_0, T_1], \tag{5}$$

where $\hat{\beta}_u^{\mathrm{D}}$ and $\hat{\gamma}_u^{\mathrm{D}}$ depend on the observations of the adjacent $2m + 1$ days. We denote $M := 2m + 1$ as the bandwidth of the estimation. The formulas (4), (5) can be obtained by discretizing (3b), (3c) according to the Euler scheme, where the smoothing of the numerators and denominators allows the estimates to be more robust. This can be regarded as a simplified version of the nonparametric estimates in Sun et al. (2020a). The estimation approach is recorded in detail in Appendix A.

The bandwidth M determines the degree of the estimates' smoothness. Using the United States as an example, Fig. 1 explores the effect of different degrees of smoothness on daily and monthly estimates. The gray circles mark all the estimates under bandwidth $M = 1, 3, 5, 7, 9, 11, 13, 15$. The figure shows that as time progresses, the different bandwidths have a decreasing impact on the estimates, but they significantly impact the robustness of the estimates in the beginning. In particular, in the left panel of Fig. 1, the first half of the estimates under the bandwidth $M = 1$ (i.e., the estimates without smoothing), shown in the red triangular dashed line, oscillated severely. The right panel shows that $M = 1$ tends to overestimate the infection rate in the pandemic's beginning phase. Note that in the figure, the monthly medians of $\hat{\beta}_u^{\mathrm{D}}, \hat{\gamma}_u^{\mathrm{D}}$ in equations (4) and (5) are denoted as $\hat{\beta}_t, \hat{\gamma}_t$, $t \in [T_0, T_1]$, respectively.

In the following empirical analysis, $M = 5$, i.e., the green line in Fig. 1, which is relatively small but sufficient to achieve a smoothing effect.[8] To have an intuitive understanding of why $M = 5$ can achieve sufficient smoothness, one can assume the perspective of smoothing as a modification for the observation errors of the data. From the available literature, there is evidence that the median incubation period for

[5] In general, the order p can be determined using the Bayesian information criterion (BIC). In the hierarchical BVAR model, the prior distributions determined by low-dimensional hyperparameters are specified, which avoids problems such as overfitting caused by the high-dimensional coefficients $\{C, A_j\}$.

[6] The vSIR model (3a)-(3c) consists of three continuous-time ordinary differential equations. By convention, the subscript in equations (3a)-(3c) is still marked with t, although it has a different meaning from the subscript t in formulas elsewhere in this paper. After discretizing the continuous-time equations into daily frequency, we use the subscript u instead.

[7] In this paper, only the series with the superscript D are of daily frequency, and the others are of monthly frequency. The purpose of using daily confirmed case data is to calculate the indicators of the pandemic more accurately. The subscripts u and $u - 1$ of the daily frequency variables represent two adjacent calendar days, while t and $t - 1$ of the monthly frequency variables represent two adjacent months. This alleviates confusion when the variables of daily frequency are all marked with the superscript D.

[8] Fig. 1 shows that, except for $M = 1$, the differences of the estimates under the other bandwidths are relatively small. We also performed experiments for $M = 3$ and $M = 7$ in this paper and obtained conclusions similar to $M = 5$. Therefore, in the following, we only show the data analysis results of $M = 5$.

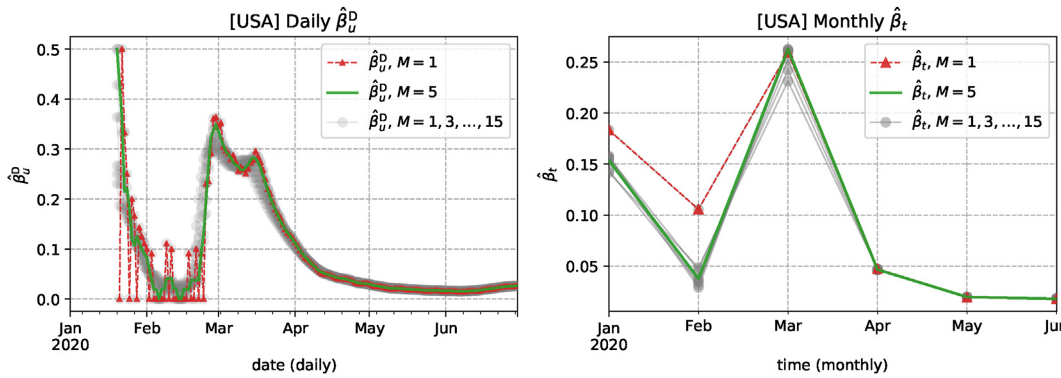

Fig. 1. Daily estimates $\widehat{\beta}_u^{\mathrm{D}}$ (left) and monthly estimates $\widehat{\beta}_t$ (right) in the United States from February 2020 to June 2020. The red dashed line represents the estimates of $\widehat{\beta}$ when $M=1$, the green line represents the estimates of $\widehat{\beta}$ when $M=5$, and the gray circle lines represent the estimates of $\widehat{\beta}$ when $M=1,3,5,7,9,11,13,15$. The right panel is the monthly median of the left panel. (For interpretation of the references to color in this figure legend, the reader is referred to the Web version of this article.)

COVID-19 is approximately five days; see Lauer et al. (2020) and Zhang et al. (2020b).

For the monthly forecast previously mentioned (ii), once the estimates (or predictions) of the time-varying parameter path $\{\widehat{\beta}_u^{\mathrm{D}}, \widehat{\gamma}_u^{\mathrm{D}}; u \in (T_1, T_2]\}$ are provided, the number of infectious individuals I_u^{D} during this future time period can easily be predicted according to Euler discretization of equations (3a)-(3c). Specifically, starting from the latest observations $S_{T_1}^{\mathrm{D}}, I_{T_1}^{\mathrm{D}}, R_{T_1}^{\mathrm{D}}$, the subsequent path of the pandemic can be predicted as follows:

$$\widehat{S}_{u+1}^{\mathrm{D}} = \widehat{S}_u^{\mathrm{D}} - \widehat{\beta}_u^{\mathrm{D}} \frac{\widehat{S}_u^{\mathrm{D}} \widehat{I}_u^{\mathrm{D}}}{N}, \tag{6a}$$

$$\widehat{I}_{u+1}^{\mathrm{D}} = \widehat{I}_u^{\mathrm{D}} - \widehat{\beta}_u^{\mathrm{D}} \frac{\widehat{S}_u^{\mathrm{D}} \widehat{I}_u^{\mathrm{D}}}{N} - \widehat{\gamma}_u^{\mathrm{D}} \widehat{I}_u^{\mathrm{D}}, \tag{6b}$$

$$\widehat{R}_{u+1}^{\mathrm{D}} = \widehat{R}_u^{\mathrm{D}} + \widehat{\gamma}_u^{\mathrm{D}} \widehat{I}_u^{\mathrm{D}}, \tag{6c}$$

for $u \in (T_1, T_2]$. Similarly, we take the monthly medians of $\widehat{I}_u^{\mathrm{D}}$ as $\widehat{I}_t$, $t \in (T_1, T_2]$.

We aim to quantify the expectations for economic recovery in the later stages of the pandemic. The next problem is that the time-varying β_t and γ_t in $(T_1, T_2]$ are difficult to correctly predict at the current moment $t = T_1$. Note that the time-varying β_t in the vSIR model incorporates several factors, such as mutations, policies, economics, and society, making the pandemic's future state highly uncertain. Sun et al. (2020a) introduced a type of monotonic decreasing function as the prediction function, which is equivalent to assuming that the pandemic infectious rate is continuously decreasing. However, there are still no apparent indications of such a scenario for many countries worldwide. Therefore, we combine the ideas of International Monetary Fund (2020b) and make the following two scenario assumptions for the β_t forecasts across countries:

- *Scenario DN.* Effective prevention and control measures (e.g., social distancing and vaccine coverage) would control the pandemic.
- *Scenario UP.* As social restrictions end and economies restart, a new round of severe pandemics would break out when effective pharmaceutical interventions are still lacking.

We thus construct two functions, (7) and (8), to characterize these two hypotheses:

$$\widehat{\beta}_{T_1+\Delta T}^{\mathrm{D(DN)}} := \frac{1}{2^{\frac{\Delta T}{\lambda}}} \widehat{\beta}_{T_1}^{\mathrm{D}}, \tag{7}$$

$$\widehat{\beta}_{T_1+\Delta T}^{\mathrm{D(UP)}} := \frac{2\eta^2}{(\Delta T - \eta)^2 + \eta^2} \widehat{\beta}_{T_1}^{\mathrm{D}}, \tag{8}$$

where $\Delta T \geq 0$ is the number of days away from the last day of month T_1, and $\lambda > 0, \eta > 0$ are the given constants. It is apparent that when $\Delta T = 0$, both scenarios start from $\widehat{\beta}_{T_1}^{\mathrm{D}}$. Formula (7) is a monotonic decreasing function, and the parameter λ represents the period in which β is halved.[9] Formula (8) is a heavy-tailed unimodal function where the parameter η represents the number of days from the peak of β to T_1. At this point, for the two daily frequency scenarios, $\widehat{\beta}_u^{\mathrm{D(UP)}}$ and $\widehat{\beta}_u^{\mathrm{D(DN)}}$, the predicted number of infections, $\widehat{I}_u^{\mathrm{D(UP)}}$ and $\widehat{I}_u^{\mathrm{D(DN)}}$, can be calculated based on the recursive formulas (6a)-(6c), $u \in (T_1, T_2]$. In addition, for simplicity, the removal rate $\widehat{\gamma}_u^{\mathrm{D}}$ is approximated by the average value over $u \in [T_0, T_1]$, according to formula (5) in the following empirical analysis. We let $\lambda = \eta = 90$ days, representing that COVID-19's predicted infectious rate has an increasing or decreasing trend within a quarter. Using the United States as an example, the left-hand panel of Fig. 2 shows the trends of daily $\widehat{\beta}_u^{\mathrm{D}}$ and $\widehat{I}_u^{\mathrm{D}}/N$, from September 2020 to December 2021, for the UP and DN scenarios, with orange dashed lines and green dotted dashed lines, respectively.

The monthly frequency variables $\widehat{\beta}_t^{\mathrm{DN}}, \widehat{\beta}_t^{\mathrm{UP}}, \widehat{I}_t^{\mathrm{DN}}, \widehat{I}_t^{\mathrm{UP}}$ are defined as the monthly median of daily frequency variables $\widehat{\beta}_u^{\mathrm{D(DN)}}, \widehat{\beta}_u^{\mathrm{D(UP)}}, \widehat{I}_u^{\mathrm{D(DN)}}, \widehat{I}_u^{\mathrm{D(UP)}}$. We also use the symbol $\widehat{\beta}_t^{\mathrm{UP}} = \widehat{\beta}_t^{\mathrm{DN}} = \widehat{\beta}_t$ within $t \in [T_0, T_1]$ in the following, but note that they are estimated by formula (4), rather than (7,8). Similarly, $\widehat{I}_t^{\mathrm{UP}} = \widehat{I}_t^{\mathrm{DN}} = \widehat{I}_t$, $t \in [T_0, T_1]$. For the trends of daily and monthly frequency data, see Fig. 2. The following section establishes the relationship between monthly pandemic estimates and economic indicators.

3.3. Pandemic effect regression under different pandemic scenarios

Due to the impact of the pandemic, economic indicators y_t can change drastically. Within the time interval $t \in [T_0, T_1]$ already experienced since the pandemic, the prediction error between the real economic variable y_t and each of the baseline estimation paths $\widehat{y}_t^{(n)}$ can be calculated, measured as $r_t^{(n)} = \log \frac{y_t}{\widehat{y}_t^{(n)}}$, $t \in [T_0, T_1]$. The average prediction error can be defined based on the baseline estimation as $r_t = \log \frac{y_t}{\widehat{y}_t}$, $t \in [T_0, T_1]$.

[9] This scenario is assumed to be similar to Sun et al. (2020a).

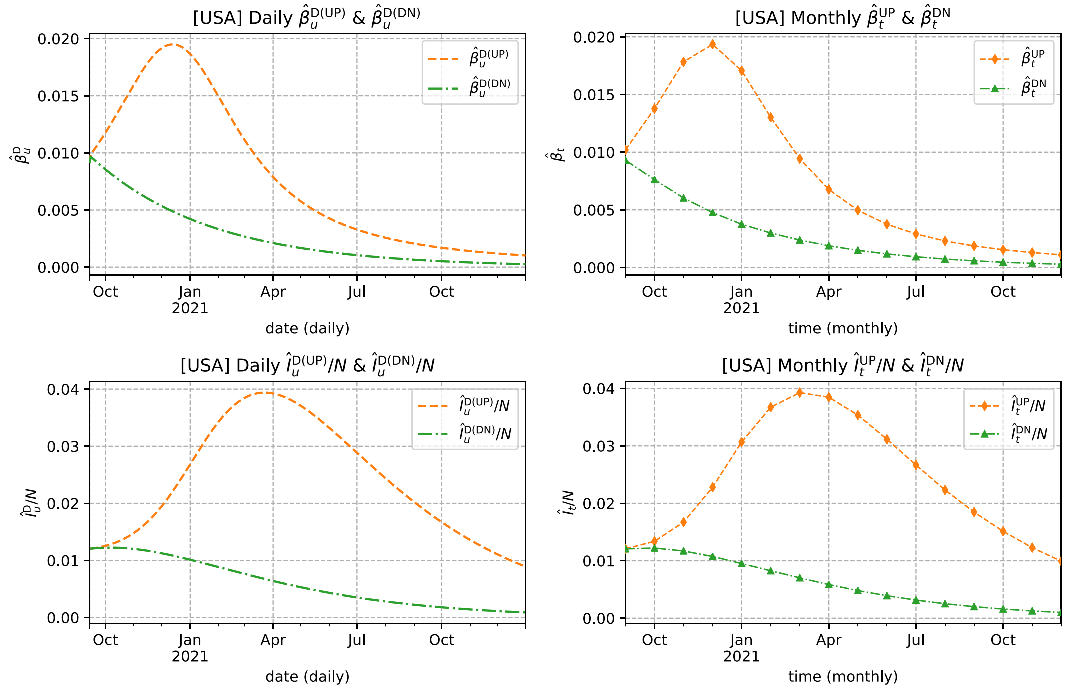

Fig. 2. The DN and UP scenarios of COVID-19 in the United States from September 15, 2020 are estimated based on formulas (7) and (8). The parameters $\lambda = \eta = 90$. The left-hand side shows the daily frequency scenarios, and the right-hand side shows the corresponding monthly frequency scenarios.

