Covid-19’s impact on China’s economy: a prediction model based on railway transportation statistics

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The outbreak of Covid-19 in China during the Spring Festival of 2020 has changed life as we knew it. To explore its impact on China’s economy, we analyse the daily railway passenger volume data during the Spring Festival travel rush and establish two RegARMA models to predict GDP in the first quarter. The models forecast China might lose 4.8 trillion yuan in the first quarter of 2020 due to Covid-19, an expected decrease of 20.69 percent (year-on-year drop 15.60 percent). However, comparing our forecast GDP without Covid-19 (23.2 trillion yuan) with the real GDP (20.65 trillion yuan), there is a smaller drop of 2.55 trillion yuan, a gap of 12.35 percent. The reason for this overestimation is that some positive factors, including macro-control policies, are neglected in these models. With the global spread of Covid-19, China should adopt a policy of focusing on balancing both domestic and external affairs against the instability of the world economy.

Keywords: China’s GDP prediction, Covid-19, RegARMA model, Spring Festival travel rush, transportation data

Introduction

Background

At the beginning of 2020, Covid-19 swept across China, creating a public health emergency that had the fastest transmission, the widest scope of infection and the most difficult to prevent and control since the founding of the People’s Republic of China. Under the leadership of the Chinese government, the city of Wuhan closed and cut off all traffic on 23 January 2020 (the day before New Year’s Eve) (Yang et al., 2020; Yue et al., 2020). After the start of the battle against the pandemic in Wuhan most cities across the country adopted strict protective measures during the Spring Festival. Consequently, during the Chinese New Year in 2020, “home” became the main theme of Chinese people, and the consensus across society was “no meals, no gathering, less going out, less flowing”. The Chinese government has taken strong measures to fight against Covid-19—restaurants, tourism, cultural and entertainment venues were temporarily closed; cities were closed with strict regional regulatory restrictions; the Lunar New Year holiday was extended; the new year school was delayed (Wang et al., 2020). These measures restricted the movement of the population and greatly reduced the amount of transportation in
China, which thus limited the source of infection, cut off transmission, protected vulnerable populations and effectively protected the lives and health of the people (Fan et al., 2020; Zhao, Li et al., 2020). At the same time, the Chinese government has been soberly aware that the outbreak directly led to the shutdown of a large number of Chinese enterprises, especially the service industry. Therefore, it is necessary to correctly estimate the economic losses caused by the pandemic and deal with the resulting difficulties and challenges to building a moderately prosperous society in all respects.

Pandemics often arise from nature and spread to humans on a large scale because of our social attributes. Their impact on the economy and society is extensive and far-reaching (Hunter, 2007; Smith et al., 2009; Abodunrin, Oloye, and Adesola, 2020; Açikgöz and Günay, 2020; Sharif, Aloui, and Yarovaya, 2020). From the perspective of mechanism, the pandemic affects the economy mainly through production, consumption and price. First, during a pandemic, contact between people is heavily reduced, and production conditions are destroyed (He, Niu et al., 2020). Then global supply chains fail to work normally (Bonadio et al., 2020; de Paulo Farias and de Araújo, 2020; Gregoriao and Ancog, 2020; Hobbs, 2020; Ivanov, 2020; Ranney, Griffith, and Jha, 2020; Sarkis et al., 2020). Second, the pandemic inhibits consumption (Baker et al., 2020; Hall, Jones, and Klenow, 2020) and both enterprises and consumers adjust their price expectations. Changes in supply and demand cause prices to change, which in turn affects the economy (Balleer et al., 2020; Prabheesh, Padhan, and Garg, 2020).

Covid-19’s impact on the world and China’s economy in early 2020 is a broad and far-reaching research topic. The background research for this paper includes economy (Altig et al., 2020; Fernandes, 2020; Usman et al., 2020), energy (Nourozi et al., 2020) and environment (Han et al., 2021; He, Pan et al., 2020). In this paper, we focus on estimating the Chinese economic losses caused by the pandemic. It requires us to predict the Chinese economy under normal conditions (without Covid-19), as in this analysis of the economic impact of SARS on Beijing (Beutels et al., 2009). For proper estimation, it is key to find suitable daily data to characterise the changes of China’s economy. Considering that the outbreak happened during the Spring Festival and the unavailability of typical economic data (for example, the stock and bond markets are closed during the Festival), this paper attempts to facilitate the Spring Festival transportation data released by the Ministry of Transport to predict Covid-19’s impact on China’s economy.

