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Assessing the Impacts of COVID-19 on the Industrial Sectors and Economy of China

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Since December 2019, the COVID-19 epidemic has been spreading continuously in China and many countries in the world, causing widespread concern among the whole society. To cope with the epidemic disaster, most provinces and cities in China have adopted prevention and control measures such as home isolation, blocking transportation, and extending the Spring Festival holiday, which has caused a serious impact on China's output of various sectors, international trade, and labor employment, ultimately generating great losses to the Chinese economic system in 2020. But how big is the loss? How can we assess this for a country? At present, there are few analyses based on quantitative models to answer these important questions. In the following, we describe a quantitative-based approach of assessing the potential impact of the COVID-19 epidemic on the economic system and the sectors taking China as the base case. The proposed approach can provide timely data and quantitative tools to support the complex decision-making process that government agencies (and the private sector) need to manage to respond to this tragic epidemic and maintain stable economic development. Based on the available data, this article proposes a hypothetical scenario and then adopts the Computable General Equilibrium (CGE) model to calculate the comprehensive economic losses of the epidemic from the aspects of the direct shock on the output of seriously affected sectors, international trade, and labor force. The empirical results show that assuming a GDP growth rate of 4–8% in the absence of COVID-19, GDP growth in 2020 would be -8.77 to -12.77% after the COVID-19. Companies and activities associated with transportation and service sectors are among the most impacted, and companies and supply chains related to the manufacturing subsector lead the economic losses. Finally, according to the calculation results, the corresponding countermeasures and suggestions are put forward: disaster recovery for key sectors such as the labor force, transportation sector, and service sectors should be enhanced; disaster emergency rescue work in highly sensitive sectors should be carried out; in the long run, precise measures to strengthen the refined management of disaster risk with big data resources and means should be taken.

KEY WORDS: COVID-19; disasters; economic loss; production and supply chain; static CGE models

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1. INTRODUCTION

At present, COVID-19 patients have appeared in more than 200 countries and regions including the United States, India, Brazil, Russia, England, France, Turkey, Italy, and Spain. By 8 p.m. on July 24, 2021 (Beijing time), in China, there were 120,090 confirmed cases nationwide, and 5,634 deaths; and in the world, there were 194,208,560 confirmed cases and 4,178,261 deaths. On the evening of January 30, 2020, the World Health Organization (WHO) announced the COVID-19 epidemic as a Public Health Emergency of International Concern (hereinafter referred to as PHEIC). Some countries such as Japan evacuated their nationals from Wuhan, and the United States and other countries suspended flights with China. The COVID-19 epidemic disaster has caused widespread concern among governments and people around the world.

Coronavirus is unseen and often hard to understand and predict, along with being highly infectious and lethal (Chan et al., 2020). For COVID-19', the tracing has not been completed and the patterns are not yet clear, the shortage of medical and health resources, and the constraint of the management system of medical research and development, it is difficult for some vulnerable people to receive timely and effective treatment, which constantly affects other vulnerable groups and intensifies the public panic. However, the development of vaccines requires a certain period, which further increases the negative impact caused by disasters (Prager, Wei, & Rose, 2017). In order to cut off the route of transmission and curb the rapid spread of the epidemic, Chinese government at all levels has adopted policies and measures focusing on isolation to reduce the gathering and flow of people and cut off the route of transmission, such as blocking traffic, cities, towns, and villages, residential areas, controlling travel, restricting public gatherings, and extending the Spring Festival holiday for schools, enterprises, and public institutions. From January 23 to March 23 in 2020, 1.4 billion people living in China were isolated at home or in hospitals. On the one hand, these measures effectively cut off the transmission routes, but on the other hand, the transportation during Spring Festival in China has almost stopped, and transportation, tourism, catering, and other service sectors have closed, leading to a huge negative impact on these sectors.

Meanwhile, with the rapid development of the economy, the division of labor and cooperation within and outside a country is becoming more and more complex, and the interconnectedness between regions and sectors is deepening, forming complex domestic and global supply chain networks and value networks. Thus, when some regions or sectors are affected by the epidemic, the decrease of production and operation activities will spread to other industrial sectors through forward and backward links of the supply chain or value chain, which will have a regional and global impact and pose great risks to the safe operation of social and economic systems (Acemoglu, Carvalho, Ozdaglar, & Asuman, 2012; Helbing, 2013; Putri, Muscatello, Stockwell, & Newall, 2018; Rose & Lim, 2002). At present, key medical supplies such as face masks, gel alcohol, and ventilators are in shortage, because the global capacity is unable to cope with the current demand and/or inputs are not available to manufacture them. So, how much is the loss caused by the COVID-19 epidemic and how to assess its impact? At present, there are few studies based on quantitative models to assess the economic losses for China because of COVID-19. Although the COVID-19 epidemic is still in a continuous diffusion and control period in China and the world, developing and providing mathematical methods of assessing its potential impact on China's economic system and on various sector in advance can provide timely data and quantitative tools to support the complex decision-making process for government agencies responding to this epidemic and maintaining stable economic development. This is one of the main purposes of this study.