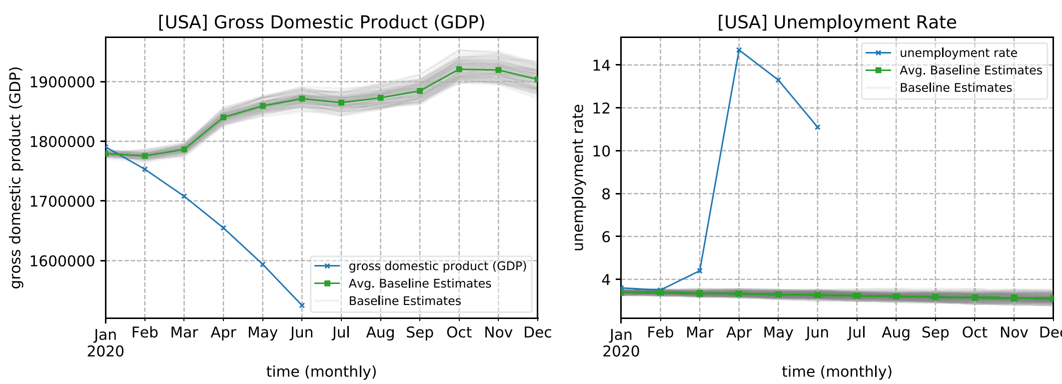

Fig. 3. Expectation bias for the US to be affected by the pandemic in January–June 2020. Baseline estimations fail to capture the sudden attack of the pandemic on GDP and employment.

Using the United States, we take the GDP and the unemployment rate as examples to explain the economic implications of $r_t^{(n)}$. Fig. 3 shows the actual pandemic effect on the US GDP and unemployment rate from January to June 2020 (blue x-line), along with the path of the baseline estimations assuming no pandemic effect (gray lines). Although the parameter uncertainty assumption based on the BVAR model derives the paths of the baseline estimation under different economic conditions, the pandemic's impact still makes the two economic indicators different from expectations. This deviation in expectations can be portrayed by $r_t^{(n)}$.

From another perspective, $r_t^{(n)}$ measures the level of economic recovery during (or after) the pandemic. If the absolute value of $r_t^{(n)}$ increases as the pandemic progresses, it indicates that the destructive effect of the pandemic on the economy intensifies; conversely, if the absolute value of $r_t^{(n)}$ decreases, it indicates that the economy is recovering to some extent.

Therefore, the main goal for building the pandemic impact model is to explain the deviation $r_t^{(n)}$ with the pandemic-related variables $\hat{\beta}_t$ and $\hat{I}_t$, $n = 1, 2, \ldots, N_{\text{path}}$. The effect of the pandemic on the economy can be described as the relationship between the COVID-19 indicators $(\hat{\beta}_t, \hat{I}_t)$ and the economic indicators $r_t^{(n)}$ within the pandemic time interval $t \in [T_0, T_1]$.

In the vSIR model (3a-3c), the product $\hat{\beta}_t \hat{I}_t$ can usually be used as a measure of pandemic risk. Combining Figs. 1 and 2, we see that $\hat{\beta}_t$ is higher in the pandemic's early stage and decreases in the middle and late stages, while $\hat{I}_t$ is prominent in the middle stage of the pandemic. We then define the pandemic impact indicators x_t for both scenarios, as follows:

$$x_t^{\text{DN}} = \log(\hat{\beta}_t^{\text{DN}} \hat{I}_t^{\text{DN}} + 1), \ \forall t \in [T_0, T_1] \cup (T_1, T_2], \tag{9}$$

$$x_t^{\text{UP}} = \log(\hat{\beta}_t^{\text{UP}} \hat{I}_t^{\text{UP}} + 1), \ \forall t \in [T_0, T_1] \cup (T_1, T_2]. \tag{10}$$

Note that $x_t^{\text{DN}} = x_t^{\text{UP}}$ when $t \in [T_0, T_1]$. For this indicator's figures for each country, see Fig. E.6 in Appendix E. If x_t is the explanatory variable for the impact of COVID-19 on the economy, it has the following characteristics: (i) The significant impact on economic indicators in the early stages of the pandemic follows $\hat{\beta}_t$; (ii) the economic damage caused by the dramatic increase in the number of infections during the medium and late stages follows $\widehat{I}_t$; (iii) after taking the logarithm, the indicator will not exponentially explode and returns to zero at the end of the pandemic.

Through all the above preparations, as the most critical step, the economic explanatory model can then be defined as follows:

$$r_{it}^{(n)} = r_i^0 + \sum_{j=0}^{l_i} B_{ij} x_{t-j} + \epsilon_{it}^{(n)},\ \forall t \in [T_0, T_1],\ \forall n = 1, 2, \dots, N_{\text{path}}. \tag{11}$$

For the i-th element of $r_t^{(n)}$, equation (11) represents a linear regression model, with monthly l_i-period lagged terms $\{x_{t-j}\}_{j=0}^{l_i}$ to characterize the sustained impact of the pandemic on the economic variables. The intercept term r^0 represents the pandemic's "permanent" impact on the economy. The lags l and parameters $\{B_j\}$ are estimated on $t \in [T_0, T_1]$. Finally, by substituting the scenarios of the pandemic indicators x_t^{DN} and x_t^{UP} into equation (11), the future economic impacts $\widehat{r}_t^{\text{DN}}$ and $\widehat{r}_t^{\text{UP}}$, $t \in (T_1, T_2]$, can be estimated. Thus, $\widehat{r}_t$, $t \in (T_1, T_2]$, estimated by regression (11), is the expected level of economic recovery for the given pandemic scenario.

Here, we must also explain the necessity of introducing BVAR's N_{path} prediction paths, which is based on two considerations. The first is that the combination of multiple paths makes the regression model (11) more reasonable. Each path represents a multistep prediction under some sampling parameters based on BVAR. Higher uncertainty allows the baseline prediction paths to cover a larger area. Therefore, by introducing $r_t^{(n)}$, $n = 1, 2, \dots, N_{\text{path}}$ into the regression (11), it contains more economic expectations than having r_t calculated using only the average prediction path. Another point is that since the disclosure of macroeconomic data is always delayed (often more than three months), leaving the regression problem (11) of small sample size; using $r_t^{(n)}$ naturally expands the sample size.

In addition, we emphasize that simulating the path of $\widehat{y}_t^{(n)}$ on $(T_1, T_2]$ is optional in our model. In other words, our results do not rely on BVAR's excessive multistep predictions. In Figs. F.7-F.13, we plot the simulated paths of $\widehat{y}_t^{(n)}$ on $(T_1, T_2]$ to make the pandemic effects under the two scenarios appear more intuitive.

3.4. Summary of the modeling steps

Here we summarize the detailed modeling steps of the above three modules as follows.

- *Baseline estimation.*
  a. Fit BVAR model (1) on $t \in [0, T_0)$.
  b. Sample the paths of baseline estimation $\widehat{y}_t^{(n)}$, $t \in [T_0, T_1]$, $n = 1, 2, \dots, N_{\text{path}}$, based on the fitted BVAR model (1), as the predictions without the impacts of COVID-19.
- *Time-varying SIR for COVID-19 pandemic indicators.*
  c. Estimate daily time-varying $(\widehat{\beta}_u^{\text{D}}, \widehat{\gamma}_u^{\text{D}})$ based on formulas (4,5) on $u \in [T_0, T_1]$ and obtain daily $\widehat{\beta}_u^{\text{D(DN)}}$ and $\widehat{\beta}_u^{\text{D(UP)}}$ scenarios on $u \in (T_1, T_2]$ by (7) and (8), respectively.
  d. Predict $\widehat{I}_u^{\text{D(DN)}}$ and $\widehat{I}_u^{\text{D(UP)}}$ via vSIR equations (6a)-(6c) on $u \in (T_1, T_2]$, based on $\widehat{\beta}_u^{\text{D(DN)}}$ and $\widehat{\beta}_u^{\text{D(UP)}}$, respectively.
  e. Take the monthly median of $\widehat{\beta}_u^{\text{D(DN)}}, \widehat{\beta}_u^{\text{D(UP)}}, \widehat{I}_u^{\text{D(DN)}}, \widehat{I}_u^{\text{D(UP)}}$, $u \in [T_0, T_1] \cup (T_1, T_2]$ as $\widehat{\beta}_t^{\text{DN}}, \widehat{\beta}_t^{\text{UP}}, \widehat{I}_t^{\text{DN}}, \widehat{I}_t^{\text{UP}}$, $t \in [T_0, T_1] \cup (T_1, T_2]$.
  f. Calculate COVID-19 indicators x_t^{DN} and x_t^{UP} by (9) and (10), $t \in [T_0, T_1] \cup (T_1, T_2]$. Since the information on $[T_0, T_1]$ is already known, $x_t^{\text{DN}} = x_t^{\text{UP}}, t \in [T_0, T_1]$.
- *Pandemic effect regression.*
  g. Define the impact of pandemic as $r_t^{(n)} = \log \frac{y_t}{\widehat{y}_t^{(n)}}$, $t \in [T_0, T_1]$, $n = 1, 2, \dots, N_{\text{path}}$.
  h. Fit linear regressions (11) using indicator $x_t = x_t^{\text{DN}} = x_t^{\text{UP}}$ on $t \in [T_0, T_1]$, and obtain the permanent impact coefficient estimation $\widehat{r}^0$.
  i. Through the pandemic effect regression (11), estimate the future economic impact $\widehat{r}_t^{\text{DN}}$ and $\widehat{r}_t^{\text{UP}}$ on $t \in (T_1, T_2]$.

4. Empirical results

This section presents the model predictions and analysis in detail, including the seven countries mentioned in Section 2; the scope of the economic expectations covers the second half of 2020 to the end of 2021. In advance, it is necessary to state that this paper does not consider the spillover effects between countries. Additionally, considering that different countries have varying economic bases and pandemic situations, the model parameters are estimated for data specific to each country.

The hierarchical BVAR and regression components are mostly implemented by the R package BVAR (version 1.0.1) and the Python module statsmodels (version 0.11.1) (see Kuschnig and Vashold (2021) and Seabold and Perktold (2010) for more details on the packages).

4.1. Preprocessing

Since different countries have different COVID-19 situations, we initially use the month in which the first COVID-19 case appears in each country as T_0, with the specific cut-off points shown in Table B.5 in Appendix B.

Some economic variables exhibit trends and seasonal characteristics, so the preprocessing for macroeconomic variables includes logarithmization, differencing, and yearly differencing, which are implemented sequentially for stationarity. The augmented Dickey-Fuller (ADF) and Canova-Hansen (CH) tests determine whether the variables are unit root or seasonal unit root processes. Refer to Canova and Hansen (1995) for more details about the CH test. The preprocessing operations for the economic variables of each country are stated in Table B.5 in Appendix B.

4.2. Baseline estimations via BVAR model

Since the subsequent data analyses are all based on baseline estimations, we first report the statistical results of the BVAR model (1) for each of the seven countries with multidimensional monthly macroeconomic data y_t with $t \in [0, T_0)$. The BIC model selection, goodness-of-fit, and Ljung-Box (Q) test results of BVARs are shown in Table 1.

For stationarized macroeconomic variables, we still need to determine the rationality of using a vector autoregressive model, i.e., whether there are significant correlations among the (stationarized) macroeconomic variables. For example, the correlation coefficients can reflect the correlations between imports and exports, CPIs, and exchange rates. Thus, we display the Pearson correlation coefficients among the economic variables in each country in Fig. C.4 in Appendix C.

Model selection is used to determine the order of BVAR(p). We set $1 \le p \le 4$. The lag order should not be too large for multidimensional monthly data since it may lead to high-dimensional parameters of the BVAR model. Using the BIC criteria, the selected models are shown in the column Model of Table 1; i.e., the BVAR(1) models can characterize the macroeconomic data for the seven different countries. For more details on BIC model selection, see Fig. D.5 in Appendix D. In addition, the BVAR model's prior distributions and hyperparameter settings are the same as Giannone et al. (2015), and we do not list them here.