The Spring Festival is the most important festival in China and it is traditional for the Chinese to return to their hometown for its duration (Wang et al., 2013). Transportation is especially important to send people home and then back to work. As a result, every year the Chinese government announces a special transportation arrangement during the Spring Festival, which is well known as the Spring Festival travel rush (SFTR). SFTR in China, also called the largest annual human migration in the world, is a large-scale phenomenon of high transportation pressure occurring around the Lunar New Year. It lasts a total of 40 days, 15 days before and
25 days after the Lunar New Year, and always happens in the first quarter of the solar calendar. The passenger volume of various forms of transportation during SFTR of 2000–2020 is displayed in Figure 1(a). Most of the total passenger volume during SFTR is borne by road transportation, which reached a peak of 3.4 trillion people in 2013 and gradually flattened out after 2015; while railway and air transportation passenger volume has gone up year by year, with 410 million and 73 million in 2019 respectively.

In this paper, we choose the railway passenger volume (RPV) as the indicator of economy. Railway transportation is currently the most important type of transportation in China. High-speed railway transportation has gradually become the first

**Figure 1a. Passenger Volume (PV) of SFTR in 2000-2020**

**Figure 1b. Passenger Volume (PV) of SFTR, Q1GDP and GDP in 2000-2019**
choice of travel in contemporary China due to its convenience and comfort (Zhao, Lin et al., 2020). The reason for choosing RPV instead of road passenger traffic or total passenger traffic is mainly because railway transportation undertakes a large portion of long-distance bulk cargo and medium- and long-distance passenger transportation tasks (Dong, Zheng, and Kahn, 2020; Kong, Liu, and Yang, 2020; Shi et al., 2020; Zhang, Chong et al., 2020). There are a large number of empirical studies showing that the Chinese economy is highly related to railway transportation (Wang et al., 2009; Ahlfeldt and Feddersen, 2018; Diao, 2018), especially China’s high-speed railway (Jia, Zhou, and Qin, 2017; Li et al., 2018). In turn, railway transportation has spurred economic growth and promoted regional economic convergence (Chen and Haynes, 2015, 2017). Although the passenger volume of road transportation is huge, it mainly undertakes short-distance transportation (such as inter-city, county-level transportation). To this view, it is difficult to reflect the population migration during SFTR in China. Some studies estimate that the sharing rate of RPV between Beijing and Tianjin reached 78.3 percent, with that of road passenger volume only 21.7 percent (Nie and Han, 2008); while in the Chengdu-Chongqing channel, the sharing rate of RPV reached 79.7 percent (Huang, Ding, and Zhou, 2012). This shows that railway transportation has become the first choice for long-distance migration and large-volume inter-city passenger transportation.

From a statistical perspective, it can also be observed that RPV has an impact on the economy. In Figure 1, China’s economy has been in a growth stage since 2015. Currently, RPV is still increasing, while road passenger volume lies in a stable state. There is a statistical correlation between railway passenger traffic and China’s economic development, which is higher than road transportation volume. For forecasting, if there is a correlation between two time series then their trends are consistent (called cointegration in statistics). And a simple regression model is enough to make predictions. To this end, it is necessary to ensure that no variables are omitted. In this paper, we need to control the impact of other variables (sectors such as agriculture, construction industry, etc.) on the economy. But the unavailability of data brings difficulties. Therefore, we applied the RegARMA structure to improve the prediction model. The setting of the RegARMA model used the lag term of the explanatory variable (dependent variable) to replace the omitted variables, which not only improved the predictive ability of the statistical model, but also focused the research problem on the passenger volume, in our case, RPV.

Synthesising the above analysis, the transmission pathway of Covid-19’s impact on China’s economy is constructed as “Epidemic- Transportation (Railway)-Economy” (see Figure 2). First, the reduction in passenger volume caused by Covid-19 can be divided into two parts: people’s spontaneous reduction and government-restricted reduction. For the spontaneous reduction, it is natural for people to stay at home during the holiday and to avoid being infected. And the infected patients will be strictly controlled. On the other hand, after the outbreak, the Chinese government quickly conducted response policies (i.e. the shutdown of
cities, the extension of the holidays) to control the epidemic, which also reduced transportation and shut down some economic production. We assume the sum is the total impact of Covid-19 on China’s economy, which is represented by RPV. Thus, the RPV during SFTR is chosen as the main indicator to measure Covid-19’s impact on China’s economy. It can be observed intuitively from Figure 1(b) that the exponential trend of China’s RPV during SFTR is consistent with the first quarter’s gross domestic product (GDP) (Q1GDP) and annual GDP. More specifically, the RPV during SFTR increased from 128 million in 2000 to 410 million in 2019 gradually, at an average annual rate of 6.35 percent; while Q1GDP went up from 2.13 trillion yuan in 2000 to 21.81 trillion yuan in 2019, with an average annual rate of 13.02 percent.