In this article, we propose a hypothetical scenario and then adopt the static Computable General Equilibrium (CGE) model to estimate the comprehensive economic losses caused by the COVID-19 epidemic. Reasons to use it mainly include: First, the CGE model can establish a quantitative relationship between the various components (such as production, consumption, investment, labor, government departments, enterprises, among others) of the economic system. It allows us to analyze the impact of disturbances in one component of the economic system on the other component by simulating the resource losses and output reduction caused by catastrophic events such as COVID-19. It is a common method to analyze the comprehensive economic impact of natural disasters, technical accidents, terrorist attacks, among others (Xie et al., 2018). Due to its flexibility, it can support policymakers and decisionmakers in evaluating and deciding on choices to allocate scarce resources to mitigate the negative impacts of COVID-19. Second, the CGE model can overcome some limitations of other models. For example, econometrics usually focuses on analyzing the correlation between variables, but it is difficult to describe the mechanism of the relationship between variables. Moreover, it is often difficult to follow the strict distribution hypothesis with the collected data. On the other hand, the input–output coefficient of the input–output model (hereinafter referred to as the IO model) is linear and rigid, without considering the inherent elasticity of the economic system, and the results are thus overestimated (Okuyama & Santos, 2014; Rose, 2004). The CGE model overcomes the coefficient linear constraint of the IO model and is more in line with the actual situation of economic activities (Tan, Wu, Xu, & Li, 2019). Therefore, this model is adopted in this article for quantitative analysis.

The rest of this article is organized as follows: the second section is the literature review; the third section is the model construction; the fourth section is scenario setting; the fifth section is the analysis of simulation results, and the last section is the conclusion and prospect.

2. LITERATURE REVIEW

Social and economic losses caused by disasters can be divided into direct economic losses and indirect economic losses (Carrera, Standardi, Bosello, & Mysiak, 2015). Direct economic losses refer to short-term losses caused by economic factors affected by disasters, including market losses, such as losses of assets, buildings, goods and services, and nonmarket losses, such as loss of life, loss of human health, and their impact on culture and environment (Meyer et al., 2013; Natho & Thieken, 2018). Indirect economic losses refer to indirect economic changes caused by direct losses and the impact on the overall economic system (Baghersad & Zobel, 2015; Rose, 2004). Rose, Oladosu, and Liao (2007) discussed the connotation and scope of indirect economic losses in detail. For example, the cased ripple and chain reaction are considered as indirect economic losses, which refer to ripple, multiplier, general equilibrium, macroeconomic, or societal impacts (Rose, 2012). These include economic changes caused by off-site business interruption, reductions in property values, and stock market effects, as well as aspects of sociological and environmental effects (Rose, 2004). Some studies even indicate that indirect economic losses significantly increase the size of the damage as it ripples throughout the economy beyond those impacts those disasters are directly attacked (Rose et al., 2007). According to Hallegatte (2008) and Okuyama and Sahin (2009), comprehensive economic losses include direct economic losses and indirect economic losses, which can reflect the changes of the social and economic system from a larger spatial range and a longer time period, which has become the focus of scholars.