R-squares and Ljung-Box (Q) tests illustrate the rationality of BVARs. Table 1 shows that most of the R-squares are relatively high. The Ljung-Box (Q) test determines whether the BVAR models' fitted residuals are independent of each other. The null hypothesis, which supports that the residuals are independent, is rejected when the LBQ test is significant.

Table 1
Statistical results of baseline estimations of the BVAR model.

Country	Model[a]	Stats.	GDP	M2	CPI	Unemployment	Export	Import	Total Reserve	Exchange Rate
DEU	BVAR(1)	R-sq.[b]	0.975	0.996	0.972	0.955	0.279	0.499	0.839	–
		Ljung-Box (Q)	1.088	0.496	0.526	0.743	1.287	1.396	0.019	–
		Prob. (Q)[c]	0.297	0.481	0.468	0.389	0.257	0.237	0.890	–
ESP	BVAR(1)	R-sq.	0.980	–	0.924	0.996	0.563	0.366	0.963	0.904
		Ljung-Box (Q)	0.297	–	0.266	0.563	4.944	7.632	0.881	0.487
		Prob. (Q)	0.586	–	0.606	0.453	0.026**	0.006***	0.348	0.485
IDN	BVAR(1)	R-sq.	0.998	0.989	0.994	–	0.047	0.296	0.352	0.822
		Ljung-Box (Q)	0.004	0.310	0.199	–	1.771	3.337	0.112	1.097
		Prob. (Q)	0.951	0.578	0.656	–	0.183	0.068*	0.738	0.295
IND	BVAR(1)	R-sq.	0.993	0.933	0.982	–	−0.054	0.319	0.951	0.918
		Ljung-Box (Q)	0.246	4.391	0.012	–	1.914	0.924	0.852	0.086
		Prob. (Q)	0.620	0.036**	0.913	–	0.166	0.336	0.356	0.769
MEX	BVAR(1)	R-sq.	0.983	0.989	0.995	0.103	0.716	0.327	0.968	0.057
		Ljung-Box (Q)	0.182	0.637	1.297	2.471	6.511	6.390	0.433	0.658
		Prob. (Q)	0.669	0.425	0.255	0.116	0.011**	0.011**	0.510	0.417
RUS	BVAR(1)	R-sq.	0.987	0.992	0.995	0.834	0.623	0.705	0.988	0.915
		Ljung-Box (Q)	0.127	3.901	0.465	1.828	2.251	0.262	0.970	0.216
		Prob. (Q)	0.721	0.048**	0.495	0.176	0.134	0.609	0.325	0.642
USA	BVAR(1)	R-sq.	0.995	0.995	0.986	0.897	0.776	0.728	0.607	–
		Ljung-Box (Q)	0.000	0.041	0.833	1.095	0.110	0.861	0.392	–
		Prob. (Q)	0.996	0.839	0.362	0.295	0.740	0.354	0.531	–

Notes.
[a] Models are selected by BIC criteria.
[b] R-sq. (R-squared) represents the goodness-of-fit of the BVAR model on each economic indicator.
[c] Ljung-Box (Q) statistics and the significance test results. ***, **, and * indicate rejection at the 1%, 5%, and 10% significance level, respectively. The hypothesis that the residuals are independent is rejected when the LBQ test result is significant.

Table 1 shows that most of the model residuals are not autocorrelated.

Based on the fitted BVAR models, the monthly paths of baseline estimations $\hat{y}_t^{(n)}$, $t \in [T_0, T_2]$, $n = 1, 2, \ldots, N_{\text{path}} = 100$ can be predicted. These results are analyzed in Section 4.4.

4.3. Pandemic indicators and scenario predictions

Based on the method described in Section 3.2, we obtain the COVID-19 pandemic's daily estimation results, shown in Table 2. The COVID-19 indicators β_u^{D} and I_u^{D}/N are shown in two segments: January 2020 to June 2020 and July 2020 to December 2021, corresponding to $[T_0, T_1]$ and $(T_1, T_2]$. Fig. E.6 shows the trends of the estimated values over time.

We first compare the differences in pandemic indicators on the two segments. The average values of $\hat{\beta}_u^{\mathrm{D}}$ in Table 2 reveal that the estimates $\hat{\beta}_u^{\mathrm{D}}$ from January 2020 to June 2020 for each country are generally higher than $\hat{\beta}_u^{\mathrm{D(UP)}}$ from July 2020 to December 2021. Conversely, for $\hat{I}_u^{\mathrm{D}}$, the observed infection ratio I_u^{D}/N from January 2020 to June 2020 may not be higher than the level of $\hat{I}_u^{\mathrm{D(DN)}}/N$ from July 2020 through December 2021. The trends of $\hat{\beta}_u^{\mathrm{D}}$ and $\hat{I}_u^{\mathrm{D}}/N$ justify our choice of indicators in Section 3.2.

Another point is to observe when the maximum values of $\hat{\beta}_u^{\mathrm{D}}$ and $\hat{I}_u^{\mathrm{D}}/N$ occur. Table 2 shows that all seven countries have the highest $\hat{\beta}_u^{\mathrm{D}}$ at the beginning of the pandemic, within the period from January 2020 to June 2020. Since the maximum of the infectious rates $\hat{\beta}_u^{\mathrm{D(UP)}}$ (resp. $\hat{\beta}_u^{\mathrm{D(DN)}}$) is set at the end of 2020 (resp. September 2020), according to the vSIR dynamics, the result shows that the maximum of the infected proportions $\hat{I}_u^{\mathrm{D(UP)}}/N$ (resp. $\hat{I}_u^{\mathrm{D(DN)}}/N$) occurs in the spring of 2021 (resp. autumn 2020).

Note that the accuracy of a specific scenario cannot be evaluated because of the high uncertainty level in the pandemic's future evolution. Therefore, we focus on the differences in future economic trends resulting from the variances between the UP and DN scenarios in the latter part of the paper. Furthermore, as an analytical framework, it is advisable to design each component without excessive complexly. Hence, this paper does not consider the simple DN and UP scenario assumptions comparable to the relevant literature dedicated to pandemic prediction. Subsequent studies could enrich and refine the details of each component of this framework.

4.4. Analysis of pandemic effect regression

The linear regression equation (11) quantifies the pandemic's impact on each economy's macroeconomic indicators. The pandemic factor x_t is constituted by β_t and I_t/N, and the impact on the economic indicators is $r_t^{(n)} = \log \frac{y_t}{\hat{y}_t^{(n)}}$. When the regression is built, two questions are naturally answered. (i) The persistent impact of the pandemic on economic variables can be explained by the intercept term r^0, which can be estimated within $t \in [T_0, T_1]$. (ii) For the future $t \in (T_1, T_2]$, once the pandemic-related forecast $\hat{x}_t$ is given, it is easy to estimate the economic impact $\hat{r}_t$ through regression (11). The following two subsections illustrate these points. Figs. F.7–F.13 show details of the pandemic's effects on macroeconomic variables.

4.4.1. Model fitting and testing of pandemic effect regression

Pandemic effect regression (11) is fitted on the interval $t \in [T_0, T_1]$ where the pandemic has occurred, specifically for this paper, from January 2020 to June 2020 (the starting month of different countries is slightly different; see Table B.5 in Appendix B). Table 3 shows the model selection and country-specific model test results.

We set the lag order $0 \le l \le 2$ representing a maximum delay of two months. Table 3 shows the models selected by using the BIC criterion in the lag column. Table 3 shows that for each country, the lag order of the dependent variable is chosen to be one or two months through BIC criteria.[10] In Table 3, the results of the F-tests for regression (11)

[10] Readers may argue about the limitation of using lag order $l \le 2$. However, our experiments indicate that lag orders that are too large tend to overfit due to our pandemic data's time-length limitation. Meanwhile, $l = 2$ can cover the pandemic's trends, such as up to up, up to down, and down to down. The economic meaning of lags beyond second order is no longer significant.

Table 2
Statistic results of daily time-varying $\widehat{\beta}_u^{\mathrm{D}}$ and infected ratios $\widehat{I}_u^{\mathrm{D}}/N$.

	$\widehat{\beta}_u^{\mathrm{D}}$ (2020M01 - 2020M06)[a]			$\widehat{\beta}_u^{\mathrm{D(UP)}}$ (2020M07 - 2021M12)[b]			$\widehat{\beta}_u^{\mathrm{D(DN)}}$ (2020M07 - 2021M12)		
Country	Avg.	Std.	Max. (Max. Date)[c]	Avg.	Std.	Max. (Max. Date)	Avg.	Std.	Max. (Max. Date)
DEU	0.092	0.080	0.317 (2020-02-23)	0.052	0.038	0.124 (2020-12-13)	0.023	0.023	0.077 (2020-08-10)
ESP	0.083	0.100	0.386 (2020-02-20)	0.024	0.018	0.058 (2020-12-13)	0.010	0.009	0.033 (2020-08-17)
IDN	0.090	0.081	0.353 (2020-02-28)	0.050	0.038	0.123 (2020-12-13)	0.021	0.019	0.064 (2020-09-02)
IND	0.102	0.049	0.279 (2020-02-27)	0.064	0.047	0.152 (2020-12-13)	0.029	0.028	0.088 (2020-07-19)
MEX	0.156	0.034	0.282 (2020-03-06)	0.084	0.062	0.197 (2020-12-13)	0.038	0.039	0.155 (2020-07-07)
RUS	0.098	0.073	0.283 (2020-02-29)	0.024	0.018	0.059 (2020-12-13)	0.011	0.010	0.030 (2020-09-14)
USA	0.088	0.091	0.297 (2020-02-27)	0.009	0.007	0.029 (2020-07-09)	0.005	0.006	0.028 (2020-07-09)
	I_u^{D}/N (2020M01 - 2020M06)			$\widehat{I}_u^{\mathrm{D(UP)}}/N$ (2020M07 - 2021M12)			$\widehat{I}_u^{\mathrm{D(DN)}}/N$ (2020M07 - 2021M12)		
Country	Avg.	Std.	Max. (Max. Date)	Avg.	Std.	Max. (Max. Date)	Avg.	Std.	Max. (Max. Date)
DEU	0.022%	0.028%	0.099% (2020-04-06)	2.013%	3.767%	13.462% (2021-02-13)	0.007%	0.010%	0.030% (2020-10-05)
ESP	0.089%	0.080%	0.225% (2020-04-19)	0.650%	0.692%	2.180% (2021-02-02)	0.144%	0.239%	0.949% (2020-09-14)
IDN	0.003%	0.004%	0.012% (2020-06-30)	3.516%	6.687%	24.504% (2021-02-04)	0.011%	0.013%	0.037% (2020-11-05)
IND	0.003%	0.005%	0.019% (2020-06-30)	2.264%	4.981%	20.080% (2021-01-12)	0.020%	0.030%	0.088% (2020-10-06)
MEX	0.007%	0.009%	0.028% (2020-06-30)	0.844%	1.977%	8.185% (2021-01-23)	0.008%	0.015%	0.052% (2020-07-23)
RUS	0.058%	0.074%	0.181% (2020-06-15)	0.441%	0.499%	1.568% (2021-03-03)	0.038%	0.052%	0.163% (2020-07-06)
USA	0.169%	0.187%	0.576% (2020-06-30)	2.372%	1.137%	4.216% (2021-03-26)	0.664%	0.392%	1.235% (2020-10-11)

Notes.
[a] The data time frame in this table is divided into two parts, January 2020 to June 2020 (six months in total) and July 2020 to December 2021 (18 months in total). For the former time frame, I_u^{D}/N is calculated directly from the observed data, and $\widehat{\beta}_u^{\mathrm{D}}$ is estimated based on formulas (4) and (5). For the latter, superscripts UP and DN represent the forecasts in two different scenarios. $\widehat{\beta}_u^{\mathrm{D(DN)}}$ and $\widehat{\beta}_u^{\mathrm{D(UP)}}$ are assumed to be (7) and (8), while $\widehat{I}_u^{\mathrm{D(DN)}}$ and $\widehat{I}_u^{\mathrm{D(UP)}}$ are predicted by equations (6a)-(6c). Both the sequences are calculated in daily frequency.
[b] As of the time of writing this paper, the pandemic data from July 1, 2020, to September 14, 2020, are available, but the macroeconomic data for the third quarter (2020Q3) have not been released yet. During this time period, there exist $I_u^{\mathrm{D}} = \widehat{I}_u^{\mathrm{D(DN)}} = \widehat{I}_u^{\mathrm{D(UP)}}$ and $\widehat{\beta}_u^{\mathrm{D}} = \widehat{\beta}_u^{\mathrm{D(DN)}} = \widehat{\beta}_u^{\mathrm{D(UP)}}$.
[c] This table shows the average (Avg.), standard deviation (Std.), maximum value (Max.) of the time series, and the expected occurrence time of maximum value (Max. Date).

indicate that each null hypothesis should be rejected, i.e., all the pandemic effect regressions hold. We also present these regression models' adjusted R-squared values (Adj. R-sq.) to illustrate their fittings from January to June 2020. In the case of the United States, for example, the mean of Adj. R-sq. on all macroeconomic variables is about 0.805. As a side note, some of the R-squares are very low, such as Russia's export and exchange rate, which may be caused by the uncertainty of paths of baseline estimation (see Fig. F.12).

The intercept term r^0 is the most critical estimated parameter, representing the economic resilience of the economy to the COVID-19 pandemic. Table 3 lists the ordinary least squares (OLS) estimates $\widehat{r}^0$ and their t-test significance levels. When the result of the t-test is significant, we have a reason to reject the hypothesis of $r^0 = 0$.