**Comparison with SARS**

At the beginning of this Covid-19 outbreak, a large number of academics performed epidemiological analysis, forecasted the trend of the Covid-19 based on infectious disease models, and thought that it would be generally under control by the end of March (Fan, Liu et al., 2020; Wu, Leung, and Leung, 2020; Zhang, Chong et al., 2020; Zhao, Lin et al., 2020). The pandemic had a significant impact on all parts of China’s economy (Ruiz Estrada, Park, and Lee, 2020), particularly in the first quarter of 2020.

It is important to distinguish the similarities and differences between Covid-19 in 2020 and SARS in 2003 before determining whether the models established during the SARS period are applicable to Covid-19. The 17-year gap between these outbreaks makes a big difference. First, China’s economic development is different during the two outbreaks. In 2003, China’s nominal GDP was 13.74 tril-

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**Figure 2.** The “Epidemic-Transportation (Railway)-Economy” transmission path

- **Spontaneous reduction**
- **Government-restricted reduction**
- **Transportation**
  - Mainly railway passenger volume
lion yuan, and it had the sixth largest economy in the world. By 2019, China’s nominal GDP has reached 99.08 trillion yuan (7.2 times of that in 2003), making it the second largest economy in the world. Second, China’s economic structure has changed. In 2003, the added value of three industries in the Chinese economy accounted for 12.3 percent, 45.6 percent and 42.1 percent of GDP, respectively; by 2019 these numbers had changed to 7.1 percent, 39.0 percent and 53.9 percent. This demonstrates that the proportion of the primary industry in China’s economy declined, and that of the secondary and tertiary industries rose during this gap; GDP growth is no longer driven by the primary and secondary industries, but has been mainly driven by secondary and tertiary industries. Third, the urbanisation rate of the Chinese population has risen from 40.53 percent in 2003 to 60.60 percent in 2019 (Liang and Yang, 2019). People have access to more comprehensive health services and benefit more from social care and support (Zhang et al., 2019). In China’s cities, the number of urban health technicians has jumped from 49 per 10,000 people in 2003 to 109 in 2018.

In addition, the population’s mobility has increased significantly. In 2003, China’s railway mileage was only 73,000 kilometres and the country’s first high-speed railway, the Qinhuangdao-Shenyang special railway line, with a length of 404 kilometres, had just opened. The high speed railway was 1.81 million kilometres and it transported 15.9 billion passengers a year. But in 2019, China’s railways reached 139,000 kilometres, and high-speed railways exceeded 35,000 kilometres, including more than five million kilometres of highspeed railways, and the total number of passengers reached 17.6 billion.

Moreover, the Chinese government’s response time and treatment measures for these two outbreaks are different. In the early days of the SARS outbreak (December 2002 to February 2003), Guangdong Province lacked awareness of its contagion and failed to take timely measures, resulting in the SARS lasting until July 2003. But this time, after the official disclosure of an unexplained pneumonia in Wuhan for the first time on 31 December 2019, the Chinese government responded quickly, with only four days from the discovery of large-scale transmission on 20 January 2020 to the closure of Wuhan on 23 January. The Chinese government and people made a firm decision to fight against Covid-19, powered by China’s more complete epidemic prevention and control system than during the SARS period.

According to the above analysis, the economic and social backgrounds of the two epidemic periods are quite different, and the analysis and reasoning models of the SARS period (Keogh-Brown and Smith, 2008) cannot be applied rigidly to Covid-19. Therefore, new prediction models had to be developed.

The contributions of this paper are twofold: (1) The “Epidemic-Transportation (Railway)-Economy” transmission path is elaborated and the rationality of using RPV to construct a RegARMA model to predict China’s economy is demonstrated. (2) A two-stage prediction model is established. The first stage model tries to collect RPV during SFTR and build a relationship model between traffic volume indicators and economic indicators, which aims to quantify Covid-19’s im-
pact on China’s economy. The second stage model can predict the GDP value and help us analyse the macroeconomic impact of the epidemic on China’s economy.