Currently, the methods for assessing the direct influences of infectious diseases mainly include case analysis, investigation, and simulation methods. Also, the investigations can be grouped into three aspects. The first aspect of the investigation is the direct damage of infectious diseases to the whole social economy or animal husbandry. For example, Davison, Galligan, Eckert, Ziegler, and Eckroade (1999) estimated economic losses from bird flu outbreaks in birds in Pennsylvania in 1997 and 1998, taking five flocks as samples. The results showed that the cost of loss to the Pennsylvania poultry sector brought by H7N2 was about \$3.5 million. Simmerman et al. (2006) estimated the overall situation of the whole country with the data of influenza patients from September 2003 to August 2004 from the Sakaeo Province of Thailand and concluded that the direct economic losses caused by influenza was between \$234,000 and \$62.9 million. Keogh-brown and Smith (2008) reviewed and analyzed the economic losses caused by the SARS outbreak in 2003. By comparing the economic indicators of the countries and regions where the epidemic occurred, they found that the direct economic impact caused by SARS lasted for 1–2 quarters. Putri et al. (2018) estimated the average annual total economic burden of influenza on the healthcare system and society in the United States was \$11.2 billion. The second aspect of the investigation is the direct damage caused by labor absenteeism, hospitalization, or death. For example, Fendrick, Monto, Nightengale, and Sarnes (2003) conducted a nationwide telephone survey of U.S. households between November 3, 2000, and February 12, 2001, to evaluate the losses of viral respiratory tract infection, and they reported the costs of \$22.5 billion per year due to absenteeism for infected individuals and parents of infected children. Molinari et al. (2007) estimated the medical and costs attributable to annual influenza epidemics in the United States. They suggested that the annual influenza epidemics resulted in an average of \$10.4 billion medical costs, and \$16.3 billion projected lost earnings due to illness and death. Chen, Huang, Chuang, Chiu, and Kuo (2011) conducted a survey on a kindergarten in Taiwan that was closed due to the flu epidemic and calculated the proportion and losses of parent absenteeism caused by the kindergarten closure. The third aspect of the investigation is the cost of vaccination and treatment, as well as the control cost of epidemic prevention and control measures. For example, Sander et al. (2009) simulated flu in communities based on a discrete stochastic model and then compared the potential economic impact of seven types of flu mitigation strategies. The results suggested that without human intervention, the infection rate would reach 50% of the population, resulting in economic losses of about $187 per person. Providing vaccination or virus prevention and closing schools would improve the health of the population, but the total cost to society is about $2,700 per capita, including resource use related to the treatment of illness, cost of preventive measures, along with drug and delivery costs. Schmitt and Zacchia (2012) summarized and estimated all the costs related to decontamination after the "anthrax letter" attack in 2001 based on the available literature and news media reports. The study showed that it would cost $320 million to completely purify the impact of the "anthrax letter." You, Ming, and Chan (2015) used a decision tree and Monte Carlo model to study and simulate the potential costs and benefits of quadrivalent and trivalent influenza vaccines for six different age groups.

When some sectors are directly affected by the epidemic, they will indirectly affect other industrial sectors through the correlation among industrial sectors, and then transmit to the whole industrial economic system by triggering the ripple effect in multiple interconnected supply chains (Wagner & Bode, 2006). The ripple effect describes the impact of the disruption propagation on supply chain performance and thus has been recently studied in the field of supply chain disruption. This field analyzed how one or several changes ripple throughout the supply chain and affect operational and strategic economic performance and stabilization (Ivanov, Sokolov, & Dolgui, 2014). Natural disasters, man-made disasters, political crises, and financial crises have been studied as disruption supply chain problems commonly focused on the impact of one industrial sector, or a single company (Dolgui, Ivanov, & Sokolov, 2018). To the best of our knowledge, the study of disruptions triggering the ripple effect in multiple interconnected supply chains and its impact on economic performance at a country level has not been addressed yet. Currently, the methods for assessing the comprehensive economic losses by the epidemic of infectious diseases mainly include the IO model and the CGE model. The IO model takes the input-output table as the database and connects the whole economic system through the input-output coefficient matrix to reflect the economic relations of various sectors of the national economy and social reproduction links. For the evaluation of comprehensive economic losses, the IO model substitutes the demand-side reduction value of some sectors into the input–output coefficient matrix with the IO model to calculate the losses of each linked sector (MacKenzie, Santos, & Barker, 2012). CGE model is a state-of-the-art approach to evaluate the comprehensive economic losses caused by the epidemic of infectious diseases and based on scenario analysis it can support decision-makers regarding the best course of action to implement by combining the production, consumption, employment, and other behaviors of economic subjects in the social and economic system (Dormady, Roa-Henriquez, & Rose, 2019). CGE model is an optimization problem that can be also solved by transforming it into a nonlinear optimization problem (Kiuila & Rutherford, 2014), or multiple optimization problems with equilibrium constraints, or a mixed complementarity problem (Choi, 2015; Ferris & Kanzow, 2002; Ferris & Pang, 1997; Wing, 2011), which can be solved using algorithms that are now routinely embodied in modern, commercially available software systems for optimization (Ferris, Munson, & Ralph, 2000; Wing, 2011).