In addition, $\widehat{r}^0$ illustrates the magnitude of the persistent pandemic effect. As $x_t \to 0$ after the pandemic, $r_{it}^{(n)} = \log \frac{y_{it}}{\widehat{y}_{it}^{(n)}} \to r_i^0 + \epsilon_{it}$ according to the regression (11). If $r_i^0 = 0$ cannot be rejected, it indicates a high probability that the economic variable y_{it} will recover to the baseline estimations after the pandemic; conversely, it may be difficult for the economic variable to return to the corresponding expectation before the pandemic. From this perspective, Table 3 results suggest that for the seven countries, the majority of economic indicators are likely to suffer a lasting, nonrecoverable shock from the pandemic. Conversely, we find that the vast majority of estimations $\widehat{r}^0$ are within $\pm 10\%$; thus, it appears that the pandemic's long-run impact on the economy is limited based on our model results.

4.4.2. *Empirical analysis of pandemic effects under hypothetical scenarios*

We take the GDP as an example to illustrate how to identify an economy's resilience to the impact of the pandemic. For $\mathrm{GDP}_t \in y_t$, define

$$\widehat{\alpha}_t^{\mathrm{GDP}} := \frac{\mathrm{GDP}_t - \widehat{\mathrm{GDP}}_t}{\widehat{\mathrm{GDP}}_t} \times 100\%, \tag{12}$$

where $\widehat{\mathrm{GDP}}_t$ is the baseline estimation of GDP_t.[11] Then, for some interval $[T_i, T_j]$, we denote the monthly average estimates of $\widehat{\alpha}_t^{\mathrm{GDP}}$ as $\overline{\alpha}_{[T_i,T_j]}^{\mathrm{GDP}}$, namely, the *pandemic effect*. For example, according to our model, if $\overline{\alpha}_{2020\mathrm{H1}}^{\mathrm{GDP}} = -20\%$, the pandemic reduces our average GDP expectation by 20% during the first half of 2020.

Table 4 lists the following five statistics for each country and each economic variable: $\overline{\alpha}_{2020\mathrm{H1}}$, $\overline{\alpha}_{2020\mathrm{H2}}^{\mathrm{UP}}$, $\overline{\alpha}_{2020\mathrm{H2}}^{\mathrm{DN}}$, $\overline{\alpha}_{2021}^{\mathrm{UP}}$, $\overline{\alpha}_{2021}^{\mathrm{DN}}$. DN refers to the prediction under Scenario DN, while UP refers to Scenario UP.

We observe the economic situation under the pandemic during the first half of 2020 (2020H1) in Table 4. Most economic indicators drastically deteriorate in the first half of 2020, especially GDP, exports, imports, and unemployment rates. Unemployment rates rose sharply in the United States, 74.8% higher than expected. Imports and exports in various countries were also hit heavily due to delays in international transportation. At the same time, to mitigate the pandemic's economic impact, many countries adopted accommodative monetary policies. With M2 tending to rise ($\overline{\alpha}^{\mathrm{M2}} > 0$), currencies tend to depreciate, and inflation increases, reflected in changes in CPIs, total reserves, and exchange rates.

To gain insight into the economic recovery in the later stages of the pandemic, we present UP and DN scenarios for the pandemic's evolution, as stated in Section 4.3. As seen from Table 4, in general, the absolute values of the pandemic effects on the economic indicators for each country are greater in the case of pandemic worsening than in the case of pandemic remission, i.e., $|\overline{\alpha}^{\mathrm{UP}}| > |\overline{\alpha}^{\mathrm{DN}}|$.

Scenario DN. Under the scenario in which the pandemic could be controlled, the economic situation in each country would improve in 2021 compared to 2020, reflected in a near-zero pandemic effect $\overline{\alpha}_{2021}^{\mathrm{DN}}$. Countries would see a smaller $\overline{\alpha}_{2021}^{\mathrm{GDP,DN}}$ than $\overline{\alpha}_{2020\mathrm{H2}}^{\mathrm{GDP,DN}}$ and a smaller rise in unemployment rates than in 2020, indicating an accelerated recovery to approach the expected baseline levels in 2021. Hence, we can see that the economy would recover instead of remaining in recession.

[11] Recalling the definition $\widehat{r}_t^{\mathrm{GDP}} = \log \frac{\mathrm{GDP}_t}{\widehat{\mathrm{GDP}}_t}$, $\widehat{\alpha}_t^{\mathrm{GDP}}$ can be easily calculated by $\widehat{\alpha}_t^{\mathrm{GDP}} = [\exp(\widehat{r}_t^{\mathrm{GDP}}) - 1] \times 100\%$.

Table 3
Statistical results of pandemic effect regression (11).

Country	Lag[a]	F-stats.	Prob. (F-stats.)[b]	Adj. R-sq.[c]	$\hat{r}^0$	t-stats.	$P<\|t\|$[d]
Gross Domestic Product (GDP)							
DEU	2	2 615.5	0.000***	0.802	−2.12%	−16.691	0.000***
ESP	2	8 985.2	0.000***	0.916	−2.27%	−13.026	0.000***
IDN	2	38989.1	0.000***	0.985	−1.24%	−24.143	0.000***
IND	2	101284.5	0.000***	0.993	4.17%	51.666	0.000***
MEX	2	33278.1	0.000***	0.980	−2.37%	−21.127	0.000***
RUS	2	3 741.9	0.000***	0.851	10.86%	82.277	0.000***
USA	2	18530.2	0.000***	0.972	−0.12%	−1.460	0.145
Broad Money (M2)							
DEU	2	13345.0	0.000***	0.954	−0.24%	−10.490	0.000***
IDN	2	78.5	0.000***	0.119	0.82%	5.845	0.000***
IND	2	78.9	0.000***	0.103	4.00%	13.961	0.000***
MEX	2	1 807.5	0.000***	0.727	0.62%	5.679	0.000***
RUS	2	679.3	0.000***	0.510	0.44%	6.160	0.000***
USA	2	179627.6	0.000***	0.997	0.01%	0.665	0.506
Consumer Price Index (CPI)							
DEU	2	1 614.1	0.000***	0.714	0.43%	23.030	0.000***
ESP	2	1 220.9	0.000***	0.596	0.01%	0.248	0.804
IDN	2	2 559.9	0.000***	0.817	0.31%	21.957	0.000***
IND	2	472.8	0.000***	0.411	−3.00%	−40.813	0.000***
MEX	2	373.5	0.000***	0.354	1.23%	45.783	0.000***
RUS	2	1 219.7	0.000***	0.651	−0.35%	−14.257	0.000***
USA	2	4 559.8	0.000***	0.894	0.15%	6.803	0.000***
Unemployment Rate							
DEU	2	4 947.0	0.000***	0.884	5.32%	25.424	0.000***
ESP	2	6 569.4	0.000***	0.888	0.31%	2.117	0.035**
MEX	2	754.2	0.000***	0.526	14.30%	26.306	0.000***
RUS	1	5 743.6	0.000***	0.898	−1.81%	−6.873	0.000***
USA	2	132608.9	0.000***	0.996	−1.26%	−4.654	0.000***
Export (Goods)							
DEU	2	615.1	0.000***	0.487	−4.29%	−5.482	0.000***
ESP	1	1 325.7	0.000***	0.616	−0.59%	−0.767	0.443
IDN	2	159.4	0.000***	0.216	13.14%	10.990	0.000***
IND	2	6 821.2	0.000***	0.910	12.42%	20.245	0.000***
MEX	2	2 287.6	0.000***	0.771	7.79%	8.010	0.000***
RUS	2	5.1	0.025**	0.006	−22.90%	−27.694	0.000***
USA	2	3 297.9	0.000***	0.859	1.70%	3.757	0.000***
Import (Goods)							
DEU	2	726.7	0.000***	0.529	−7.77%	−15.459	0.000***
ESP	2	1 446.8	0.000***	0.636	1.26%	1.762	0.078*
IDN	2	165.4	0.000***	0.223	0.56%	0.398	0.691
IND	2	3 746.4	0.000***	0.847	4.47%	5.361	0.000***
MEX	2	1 350.8	0.000***	0.665	2.66%	2.746	0.006***
RUS	2	1 462.1	0.000***	0.691	−6.66%	−16.573	0.000***
USA	1	1 216.7	0.000***	0.693	−0.23%	−0.588	0.557
Total Reserve							
DEU	2	249.2	0.000***	0.277	7.18%	54.992	0.000***
ESP	2	734.0	0.000***	0.470	−0.25%	−4.833	0.000***
IDN	2	630.5	0.000***	0.523	−3.64%	−23.709	0.000***
IND	2	163.7	0.000***	0.194	2.56%	27.735	0.000***
MEX	2	514.0	0.000***	0.430	−0.01%	−0.195	0.845
RUS	2	872.0	0.000***	0.572	0.20%	2.040	0.042**
USA	2	157.1	0.000***	0.225	−0.79%	−9.273	0.000***
Exchange Rate							
ESP	2	63.2	0.000***	0.070	−0.53%	−7.553	0.000***
IDN	2	3 613.6	0.000***	0.863	0.09%	0.747	0.455
IND	1	1 760.5	0.000***	0.722	−0.05%	−0.491	0.624
MEX	2	1 475.3	0.000***	0.685	0.02%	0.074	0.941
RUS	2	117.8	0.000***	0.152	9.35%	35.170	0.000***

Notes.
[a] Lags of pandemic indicator x_t are selected by BIC criteria.
[b] Prob. (F-stats.) shows the significance level of F-test. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.
[c] Adj. R-sq. (Adjusted R-squared) represents the goodness-of-fit of the OLS model.
[d] $\hat{r}^0$ shows estimation of the intercept of regression (11). $P<|t|$ shows the significance level of t-test on coefficient $\hat{r}^0$. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively. Significance implies that the hypothesis of permanent effect $r^0=0$ should be rejected; otherwise, the permanent effect is considered to be zero.

Table 4
Pandemic effects analysis based on estimates of $\overline{\alpha}$.

Country	Stats.[a]	GDP	M2	CPI	Unemployment	Export	Import	Total reserve	Exchange rate
DEU	2020H1	−5.59%	2.03%	−0.15%	19.24%	−17.30%	−16.63%	7.86%	–
	2020H2 (UP)	−11.02%	4.08%	−0.69%	33.14%	−28.82%	−24.74%	8.37%	–
	2020H2 (DN)	−10.92%	3.36%	−0.57%	29.26%	−26.18%	−22.92%	8.66%	–
	2021 (UP)	−14.15%	4.20%	−0.85%	37.49%	−29.90%	−26.03%	9.30%	–
	2021 (DN)	−4.86%	0.47%	0.20%	10.49%	−9.11%	−10.95%	7.82%	–
ESP	2020H1	−12.95%	–	−0.85%	10.72%	−18.90%	−17.02%	0.60%	−0.51%
	2020H2 (UP)	−25.86%	–	−1.75%	22.05%	−36.42%	−35.68%	1.23%	−0.35%
	2020H2 (DN)	−24.74%	–	−1.60%	19.86%	−34.09%	−33.58%	1.09%	−0.29%
	2021 (UP)	−21.77%	–	−1.30%	15.86%	−27.41%	−27.57%	0.70%	−0.21%
	2021 (DN)	−9.02%	–	−0.39%	4.71%	−9.28%	−8.55%	−0.04%	−0.40%
IDN	2020H1	−8.88%	1.96%	−0.20%	–	1.32%	−11.92%	−3.02%	5.84%
	2020H2 (UP)	−20.43%	3.42%	−1.33%	–	−16.42%	−30.86%	2.51%	2.06%
	2020H2 (DN)	−18.71%	2.95%	−1.25%	–	−13.30%	−28.35%	−3.63%	−1.53%
	2021 (UP)	−23.67%	3.53%	−1.91%	–	−19.60%	−35.17%	8.59%	−7.34%
	2021 (DN)	−8.38%	1.58%	−0.39%	–	3.35%	−11.27%	0.55%	−4.23%
IND	2020H1	−11.53%	5.94%	−4.21%	–	−19.78%	−27.36%	1.75%	3.67%
	2020H2 (UP)	−50.24%	9.02%	−5.31%	–	−2.21%	−39.46%	2.80%	7.23%
	2020H2 (DN)	−47.85%	7.63%	−4.57%	–	27.46%	−24.89%	3.48%	5.16%
	2021 (UP)	−41.94%	6.77%	−3.76%	–	92.17%	9.17%	4.42%	2.70%
	2021 (DN)	−14.96%	4.98%	−3.08%	–	53.26%	14.54%	3.47%	0.37%
MEX	2020H1	−16.64%	4.85%	1.56%	25.29%	−21.94%	−22.07%	0.66%	12.16%
	2020H2 (UP)	−35.90%	4.47%	2.87%	27.73%	−10.51%	−28.80%	2.19%	7.36%
	2020H2 (DN)	−31.81%	2.04%	2.81%	29.57%	7.29%	−18.60%	1.97%	−1.45%
	2021 (UP)	−23.73%	0.72%	2.59%	24.37%	29.29%	−5.26%	1.61%	−3.76%
	2021 (DN)	−4.73%	0.01%	1.45%	13.67%	20.67%	6.15%	0.20%	−1.85%
RUS	2020H1	5.11%	1.94%	0.34%	15.38%	−20.84%	−16.70%	−2.03%	10.49%
	2020H2 (UP)	−4.01%	3.83%	1.04%	33.81%	−24.36%	−14.74%	−4.67%	5.47%
	2020H2 (DN)	−2.99%	3.46%	0.89%	29.77%	−24.31%	−11.80%	−4.22%	4.91%
	2021 (UP)	−3.15%	3.48%	0.89%	30.29%	−24.51%	−10.47%	−4.24%	4.41%
	2021 (DN)	6.85%	1.33%	−0.01%	6.24%	−21.99%	−5.41%	−1.10%	7.53%
USA	2020H1	−7.98%	7.61%	−1.02%	74.84%	−15.74%	−9.50%	−0.16%	–
	2020H2 (UP)	−18.03%	17.01%	−2.07%	137.87%	−33.17%	−19.34%	1.36%	–
	2020H2 (DN)	−17.49%	16.31%	−1.96%	130.72%	−31.96%	−18.64%	1.33%	–
	2021 (UP)	−17.71%	16.51%	−1.96%	129.91%	−32.08%	−18.73%	1.41%	–
	2021 (DN)	−12.92%	11.40%	−1.32%	89.47%	−23.29%	−13.57%	0.81%	–

Notes.
[a] Data in this table are all pandemic effect estimates $\overline{\alpha}$. 2020H1: $\overline{\alpha}_{2020H1}$, 2020H2 (UP): $\overline{\alpha}^{UP}_{2020H2}$, 2020H2 (DN): $\overline{\alpha}^{DN}_{2020H2}$, 2021 (UP): $\overline{\alpha}^{UP}_{2021}$, 2021 (DN): $\overline{\alpha}^{DN}_{2021}$.