The following sections of this paper are as follows. The first includes two RegARMA models. One (Model I) develops a model of daily RPV (DRPV) during SFTR to predict the normal situation (without being affected by the epidemic) in 2020. Adding DRPV during SFTR, the total RPV (TRPV) under normal circumstances is predicted. The other (Model II) sets up a model of TRPV and China’s Q1GDP. Using China’s RPV data and GDP data, the second section estimates empirically the parameters and gives out the forecast values. The third section concludes.

**Methodology**

In this section, we will establish the TRPV prediction model and the Q1GDP prediction model. Covid-19 occurred during the Spring Festival in China in 2020. During this period, there was no direct daily economic data (such as stock market data, bond market data) to describe the characteristics of China’s economy. Since a country’s transportation capacity is positively correlated with economic growth (Hu and Liu, 2010), DRPV data announced by the Ministry of Transport of China is promising to be an alternative indicator. We treat DRPV as a daily indicator to measure the economic characteristics during the epidemic. Considering that the epidemic outbreaks occurred in the 15th day during SFTR, we can divide the period into two parts — the former is 15 days before the Lunar New Year, which was normal, and the latter is the following 25 days affected by the pandemic. In this way, DRPV data can be effectively used to model and forecast China’s economy during the epidemic. Next, we will establish the prediction Model I from DRPV to TRPV, and the prediction Model II from TRVP to Q1GDP.

**Model I: from DRPV to TRPV**

This section first builds the daily RPV (DRPV) model during SFTR. Let $T$ be the number of days in SFTR (often $T = 40$). Denote $\{X_{j,t}\}$ as the actual DRPV of the $t$-th day ($1 \leq t \leq T$) during SFTR in year $j$ ($i_0 \leq j \leq i$), and its logarithm is $x_{j,t} = \ln X_{j,t}$. The epidemic now occurs on the $t_0$-th day ($t_0 = 15$) of the $i$-th year ($i = 2020$), then the actual DRPV during SFTR is divided into two parts by $t_0$: normal DRPV (from the 1st to $t_0$-th day) and affected DRPV (from the $(t_0 + 1)$-th to $T$-th day). In order to estimate DRPV from the first day to the $T$-th day during SFTR under normal circumstances, the following RegARMA model can be constructed:

\[
\begin{align*}
\begin{cases}
x_{j,t} = c + \alpha_1 x_{j,t-1} + \cdots + \alpha_{t_0} x_{j,t-t_0} + u_t \\
u_t = \rho_1 u_{t-1} + \cdots + \rho_p u_{t-p} + e_t + \theta_1 e_{t-1} + \cdots + \theta_q e_{t-q}.
\end{cases}
\end{align*}
\]
where the first equation of model (1) is called a mean equation and the second equation is an ARMA structure (equation); \( c \) is the intercept; \( \alpha_l, \ldots, \alpha_l \) \((1 \leq l \leq i - i_0)\) are regression coefficients; \( \rho_1, \ldots, \rho_p, \theta_1, \ldots, \theta_q \) are the coefficients of the ARMA\((p, q)\) structure; \( u_t \) is structural residual and \( e_i \) is the actual residual that meets the classical assumptions. Note that model (1) should belong to the panel regression model. But because \( i \) takes a fixed value 2020 in this paper, the above model (1) is degenerated to RegARMA model. To facilitate the expression and popularisation of the model, \( i \) will be used in the following part.

The reasons for selecting RegARMA model, or the advantages of the model are:

(a) DRPV data is divided into two parts by the epidemic. If we just use the first period of data of 2020 to predict the next 25 days, the sample size is small, resulting in imprecise trend description. Thus, the estimated normal values in the next 25 days are needed. We observe that the Spring Festival data has a vertical correlation. The trends in each year are roughly the same in Figure 2(a) they gradually decrease before the Spring Festival and gradually increase afterwards. Therefore, we combine the DRPV of the Spring Festival of each year, i.e., consider the cross-sectional structure, which constitutes the mean equation.

(b) DRPV shows daily data with an ARMA structure usually. In fact, RegARMA is a more general structure – when the corresponding regression coefficient in the mean equation is not significant, the model degenerates to ARMA model; when the corresponding regression coefficient in the ARMA structure is not significant, the model degenerates into a common regression model.

(c) Rather than simply analysing the correlation, RegARMA is a reasonable predictive model, because it uses the historical information of \( x \), which solves the problem of omitted variables.

After the \( t_0 \)-th day, it is impossible to know DRPV during SFTR under normal circumstances unless prediction. The former part of data from 1st to \( t_0 \)-th day can be used to estimate the parameters of the RegARMA model (1) where MLE is adopted to estimate the parameters, with BIC criterion to determine the lag orders \( p \) and \( q \). For more details, see Wang et al. (2018).