The investigations using the IO model and CGE model to conduct comprehensive economic loss assessment can be grouped into three aspects. The first aspect of the investigation is to evaluate the comprehensive economic losses based on the direct impact of labor employment disruption. For example, Santos, May, and Haimar (2013) and Santos, Orsi, and Bond (2009) used the dynamic inoperability IO model to evaluate the comprehensive losses caused by labor employment disruption due to the outbreak of influenza in the United States. Montibeler and Oliveira (2018) used the dynamic inoperability IO model to calculate the impact of the dengue virus on the Brazilian economy from the perspective of labor damage. The second aspect of the investigation is to evaluate the comprehensive economic losses based on the direct losses of some sectors. For example, Blake, Sinclair, and Sugiyarto (2003) used the CGE model to assess the economic impact of Aftosa on the U.K.'s tourism, agriculture, and other industrial sectors. Dixon et al. (2010) used the quarterly CGE model to assess the impact of a hypothetical

H1N1 epidemic on the United States and found that it may have a serious economic impact during the peak period of the epidemic. Duan, Wang, and Yang (2020) used the IO model to calculate the losses of the COVID-19 in China and found that in the short term, the outbreak could cause an 18% loss in the output of the transportation, tourism, retail, and entertainment sectors. The third aspect of the investigation is to evaluate the comprehensive economic losses based on the implementation of epidemic prevention and control strategies. For example, Smith, Keogh-Brown, and Barnett (2011) used the CGE model to estimate the impact of Epidemic influenza (PI) on the U.K. economy, as well as the policy effects of school closures and workers' preventive absenteeism. Prager et al. (2017) assessed the comprehensive economic losses caused by the U.S. flu outbreak by analyzing different scenarios such as different severities of patients affected by the flu and whether they are vaccinated based on changes in healthcare spending and workforce participation. From the comparison between the IO model and CGE model, the CGE model reflects the interdependence between economic factors and production activities, overcomes the shortcomings of the IO model, such as lack of behavioral response, insensitivity to market price changes, and linearity of input–output coefficient. Nevertheless, the CGE model does have limitations. For example, the assumption of behavior optimization and the elasticity setting in the model equation may lead to extreme changes of parameters like price and quantity (Gordon, Moore II, Par, & Richardson, 2009; Park, Moore, Gordon, & Richardson, 2017; Rose, 2004). However, the application of the CGE model for modeling evaluation is more in line with reality (Koks et al., 2016). Based on the above considerations, although it is still in the period of epidemic transmission, this article intends to predict the possible socioeconomic impact of the COVID-19 epidemic in advance to provide data support for government decision making. In addition, the CGE model has not yet been used to evaluate the economic losses of the COVID-19 epidemic at a country-level, nor as a decision-making support tool to assess how development scenarios will affect the interconnected industrial sectors and the entire economy of a country as we propose here. Moreover, the GTAP was planned to be used. However, the input–output table for 2014 in the GTAP is somewhat old and cannot reflect the actual trade of China with the rest of the world in 2020. In addition, the COVID-19 originally took place in Wuhan and broke out in most provinces of China. It is of little significance to analyze the impact of Wuhan's direct losses on other provinces. Therefore, the method of the multiregional CGE model is not adopted in this article.

3. MODEL CONSTRUCTION

3.1. Analysis of Influence Mechanism

According to the general equilibrium theory, before suffering exogenous shocks, the economic system is usually in the equilibrium state of supply and demand, while exogenous shocks will break this equilibrium state and trigger ripple effects in the supply chains. Only after a series of adjustments can the economic system return to a new equilibrium. According to Okuyama and Sahin (2009), the output losses caused by the change of the regional economic system from the original equilibrium state before the disaster to the new equilibrium state after the disaster can be regarded as the comprehensive economic losses of the disaster area. This article also adopts their thoughts to calculate the comprehensive economic losses of the COVID-19 epidemic under the constructed simulation scenario.