Scenario UP. Under a scenario in which the pandemic had a second outbreak, the average effects on economic indicators after June 2020 would be generally greater than those from January 2020 to June 2020; see $\overline{\alpha}_{2020H1}$, $\overline{\alpha}^{UP}_{2020H2}$, and $\overline{\alpha}^{UP}_{2021}$ in Table 4. Moreover, in Table 4, it can be observed that in many cases, the data for $\overline{\alpha}^{UP}_{2020H2}$ and $\overline{\alpha}^{UP}_{2021}$ are essentially flat, implying some degree of stabilization or recovery in their corresponding economic indicators. These results suggest that countries can take measures to stabilize the economic situation in the later stages of the pandemic, weakening its negative impacts.

In summary, the results of our empirical analysis suggest that the continuation of the pandemic will not lead to a long-term recession. Moreover, the effects under the two pandemic scenarios seem to differ significantly. The economy recovers faster under the DN scenario than the UP scenario, which to some extent affirms the implementation of active anti-pandemic policies.

5. Discussion

This paper developed a scenario-based economic recovery analysis framework for pandemic outbreaks. We built a pandemic effect regression within the time interval $[T_0, T_1]$ based on available information since the pandemic began. This regression correlates the known pandemic status with the corresponding economic impact; the former is estimated by vSIR and the latter by BVAR forecasts. Finally, within the forecast interval $(T_1, T_2]$, we used a scenario analysis approach for portraying the pandemic's status.

Since the pandemic effect regression on $[T_0, T_1]$ was fitted based on a minimal number of observations, to improve the regression's reliability, we used multiple BVAR prediction paths, obtained by MCMC sampling, and the BIC criterion to control for the upper limit of the lag order. The significance of the *F*-test and the R-squares in Table 3 indicated that the regression equation holds, characterizing economic recovery in terms of pandemic-related indicators.

In terms of uncertainty regarding the pandemic's evolution, we considered two different scenarios in $(T_1, T_2]$: that the pandemic would gradually subside and that there would be another outbreak. Because of this uncertainty, it is difficult to predict the pandemic's progression accurately. As a result, we did not consider the periodic recurrence of the COVID-19 pandemic due to virus mutations when writing this paper. Nevertheless, as shown in the results in Section 4.4.2, our scenario analysis approach still provided quantitative evidence on the trade-offs between pandemic control and economic recovery in government policy formulation. A more accurate forecast of pandemic progression considering various virus mutations or additional pandemic scenarios could improve our results.

We assessed the economic resilience of seven individual countries through our proposed model. After analyzing the performance of different countries under the pandemic on a country-by-country basis, some common conclusions in the empirical results are of greater interest, such as the pattern of effects on GDP and unemployment rates, presented in Section 4.4.2. Moreover, Table 4 also provides a comparison of economic resilience at the cross-sectional level for each country.

Nevertheless, one of this paper's shortcomings is that the spillover effects among different countries are not considered.

6. Conclusions

The global COVID-19 pandemic poses a severe challenge to governments worldwide. Currently, most countries are actively controlling the pandemic and taking various measures to revive their economies. This paper's proposed framework can predict the future economy under different conditions of pandemic uncertainty. Under the proposed UP and DN scenarios in the seven economies chosen in this paper, the empirical analysis demonstrates recovery trends in 2021 rather than a sustained recession. At this time, countries can gradually increase their promotion of economic recovery while improving healthcare systems.

It should be noted that additional scenarios deserve further examination under the proposed model framework, such as more severe pandemics than this paper's UP scenario. We also hope to further study potential modeling approaches with a Bayesian framework by dynamically updating expectations as the pandemic evolves.

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Declaration of competing interest

The authors declare that they have no competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A. Daily frequency time-varying estimations: $\widehat{\beta}_u^{\mathrm{D}}$ and $\widehat{\gamma}_u^{\mathrm{D}}$

Consider $2m+1$ days' observations $(S_z^{\mathrm{D}}, I_z^{\mathrm{D}}, R_z^{\mathrm{D}})$ around day u, i.e., $z \in [u-m, u+m]$, for estimating $\widehat{\beta}_u^{\mathrm{D}}$ and $\widehat{\gamma}_u^{\mathrm{D}}$. By applying the Euler-Maruyama discretization to equation (3c), we obtain

$$\frac{R_z^{\mathrm{D}} - R_{z-1}^{\mathrm{D}}}{h} = \widetilde{\gamma}_z^{\mathrm{D}} I_z^{\mathrm{D}}.$$

Set the time interval $h = 1$ for daily data; i.e., we have

$$I_z^{\mathrm{D}} \widetilde{\gamma}_z^{\mathrm{D}} = R_z^{\mathrm{D}} - R_{z-1}^{\mathrm{D}}, \tag{A.1}$$

for $z \in (u-m, u+m]$. In a similar manner, by substituting (3c) into (3b) and discretizing, $\widetilde{\beta}_z^{\mathrm{D}}$ satisfies:

$$\frac{I_z^{\mathrm{D}} - I_{z-1}^{\mathrm{D}}}{h} + \frac{R_z^{\mathrm{D}} - R_{z-1}^{\mathrm{D}}}{h} = \widetilde{\beta}_z^{\mathrm{D}} \frac{S_z^{\mathrm{D}} I_z^{\mathrm{D}}}{N},$$

which can be simplified as

$$S_z^{\mathrm{D}} I_z^{\mathrm{D}} \widetilde{\beta}_z^{\mathrm{D}} = (I_z^{\mathrm{D}} - I_{z-1}^{\mathrm{D}} + R_z^{\mathrm{D}} - R_{z-1}^{\mathrm{D}})N, \tag{A.2}$$

for $z \in (u-m, u+m]$. Obviously, equations (A.1) and (A.2) derive instantaneous estimates of γ_t and β_t in the vSIR model.

However, the instantaneous estimates are not robust. We introduce the following two assumptions: (i) The daily $S_u^{\mathrm{D}}, I_u^{\mathrm{D}}, R_u^{\mathrm{D}}$ contains observation error because the recorded confirm and cure time may not be the same as the actual time. Therefore, it makes sense to use some average values over a short period to better characterize the actual trend. (ii) The infection and recovery rates are locally stable over short time intervals, leading to estimates $\widehat{\beta}_u^{\mathrm{D}} \approx \widetilde{\beta}_z^{\mathrm{D}}, \widehat{\gamma}_u \approx \widetilde{\gamma}_z^{\mathrm{D}}$, $z \in (u-m, u+m]$ being reasonable. Under the above two assumptions, based on equations (A.1) and (A.2), one can obtain:

$$\left(\sum_{z=u-m+1}^{u+m} I_z^{\mathrm{D}}\right) \widehat{\gamma}_u^{\mathrm{D}} = \sum_{z=u-m+1}^{u+m} (R_z^{\mathrm{D}} - R_{z-1}^{\mathrm{D}}), \tag{A.3}$$

$$\left(\sum_{z=u-m+1}^{u+m} S_z^{\mathrm{D}} I_z^{\mathrm{D}}\right) \widehat{\beta}_u^{\mathrm{D}} = \sum_{z=u-m+1}^{u+m} (I_z^{\mathrm{D}} - I_{z-1}^{\mathrm{D}} + R_z^{\mathrm{D}} - R_{z-1}^{\mathrm{D}})N. \tag{A.4}$$

This yields the estimates (4) and (5).

Appendix B. Preprocessing of macroeconomic variables for BVARs

Table B.5 shows details of preprocessing on macroeconomic variables for BVARs.

Table B.5
Preprocessing of macroeconomic variables of each country.

Country	$[0, T_0)$ & $[T_0, T_1]$	PreProc.	GDP	M2	CPI	Unemployment	Export	Import	Total Reserve	Exchange Rate
DEU	$[0, T_0)$: 2016M01-2019M12	Log	x	x	x	x	x	x	x	–
	$[T_0, T_1]$: 2020M01-2020M06	diff(1)[a]	x	x	x	x	x	x	x	–
		diff(12)[b]	x		x		x	x		–
ESP	$[0, T_0)$: 2016M01-2019M12	log	x	–	x	x	x	x	x	x
	$[T_0, T_1]$: 2020M01-2020M06	diff(1)	x	–	x	x	x	x	x	x
		diff(12)	x	–	x		x	x		
IDN	$[0, T_0)$: 2016M01-2020M01	log	x	x	x	–	x	x	x	x
	$[T_0, T_1]$: 2020M02-2020M06	diff(1)	x	x	x	–	x	x	x	x
		diff(12)	x	x	x	–	x	x	x	x
IND	$[0, T_0)$: 2016M01-2019M12	log	x	x	x	–	x	x	x	x
	$[T_0, T_1]$: 2020M01-2020M06	diff(1)	x	x	x	–	x	x	x	x
		diff(12)	x		x	–	x			
MEX	$[0, T_0)$: 2016M01-2020M01	log	x	x	x	x	x	x	x	x
	$[T_0, T_1]$: 2020M02-2020M06	diff(1)	x	x	x	x	x	x	x	
		diff(12)	x	x	x		x	x		x
RUS	$[0, T_0)$: 2016M01-2019M12	log	x	x	x	x	x	x	x	x
	$[T_0, T_1]$: 2020M01-2020M06	diff(1)	x	x	x	x	x	x	x	
		diff(12)	x	x	x		x	x		
USA	$[0, T_0)$: 2016M01-2019M12	log	x	x	x	x	x	x	x	–
	$[T_0, T_1]$: 2020M01-2020M06	diff(1)	x	x	x	x	x	x	x	–
		diff(12)	x	x	x		x	x	x	–

Notes.
[a] Differencing is determined by the ADF test results, with significance at the 5% level. An "x" in the table indicates the implementation of the item.
[b] Yearly differencing is determined by the results of the CH test based on Canova and Hansen (1995), with significance at the 5% level.

Appendix C. Figures: Correlations of macroeconomic variables

Figure C.4 shows the correlations of macroeconomic variables.