After obtaining the estimated values of each parameter, DRPV under normal conditions in the \( i \)-th year from \((t_0 + 1)\)-th to \( T \)-th day can be predicted, called as normal DRPV, which is defined as \( \hat{X}_{i,t} \), when \( 1 \leq t \leq t_0 \) the normal DRPV on the \( t \)-th day is equal to the actual DRPV; when \( t_0 + 1 \leq t \leq T \), the normal DRPV is the predicted value \( \hat{X}_{i,t} \) obtained by the model (1). Estimating DRPV of SFTR and adding them up, TRPV is obtained and denoted \( \hat{X}_i = \sum_{t=1}^{T} X_{i,t} \) as normal TRPV of year \( i \), and \( \hat{X}_i = \sum_{t=1}^{T} X_{i,t} \) the affected TRPV, respectively.

**Model II: from TRPV to Q1GDP**

In this section, the relationship between TRPV and Q1GDP will be modeled to forecast Q1GDP of year \( i \). Denote \( Z_k \) as TRPV during SFTR in year \( k \) \((k_0 \leq k \leq i - 1)\),
\[ i - 1 - k_0 = K, \] \( Y_k \) as Q1GDP in year \( k \), whose natural logarithms are represented by lowercase letters. The RegARMA model can be set up as follows:

\[
\begin{align*}
    y_k &= c' + b x_k + v_k \\
    v_k &= \rho_1 v_{k-1} + \cdots + \rho_r v_{k-r} + \varepsilon_k + \theta'_1 \varepsilon_{k-1} + \cdots + \theta'_s \varepsilon_{k-s},
\end{align*}
\]

where \( c' \) is the intercept; \( b \) is the regression coefficient; \( \rho_1, \cdots, \rho_r, \theta'_1, \cdots, \theta'_s \) are the coefficients of the ARMA(\( r, s \)) structure; \( v_k \) is structural residual and \( \varepsilon_k \) is the actual residual that meets the classical assumptions. The main idea of the RegARMA model (2) is similar to model (1). First, TRPV is related to Q1GDP and this is captured by the mean regression. Second, we argue that there is usually an ARMA structure in the time series. Third, the problem of omitted variables can be solved. In addition to transportation, other economic sectors have been impacted by Covid-19. The proposed RegARMA model can measure these impacts with the lag of indicators. In this way, we can not only take advantage of the available transportation data, but also fully consider other economic sectors.

The parameters of model (2) can be estimated by the data of previous \( K \) years. Among them, \( x_k \) takes \( \hat{x}_k = \log \hat{X}_l \) predicted by the model (1), and \( x_i = \log X_i \), the logarithm of affected TRPV, respectively. Substituting the normal and affected TRPV into the model (2) for prediction, the forecast value of normal and affected Q1GDP can be obtained.

### Prediction analysis

#### Data description

The two proposed prediction models need to apply different data for modelling and prediction. To facilitate the comparisons, all data are collated in Table 1 below.

This paper uses a logarithmic series of each variable for modelling. The logarithmic series of variables has good properties and has been widely used in econometric models. First, the logarithm of each data does not change the nature and relationship of the data, and the obtained data is easy to eliminate heteroscedasticity. Second, economic variables have the meaning of elastic after taking the logarithm.

#### Table 1. Data selection

| Model   | Data for estimation                  | Data for prediction                  | Length  |
|---------|-------------------------------------|-------------------------------------|---------|
| Model (1) | DRPV of first 15 days of SFTR in 2018–2020 | DRPV of last 25 days of SFTR in 2018–2020 | 40 days |
| Model (2) | TRPV of SFTR and Q1GDP in 2000–2019 | Q1GDP in 2020                                      | 20 years |
so generally the variables take logarithmic form. Besides, the logarithm of the sequence of economic variables is often stable.

Before the prediction, the stationarity test is performed on each series. This paper uses the ADF test to test the logarithmic series of each indicator. The test results illustrate that the logarithmic series of each variable is stationary. Then we perform analysis using the methods above.

**DRPV prediction**

In this section, we first forecast normal DRPV of SFTR in 2020. Considering the complexity of the model and the availability of data, 40 days’ DRPV of SFTR during 2018–2020 is used in this paper, as drawn in Figure 3(a). Coincidentally, the New Year’s Eve and New Year’s Day are the two lowest days of DRPV due to the city’s closure. Then data of DRPV in SFTR is naturally divided into two parts. Data of the first 15 days are normal, and the last 25 days are affected by the virus. Next, we attempt to employ the normal data of the first 15 days to estimate the model and to predict the normal DRPV of the last 25 days of SFTR in 2020.

Based on the normal data of the first 15 days of SFTR, the estimated parameters of the optimal model (1) are listed in Table 2:

Getting the estimated values of each parameter of the model (1), the DRPV of last 25 days of SFTR in 2020 can be predicted in Figure 3(b).

As shown in Figure 3 (b), if not affected by the epidemic, the trend of DRPV in 2020 will be roughly the same as that in 2018. Actually, DRPV has almost been cut during SFTR in 2020, from an average of 12 million daily trips to less than 2 million. Adding the actual value of the 15 days to the forecast value of the last 25 days, the forecast value of TRPV during SFTR in 2020 is around 447 million daily trips, which is almost the same as the official estimation of 440 million released by the Chinese government. The actual TRPV during SFTR in 2020 was only 210 million, which is a decrease of half. In other words, the epidemic has caused the vast majority of Chinese people to abandon their original travel plans and stay home. The epidemic has seriously affected China’s economy, from the perspective of TRPV.

| Table 2. Estimation results of parameters in model (1): from DRPV to TRPV |
|-----------------|-------|-------|-------|-------|
| **Parameter**   | **c** | **α_1** | **α_2** | **ρ_1** |
| Estimator       | -1.3765 | 0.4545 | 0.7803 | 0.6376 |
| Standard error  | 0.6274 | 0.2529 | 0.2760 | 0.2218 |
| t-statistics    | -2.1939 | 1.7974 | 2.8266 | 2.8742 |
| p-value         | 0.0530 | 0.1025 | 0.0180 | 0.0165 |

R² = 93.08%, Adj R² = 90.31%, F-statistics = 33.6298 (p-value < 0.0001), BIC = -2.2812
Q1GDP prediction

In this section, the model (2) will be estimated by the data of TRPV and Q1GDP from 2000 to 2019, and then Q1GDP in 2020 will be predicted. Estimation results of model (2) are given in Table 3:

By substituting the actual affected TRPV and the normal TRPV predicted by model (1) into model (2), Covid-19’s impact on China’s normal Q1GDP in 2020 can be predicted. Under the influence of the epidemic, the point prediction of Q1GDP is just 18.4 trillion yuan, with prediction interval [15.5, 21.9] trillion yuan; while in normal circumstances, the point forecast value is 23.2 trillion yuan,
with prediction interval [21.1, 25.5] trillion yuan. There is a difference of 4.8 trillion yuan and a 20.69 percent decrease on average. Namely, the models illustrate the epidemic might cause a loss of 4.8 trillion yuan in the first quarter of China in 2020, a reduction of 15.60 percent compared with the first quarter of 2019 (21.8 trillion yuan).

### Analysis and discussion

The model predicts that, due to the impact of the epidemic, the Chinese economy will lose 4.8 trillion yuan in the first quarter in 2020. It is expected to be 20.69 percent lower than normal and 15.60 percent lower than the same period last year. According to the data released by the National Bureau of Statistics, Q1GDP in 2020 was 20.65 trillion yuan, with a decrease of 6.8 percent year-on-year. This value falls in our prediction interval, fully explaining the effectiveness of model prediction. Based on our predicted value without Covid-19, Q1GDP fell by \((23.2 - 20.65 =) 2.55\) trillion yuan, a decrease of 12.35 percent.

Compared with the official GDP data of 20.65 trillion yuan, our proposed models overestimate Covid-19’s impact on China’s economy in the first quarter. There are several issues in the model deserving further analysis and discussion.

First, since the outbreak, the economy has shifted from offline to online. The “online economy” or “digital economy”, including “online work” and “online education”, has experienced unprecedented development (Soto-Acosta, 2020). In the field of intelligent mobile office, it is expected that there will be tens of millions of companies and nearly 200 million people working from home during the epidemic using DingTalk, the largest online work platform in China. The number of daily active users on DingTalk rose from 26.1 million to 150 million between 1 January and 21 February 2020. There was also rapid development of new industries, such as online mental health services (Liu, Yang et al., 2020) and e-Sports (Kim, Nauright, and Suveatwatanakul, 2020). This part of the “online economy” is changing from passive to active, which is both a challenge and an opportunity for China’s economic transformation (Li, 2020), but it is not measured in the models.