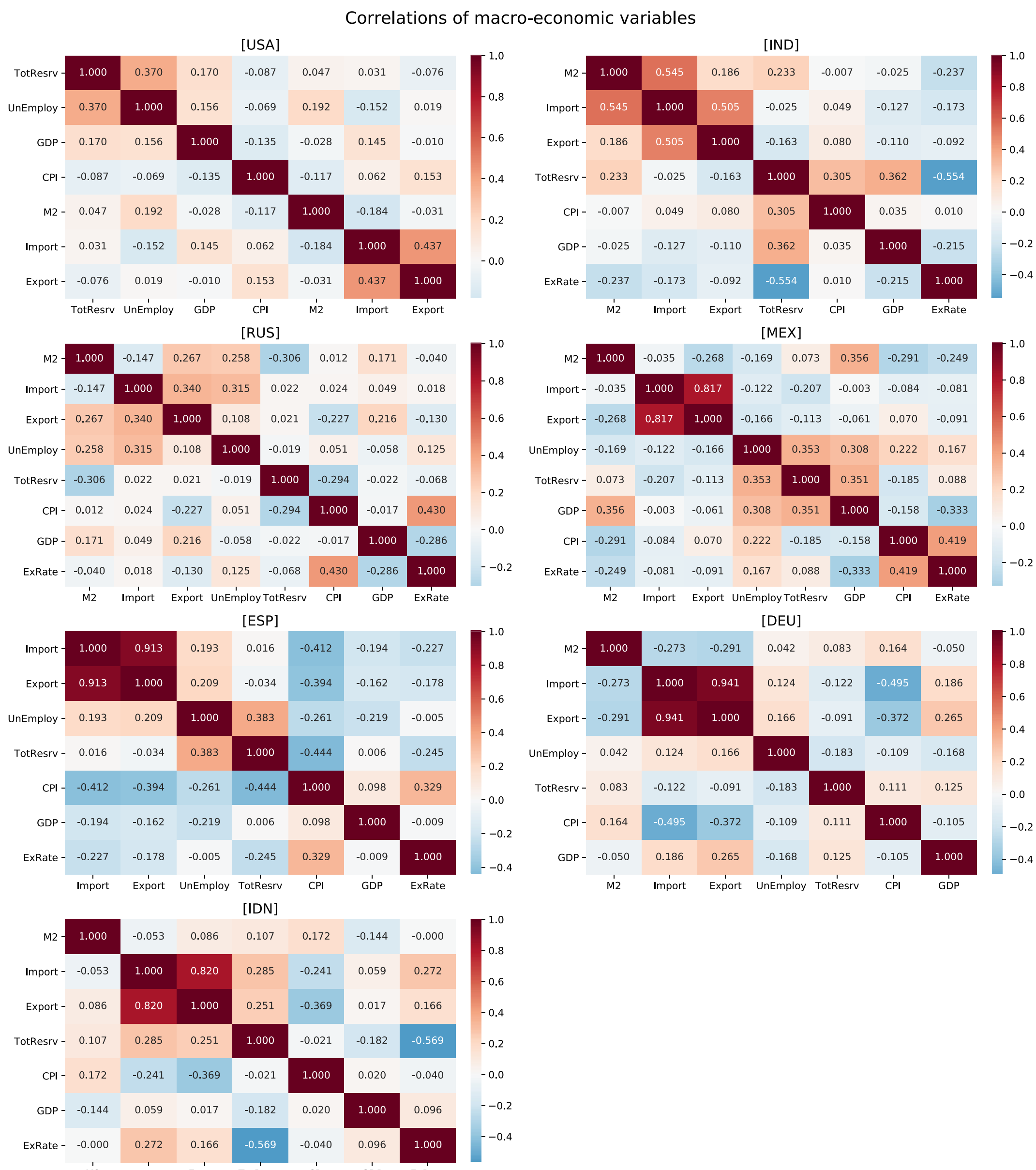

Fig. C.4 The correlations of macroeconomic variables of each country are shown in a heat map. Red indicates a positive correlation, and blue indicates a negative correlation.

Appendix D. Results of BICs of BVAR(p) selection

Figure D.5 shows the results of BICs of BVAR(p) selection.

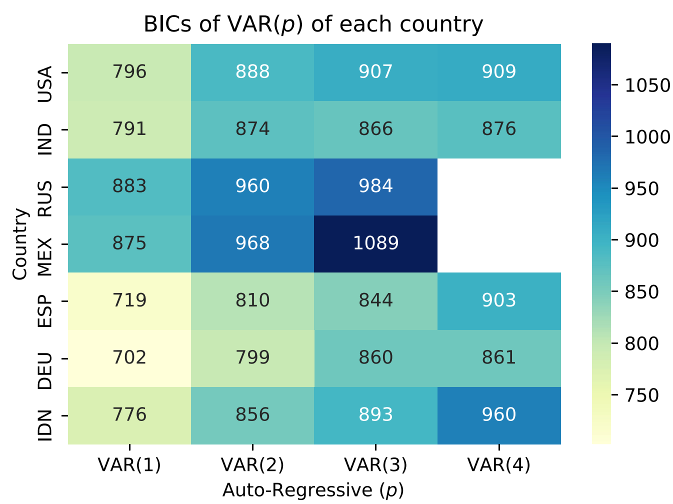

Fig. D.5 BICs of BVAR(p) selection for macroeconomic data. The parameters range $p \in \{1, 2, 3, 4\}$. The values of BICs are shown in a heat map. We choose p with the minimum BIC value. The figure shows that, in general, the values on the left side of the heat map are smaller than those on the right side, implying that the p of the model is small.

Appendix E. Figures: Estimations of vSIR and COVID-19 scenarios

Figure E.6 shows the estimations of vSIR and COVID-19 scenarios.

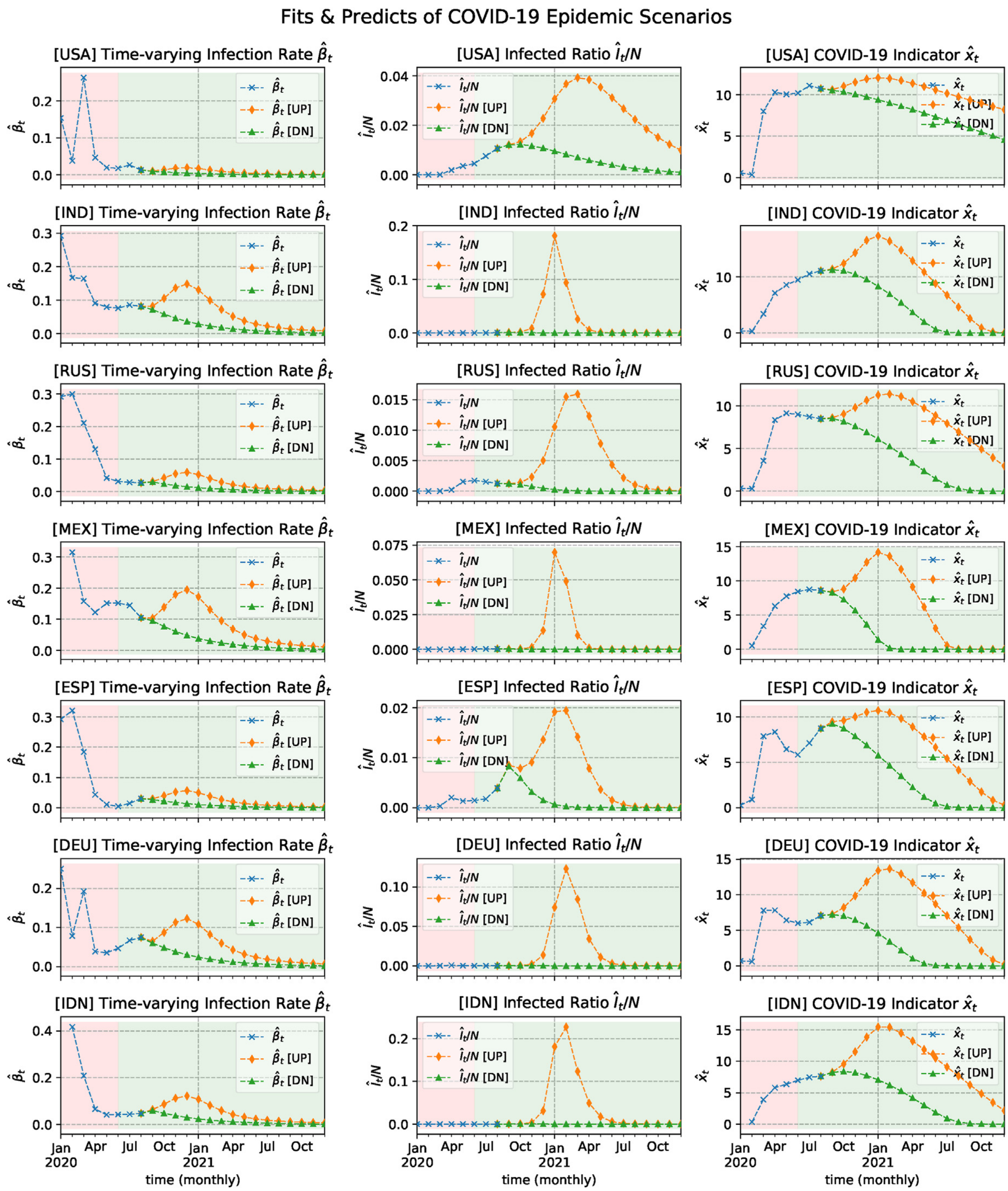

Fig. E.6 Estimates of vSIR and COVID-19 scenario predictions. We use a red background for January 2020–June 2020 and a green background for June 2020–December 2021, with the former curve representing data-dependent estimations and the two curves for the latter representing UP/DN scenarios. Each figure in the first column shows the time-varying infectious rate $\hat{\beta}_t$ for each country, the second column shows the infection ratio I_t/N, and the third column plots the COVID-19 indicator $\hat{x}_t$.

Appendix F. Figures: Pandemic effects of macroeconomic variables

Figs. F.7-F.13 present the pandemic effects on macroeconomic variables. Each figure is divided into three parts with different background colors: 2016–2019 (blue), January 2020–June 2020 (red), July 2020–December 2021 (green). We plot three categories of curves: (i) real macroeconomic data for the period from 2016 to June 2020; (ii) paths of baseline estimation; (iii) economic predictions for the period from July 2020 to December 2021 under the UP/DN pandemic scenarios.

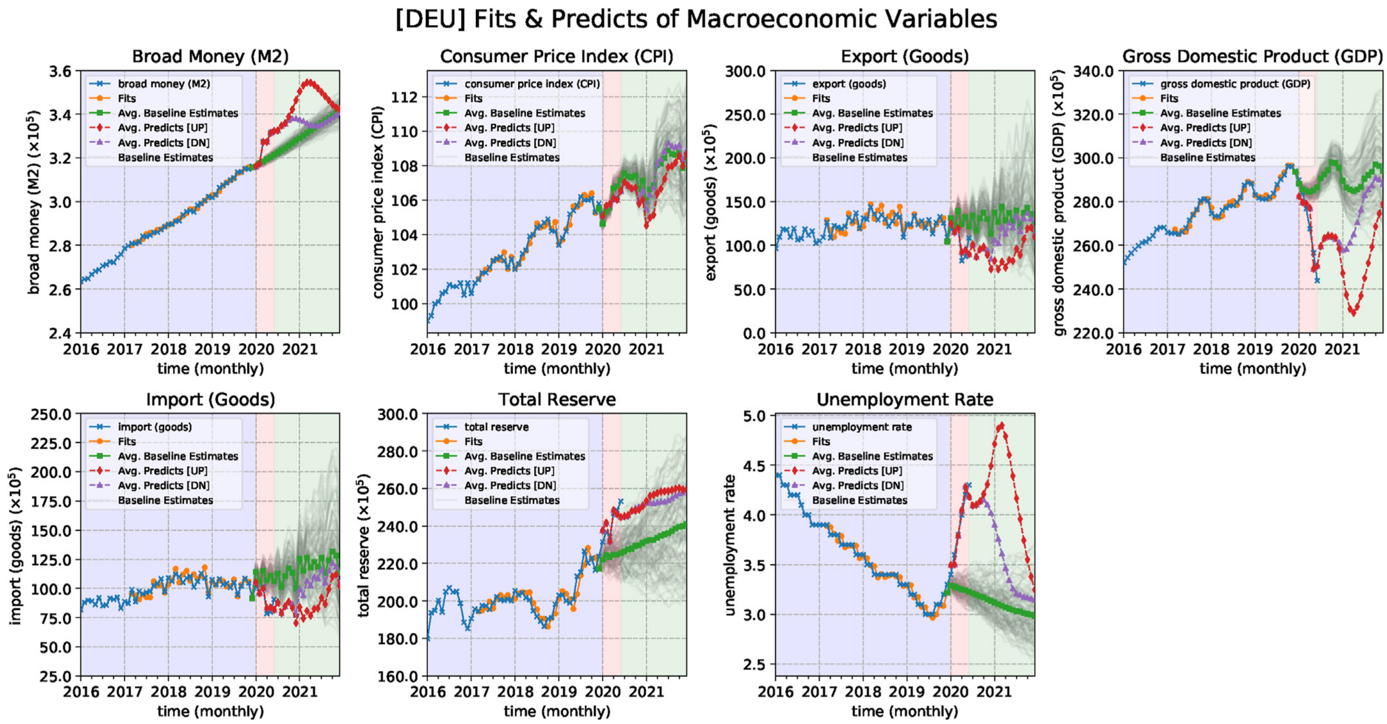

Fig. F.7 Germany (DEU): fits & forecasts of macroeconomic variables.