Second, from the perspective of transportation, although there is no peak for China’s DRPV in 2020, the transportation industry will also recover to a large

### Table 3. Estimation results of parameters in model (2): from TRPV to Q1GDP

| Parameter    | \(c'\)   | \(b\)   | \(\rho'_1\) | \(\rho'_2\) |
|--------------|----------|---------|-------------|-------------|
| Estimator    | 10.7476  | 0.3053  | 1.9234      | -0.9336     |
| Standard error | 1.4227  | 0.0958  | 0.1599      | 0.1526      |
| t-statistics | 7.5544   | 3.1868  | 12.0311     | -6.1175     |
| p-value      | <0.0001  | 0.0061  | <0.0001     | <0.0001     |

R²=99.76%, Adj R²=99.69%, F-statistics=1538.5080 (p-value<0.0001), BIC = -2.5864

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Covid-19’s impact on China’s economy: a prediction model based on railway transportation statistics
extent after the Covid-19 situation is controlled in the next quarter. This will cause a certain increase in the second quarter of 2020. In other words, the epidemic only transforms the centralised transportation of passengers into decentralised transportation, rather than stagnating at a low level, which is also not considered in this paper. Despite the record low RPV of SFTR in 2020, the railway freight volume has reached a new high. During the Spring Festival, the Beijing Railway Bureau transported a total of 37.9 million tons of cargo, a year-on-year increase of 21.8 percent. According to data released by the China State Railway Group Co. Ltd., China’s railways sent a total of 824 million tons of cargo in the first quarter in 2020, a rise of 3.1 percent year-on-year. This demonstrates how the economic changes brought by passenger to freight transportation are neglected in the models.

Third, to adjust the economy and make up for the market failure to a certain extent during the outbreak, the Chinese government launched the joint prevention and control mechanism and issued a series of fiscal and financial policies, including social security relief policies, tax relief policies, fiscal and financial support policies, cost reduction and burden reduction policies, stable employment policies, etc. (He, Shi et al., 2020). Some key policies are shown in Table 4. In the process of modelling and forecasting, we assume that the external conditions of the macro economy will not change. In fact, in the field of macroeconomics, the central government plays a key role in economic regulation. As pointed out by the Political Bureau of the CPC Central Committee on 21 February 2020, “Fiscal policy should be more pro-active and play the role of policy finance well. Monetary policy should be more flexible and appropriate to alleviate the difficulties of financing and expen-

**Table 4. Some fiscal and monetary policies and measures formulated by Chinese government**

| Time   | Department                                   | Policy                                                                                                                                                                                                 |
|--------|----------------------------------------------|--------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|
| 26 Jan | China Banking and Insurance Regulatory Commission (CBIRC) | Extend repayment plans for personal mortgage loans and credit cards of people who temporarily lose their income source due to the epidemic.                                                                 |
| 30 Jan | State Administration of Taxation (SAT)       | Extend the tax declaration period for epidemic prevention and control.                                                                                                                                   |
| 2 Feb  | Ministry of Finance of China (FMC)           | Optimise the financing guarantee services for the enterprises affected by the epidemic, and encourage financial institutions to provide credit loan support to the key protection enterprises for the epidemic prevention and the small and micro enterprises affected greatly by the epidemic. |
| 6 Feb  | FMC, SAT                                     | The longest carry-over period for losses incurred by enterprises in difficult industries affected by the epidemic in 2020 is extended from five to eight years.                                        |
| 11 Feb | FMC                                          | An additional 1.848 trillion yuan of local government debt limit was set for 2020.                                                                                                                    |
| 12 Feb | Executive meeting of the State Council      | Implement temporary measures like reducing or exempting the rent on state-owned properties, lower the interest rate on loans, and extend the repayment of principal and interest to support private enterprises, small and micro enterprises. |
| 20 Feb | The People’s Bank of China (PBOC)           | China’s one-year loan prime rate (LPR) came in at 4.05 percent, down from 4.15 percent a month earlier. The above-five-year LPR fell 0.05 percentage points from the previous reading to 4.75 percent. |
Covid-19’s impact on China’s economy: a prediction model based on railway transportation statistics

S89

sive financing. And it should provide accurate financial services for epidemic control, work resumption and real economy.” This is another critical reason as to why the model underestimates the real economy.

Additionally, resilience in various fields of economy and society is an important factor in the recovery of vitality after a disaster (Rose, 2007), which are neglected in the model. Resilience is often used to analyse the recovery processes of systems from the shock. Resilience describes how systems recover from shocks or can build up capabilities to deal with future shocks (Wilson, 2018). It is used in several academic disciplines, such as psychology, ecology and planning. Experts agree that resilience is defined differently in the context of individuals, families, organisations, societies and cultures (Southwick et al., 2014). Studies have shown that, thanks to the resilience of governments and general population, Chinese society can regain vitality quickly after Covid-19 (see Table 5).

To sum up, in this paper we propose two RegARMA models by RPV to underestimate the real GDP. The estimated value may be considered as a bottom line thinking of Covid-19’s impact on China’s economy. In fact, a negative GDP growth rate does not mean no growth. In the world, China is one of a small number of countries that have not experienced negative growth in recent decades. If short-term negative economic growth pushes the transformation of economic structure and the stimulation of new economic vitality, it will be of benefit to subsequent economic development. Note that the above results are estimated without changing the global economic context. As the epidemic spreads further across the globe, world public health security is challenged (Anderson et al., 2020; Heymann and Shindo, 2020), the world economy becomes increasingly unstable (Ruiz Es-

### Table 5. Resilience in many aspects during Covid-19 in China

| Type of Resilience                  | Specific Performance                                                                 |
|-------------------------------------|--------------------------------------------------------------------------------------|
| Regional resilience                 | The long-term regional resilience in China is sufficient to deal with short-term shocks (Gong, Hissink et al., 2020) |
| Resilience of government            | China has been making unprecedented efforts in treating the confirmed cases, identifying and isolating their close contacts and suspected cases to control the source of infection and cut the route of transmission (Gong, Xiong et al., 2020) |
| Resilience of general population    | Public health emergencies could cause a poor mental health status in the general population (Qiu et al., 2020; Ran et al., 2020; Wang et al., 2020a), but there is a significant reduction in psychological impact four weeks after Covid-19 outbreak (Wang et al., 2020b) |
| Resilience of workers               | Returning to work did not cause a high level of psychiatric symptoms in the workforce (Tan et al., 2020) |
| Resilience of healthcare providers  | Healthcare providers identified many sources of social support and used self-management strategies to cope with the situation. They also achieved transcendence from this unique experience (Liu, Luo et al., 2020) |
| Resilience of patients              | Resilience can protect patients with mild symptoms of Covid 19 against anxiety and depression (Zhang, Yang et al., 2020) |
| Others                              | Resilience of high-performing health systems (Legido-Quigley et al., 2020) and resilience of college students (Ye et al., 2020) |
trada, 2020; Shi, Lin et al., 2020), and the world economy could be sharply affected in the short term (McKibbin and Fernando, 2020).

Once the global epidemic affects the global economy, it will be more difficult for China to stabilise foreign trade and investment, and the process of resuming production in China will also be affected through the supply chain of the global industry (Yu and Luo, 2018). Meanwhile, the unexpected impact of the global spread of the pandemic will affect financial market trends through psychological and financial channels. The impact of global interest rate cuts and market risk aversion is also a big challenge for China’s economy (Liu and Zhang, 2020). All in all, as pointed out by the Chinese National Development and Reform Commission, China’s economy will face tremendous downward pressure during the epidemic, but the long-term positive trend of China’s economy toward growth has not changed.

Conclusion

The sudden outbreak of Covid-19’s in 2020 will have a huge impact on China’s economy. This paper adopts time series analysis methods especially Reg-ARMA models, using DRPV data during SFTR to predict TRPV (Model I), and using TRPV data to predict Q1GDP (Model II) to analyse how China’s economy was affected by the epidemic in 2020 and under normal circumstances.

The models predict that, due to the epidemic, China’s economy will lose 4.8 trillion yuan in the first quarter of 2020, which is expected to decline by 20.69 percent (a year-on-year decrease of 15.60 percent). Compared with the real GDP data of 20.65 trillion yuan released by the National Bureau of Statistics of China, there is also a difference of 2.55 trillion yuan (12.35 percent decrease) caused by the epidemic. The model neglects the positive factors that exist in the China’s economy and macroeconomic policies during the epidemic, so the forecast of GDP may be underestimated. It can be regarded as a bottom line for Covid-19’s impact on China’s economy.

This serves as a reminder that as Covid-19 spreads further around the world and the global economy changes, this instability will in turn impact China’s economy. In order to control the downside risks to the economy, the Chinese government should adopt a combination of internal and external policies to prevent the spill-back of the pandemic.

Data availability statement

All data used during the study is open source from National Bureau of Statistics of China and Ministry of Transport of China and can be downloaded from the official websites.
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