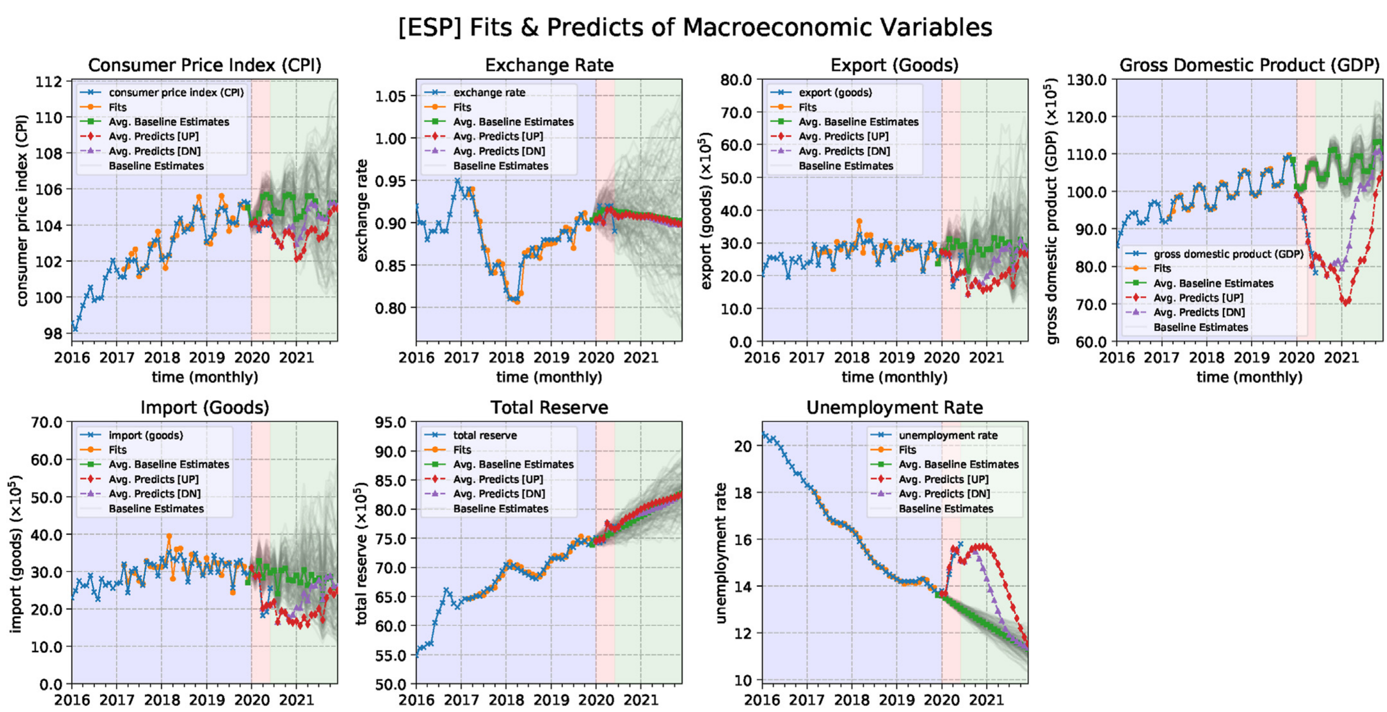

Fig. F.8 Spain (ESP): fits & forecasts of macroeconomic variables.

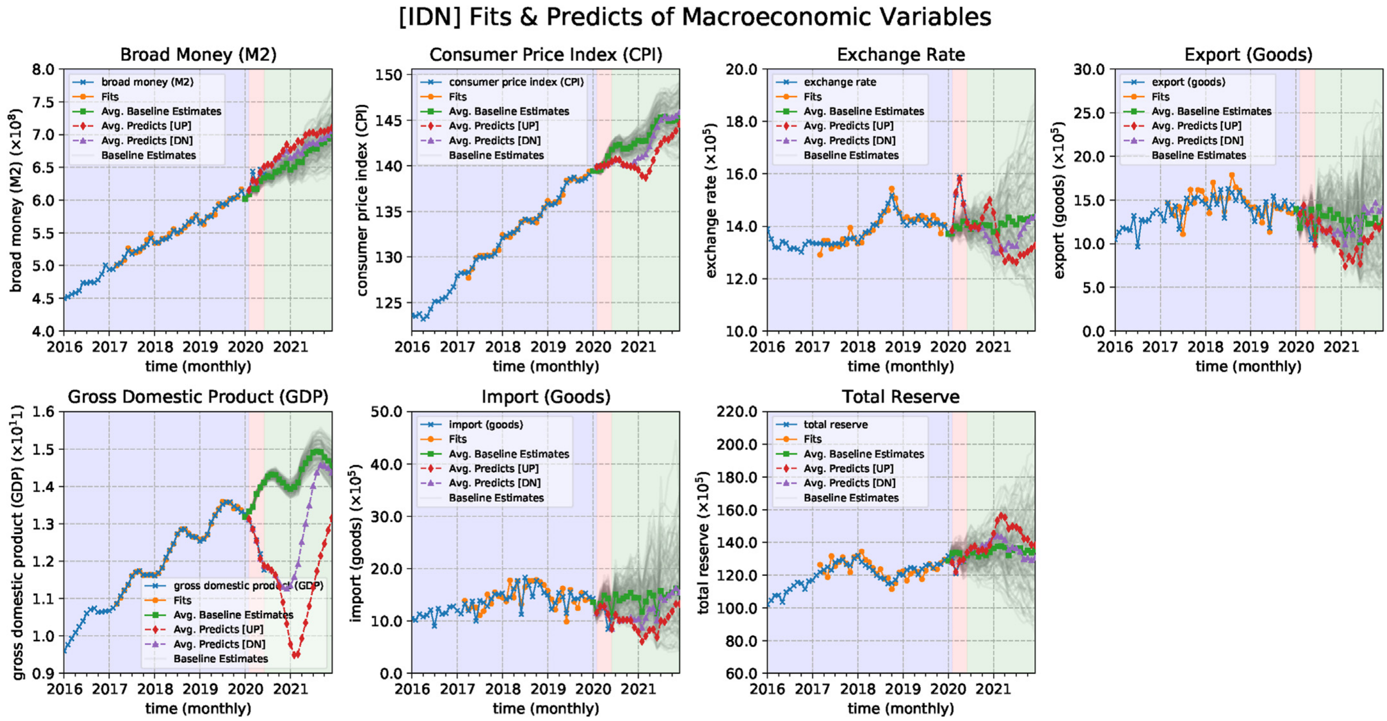

Fig. F.9 Indonesia (IDN): fits & forecasts of macroeconomic variables.

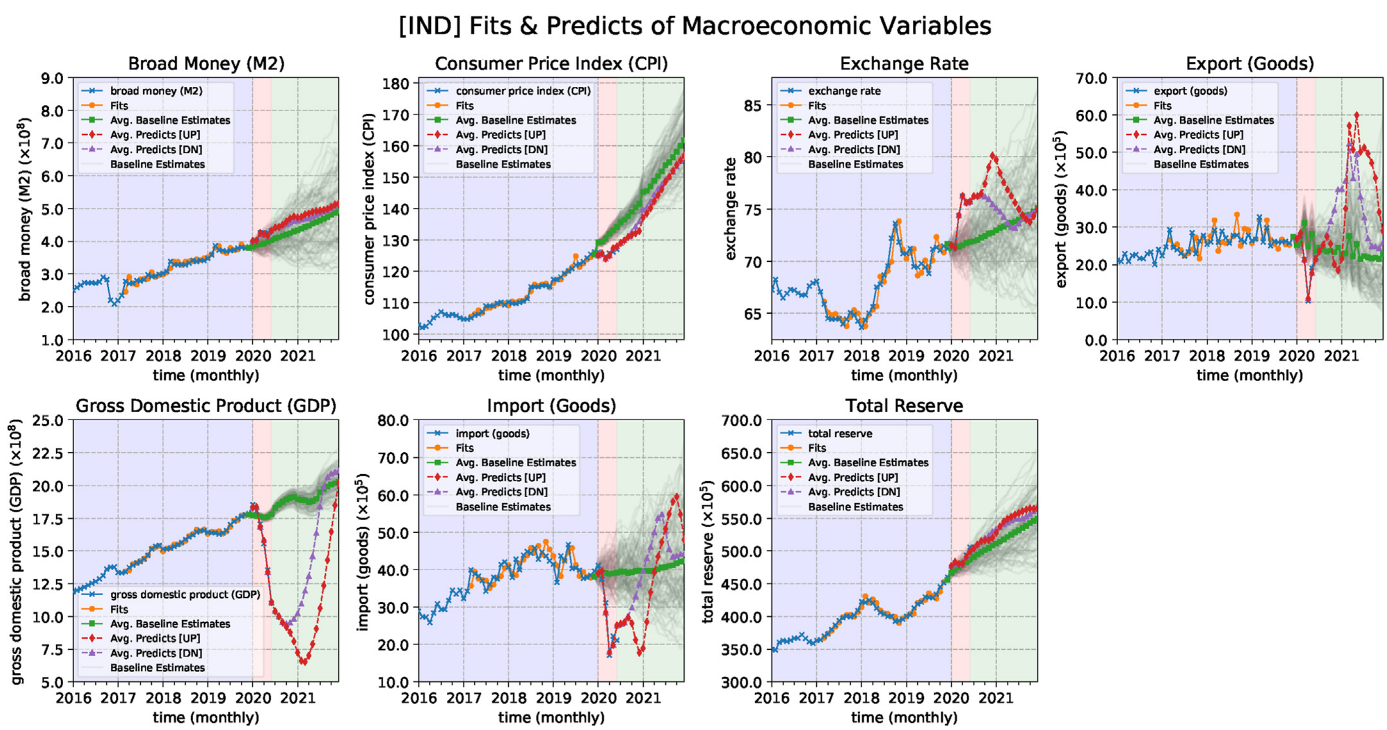

Fig. F.10 India (IND): fits & forecasts of macroeconomic variables.

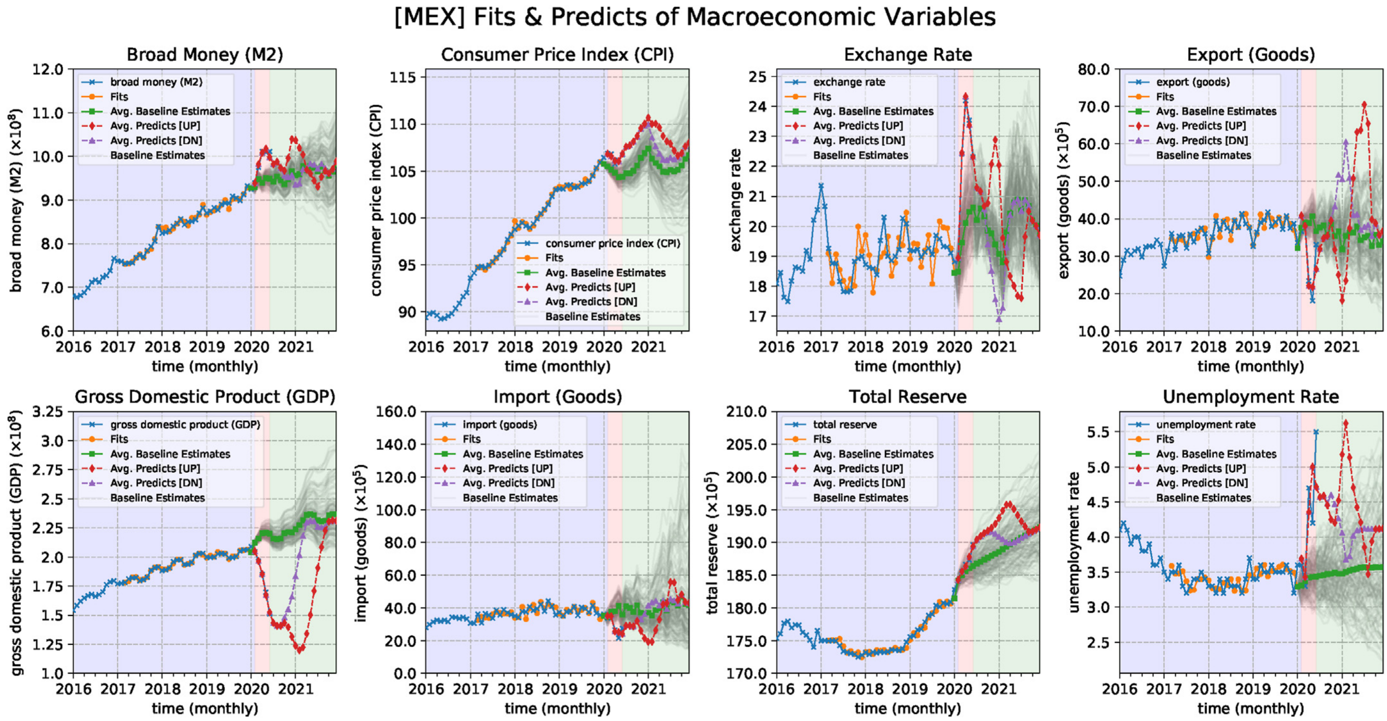

Fig. F.11 Mexico (MEX): fits & forecasts of macroeconomic variables.

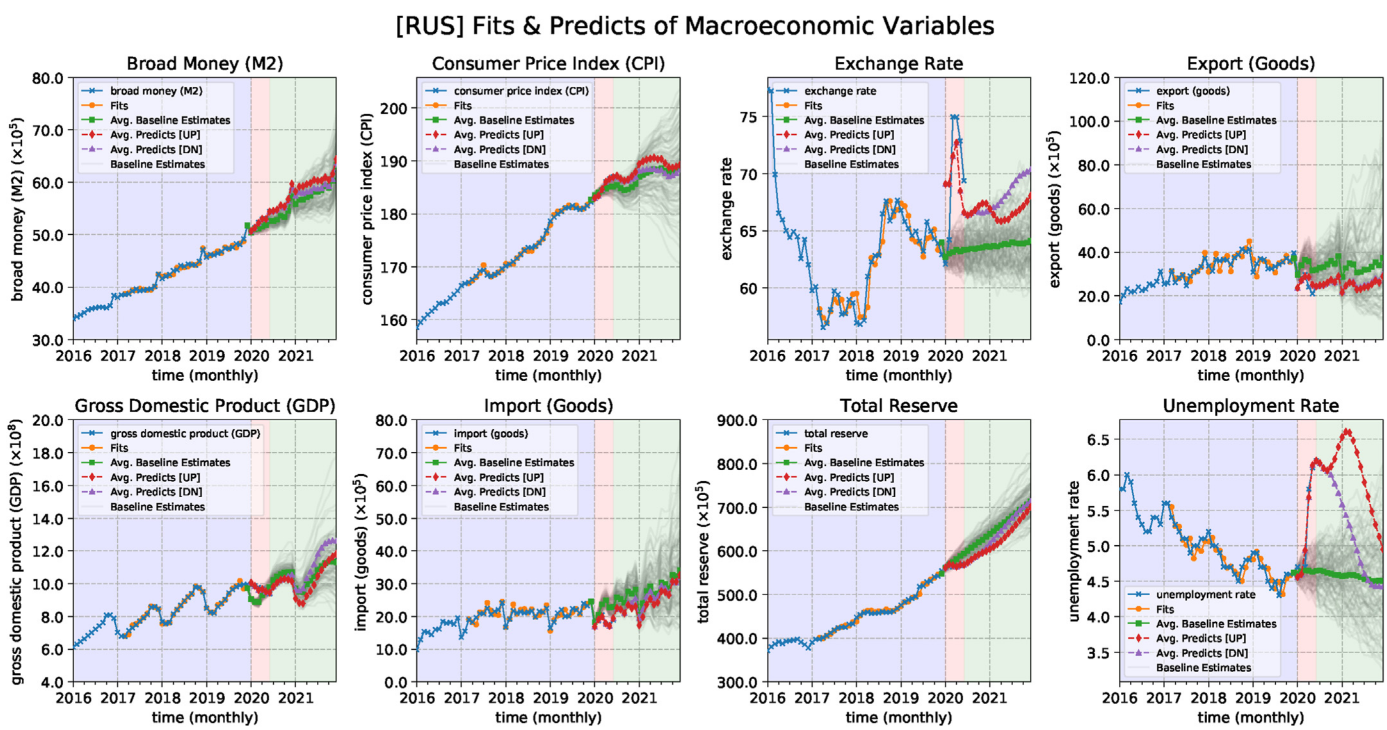

Fig. F.12 Russia (RUS): fits & forecasts of macroeconomic variables.

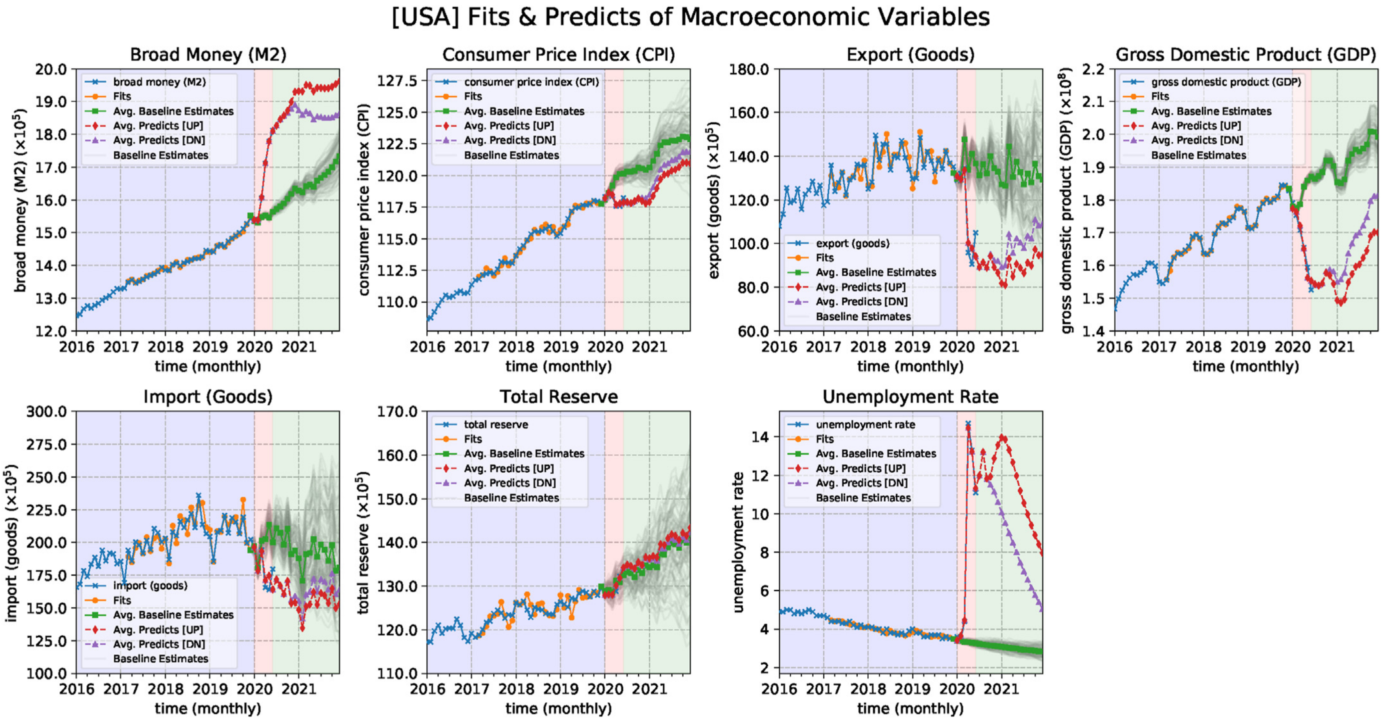

Fig. F.13 United States (USA): fits & forecasts of macroeconomic variables.

Appendix G. Supplementary data

Supplementary data and computational code to this article can be found online at https://doi.org/10.1016/j.econmod.2022.105821.

References

Akhtaruzzaman, M., Boubaker, S., Lucey, B.M., Sensoy, A., 2021. Is gold a hedge or a safe-haven asset in the COVID-19 crisis? Econ. Modell. 102, 105588, https://doi.org/10.1016/j.econmod.2021.105588.

Altig, D., Baker, S., Barrero, J.M., Bloom, N., Bunn, P., Chen, S., Davis, S.J., Leather, J., Meyer, B., Mihaylov, E., Mizen, P., Parker, N., Renault, T., Smietanka, P., Thwaites, G., 2020. Economic uncertainty before and during the COVID-19 pandemic. J. Publ. Econ. 191, 104274.

An, Z., Jalles, J.T., Loungani, P., 2018. How well do economists forecast recessions? Int. Finance 21, 100–121, https://doi.org/10.1111/infi.12130.

Ayittey, F.K., Ayittey, M.K., Chiwero, N.B., Kamasah, J.S., Dzuvor, C., 2020. Economic impacts of Wuhan 2019-nCoV on China and the world. J. Med. Virol. 92, 473–475.

Canova, F., Hansen, B.E., 1995. Are seasonal patterns constant over time? A test for seasonal stability. J. Bus. Econ. Stat. 13, 237–252, https://doi.org/10.1080/07350015.1995.10524598.

Caraka, R.E., Lee, Y., Kurniawan, R., Herliansyah, R., Kaban, P.A., Nasution, B.I., Gio, P.U., Chen, R.C., Toharudin, T., Pardamean, B., 2020. Impact of COVID-19 large scale restriction on environment and economy in Indonesia. Glob. J. Environ. Sci. Manag. 6, 65–84, https://doi.org/10.22034/GJESM.2019.06.SI.07.

Carriero, A., Clark, T.E., Massimiliano, M., 2020. Nowcasting Tail Risks to Economic Activity with Many Indicators. Federal Reserve Bank of Cleveland, https://doi.org/10.26509/frbc-wp-202013r2. Working Paper No. 20-13R.

Daehler, T.B., Aizenman, J., Jinjarak, Y., 2021. Emerging markets sovereign CDS spreads during COVID-19: Economics versus epidemiology news. Econ. Modell. 100, 105504.

Dong, E., Du, H., Gardner, L., 2020. An interactive web-based dashboard to track COVID-19 in real time. Lancet Infect. Dis. 20, 533–534.

Foroni, C., Marcellino, M., Stevanovic, D., 2022. Forecasting the COVID-19 recession and recovery: Lessons from the financial crisis. Int. J. Forecast. 38, 596–612, https://doi.org/10.1016/j.ijforecast.2020.12.005.

Ftiti, Z., Ameur, H.B., Louhichi, W., 2021. Does non-fundamental news related to COVID-19 matter for stock returns? Evidence from Shanghai stock market. Econ. Modell. 99, 105484.

Funke, M., Tsang, A., 2020. The People's Bank of China's response to the coronavirus pandemic: A quantitative assessment. Econ. Modell. 93, 465–473.

Giannone, D., Lenza, M., Primiceri, G.E., 2015. Prior selection for vector autoregressions. Rev. Econ. Stat. 97, 436–451, https://doi.org/10.1162/REST_a_00483.

Goodell, J.W., 2020. COVID-19 and finance: Agendas for future research. Finance Res. Lett. 35, 101512.

International Monetary Fund, 2020a. World Economic Outlook: the Great Lockdown. https://doi.org/10.5089/9781513539744.081, https://www.imf.org/.World Economic Outlook Reports.

International Monetary Fund, 2020b. World Economic Outlook Update: A Crisis like No Other, an Uncertain Recovery. https://www.imf.org/en/Publications/WEO/Issues/2020/06/24/WEOUpdateJune2020.

International Monetary Fund, 2021. World Economic Outlook: Managing Divergent Recoveries. https://doi.org/10.5089/9781513575025.081, https://www.imf.org/. World Economic Outlook Reports.

Kapetanios, G., Mumtaz, H., Stevens, I., Theodoridis, K., 2012. Assessing the economy-wide effects of quantitative easing. Econ. J. 122, 316–347, https://doi.org/10.1111/j.1468-0297.2012.02555.x.

Kermack, W.O., Mckendrick, A.G., 1927. A contribution to the mathematical theory of epidemics. Proc. R. Soc. Lond. A 115, 700–721, https://doi.org/10.1098/rspa.1927.0118.

Kuschnig, N., Vashold, L., 2021. BVAR: Bayesian vector autoregressions with hierarchical prior selection in R. J. Stat. Software 100, 1–27, https://doi.org/10.18637/jss.v100.i14.

Lauer, S.A., Grantz, K.H., Bi, Q., Jones, F.K., Zheng, Q., Meredith, H.R., Azman, A.S., Reich, N.G., Lessler, J., 2020. The incubation period of coronavirus disease 2019 (COVID-19) from publicly reported confirmed cases: Estimation and application. Ann. Intern. Med. 172, 577–582.

Lütkepohl, H., 2005. New Introduction to Multiple Time Series Analysis. Springer Science & Business Media.

Malliet, P., Reynès, F., Landa, G., Hamdi-Cherif, M., Saussay, A., 2020. Assessing short-term and long-term economic and environmental effects of the COVID-19 crisis in France. Environ. Resour. Econ. 76, 867–883.

McKibbin, W., Fernando, R., 2021. The global macroeconomic impacts of COVID-19: Seven scenarios. Asian Econ. Pap. 20, 1–30.

Nicola, M., Alsafi, Z., Sohrabi, C., Kerwan, A., Al-Jabir, A., Iosifidis, C., Agha, M., Agha, R., 2020. The socio-economic implications of the coronavirus pandemic (COVID-19): A review. Int. J. Surg. 78, 185–193.

Seabold, S., Perktold, J., 2010. Statsmodels: Econometric and statistical modeling with Python. In: Proceedings of the 9th Python in Science Conference. (SCIPY 2010), pp. 92–96.

Sims, C.A., 1980. Macroeconomis and reality. Econometrica 48, 1–48.

Sun, H., Qiu, Y., Yan, H., Huang, Y., Zhu, Y., Gu, J., Chen, S.X., 2020a. Tracking reproductivity of COVID-19 epidemic in China with varying coefficient SIR model. J. Data Sci. 18, 455–472, https://doi.org/10.6339/JDS.202007_18(3).0010.

Sun, Y., Wu, M., Zeng, X., Peng, Z., 2020b. The impact of COVID-19 on the Chinese stock market: Sentimental or substantial? Finance Res. Lett. 38, 101838, https://doi.org/10.1016/j.frl.2020.101838.

Sun, Y., Zeng, X., Zhao, H., Simkins, B., Cui, X., 2021. The impact of COVID-19 on SMEs in China: Textual analysis and empirical evidence. Finance Res. Lett. 45, 102211, https://doi.org/10.1016/j.frl.2021.102211.

Umar, Z., Kenourgios, D., Papathanasiou, S., 2020. The static and dynamic connectedness of environmental, social, and governance investments: International evidence. Econ. Modell. 93, 112–124.

Walmsley, T.L., Rose, A., Wei, D., 2021. Impacts on the U.S. macroeconomy of mandatory business closures in response to the COVID-19 pandemic. Appl. Econ. Lett. 28, 1293–1300, https://doi.org/10.1080/13504851.2020.1809626.

Yan, H., Zhu, Y., Gu, J., Huang, Y., Sun, H., Zhang, X., Wang, Y., Qiu, Y., Chen, S.X., 2021. Better strategies for containing COVID-19 pandemic: A study of 25 countries via a vSIADR model. Proc. R. Soc. A 477, 20200440, https://doi.org/10.1098/rspa.2020.0440.

Zhang, D., Hu, M., Ji, Q., 2020a. Financial markets under the global pandemic of COVID-19. Finance Res. Lett. 36, 101528.

Zhang, J., Litvinova, M., Wang, W., Wang, Y., Deng, X., Chen, X., Li, M., Zheng, W., Yi, L., Chen, X., et al., 2020b. Evolving epidemiology and transmission dynamics of coronavirus disease 2019 outside Hubei province, China: A descriptive and modelling study. Lancet Infect. Dis. 20, 793–802.