The COVID-19 outbreak will impact the supply of factors of production and the normal operation of the industrial sectors and international trade, impacting the interconnected supply chains and the entire economy of a country at least. First, as the main factor of production, the labor force will change. On the one hand, the epidemic will inevitably cause labor casualties and reduce labor supply time; on the other hand, the prevention and control of the epidemic needs to control population flow and concentration. Due to the rapid outbreak of the COVID-19 epidemic and its large scope, although delayed resumption of labor is a powerful measure to control the epidemic, it has further reduced labor participation and caused labor idling. For some small and medium-sized enterprises with intensive production, the short-term direct impact caused by the outbreak will not be particularly obvious. However, due to the influence of factors such as unstable return time of labor force and the influence of upstream and downstream industrial supply chain transmission, the outbreak may cause a greater impact on normal operation, and even cause production suspension along supply chains (Asgary, Anjum, & Azimi, 2012). Second, from the perspective of the impact of different industrial sectors, during the epidemic prevention and control period, the public will spend less time out and reduce the consumption demand for offline services, which is particularly obvious in tourism, catering, retail and other sectors. Subsequently, due to the redistribution of production factors and the correlation effect between industrial sectors, the upstream and downstream of the supply chains of these sectors will be affected by the epidemic, triggering the negative ripple supply chain effect and resulting in comprehensive economic losses (Otto, Willner, Wenz, Frieler, & Levermann, 2017). Finally, the mutual dependence between countries has gradually deepened due to the acceleration of the economic globalization process and the development of trade liberalization, and international trade has become an important approach linking the world. National security incidents usually induce interruptions of trade connections and reduce the trade volume (Gassebner, Keck, & Teh, 2010). Inevitably, The COVID-19 epidemic has an impact on China's international trade activities. Moreover, this impact will be transmitted to all aspects of the domestic economic system such as production and consumption.

Based on the above considerations, to provide a quantitative-based support tool for decisionmakers and policymakers, the economic losses of the COVID-19 epidemic disaster are analyzed in four steps. First, the CGE model under the benchmark scenario is constructed to simulate the production, consumption, employment, and other behaviors of each economic entity in the form of nonlinear equations. Second, the direct economic impact of this epidemic disaster on seriously affected sectors, international trade, and the labor force is introduced. Third, the comprehensive impact of the COVID-19 epidemic can be calculated in China. The direct impact of disasters makes the production factors and the output of each sector change and then spreads to various industrial sectors through the production function and factor supply function, forming a comprehensive economic impact on supply chains. Fourth, uncertainty discussion and sensitivity analysis are carried out.

3.2. Model Structure

According to the research framework of Rose and Liao (2005), a country or region is regarded as an economic system. Based on the industrial classification for national economic activities (GB/T 4754-2017) issued by National Bureau of Statistics of China, the industry is divided into five major departments and 19 industrial sectors of similar nature, including agriculture, industry (mining, manufacturing, electricity, gas and water production and supply sector), construction, transportation, and services (wholesale and retail industry, accommodation and catering sector, finance, real estate sector, information transmission, software and information technology services, leasing and business services, scientific research and technical service, citizen service, repair and other services, water conservancy, environment and public facilities management, education, health and social work, culture, sports and entertainment and public management, social security, and social organizations), and establish a simultaneous nonlinear equations, build a CGE model that includes economic entities such as residents, enterprises, and governments. The main structure of the model includes the following modules:

(1) Production module: The model assumes perfect competition in the market, and all enterprises make decisions on factor input and product output according to the principle of cost minimization. The production functions use two layers of nested CESproduction functions. The total production output of the first layer is represented by the CES (constant elasticity of substitution) function, including intermediate input and added value, as shown in Equation (1). The second layer is described by Equations (2) and (3). Equation (2) describes the intermediate requirements of each department and is described by the Leontief IO matrix. Equation (3) represents value added, which is composed of labor factors and capital factors.

$$X_{\mathrm{i}} = A_i[\delta_i {A_i}^{\rho_i} + (1-\delta_i) {IT_i}^{\rho_i}]^{1/\rho_i}, \tag{1}$$

$$IT_{\mathrm{ij}} = ca_{\mathrm{ij}} \times IT_{\mathrm{i}}, \tag{2}$$

$$V_{\mathrm{i}} = AV_i[\delta V_i {L_i}^{\rho V_i} + (1-\delta V_i) {K_i}^{\rho V_i}]^{1/\rho V_i}. \tag{3}$$

In the equation, $i, j = 1, 2, 3, \cdots, n$. X_{i}represents the total output; V_{i} and IT_i represent value added and intermediate input; L_i and K_i represent the input of labor and capital factors respectively; A_i, AV_i, δ_i, and δV_i represent the scale parameters and share parameters of the total output equation and the value added equation, respectively; ρ_i, ρV_i, and ca_{ij}, respectively represent the elastic parameters of the total output equation, the value added equation and the direct consumption coefficient.

(2) Trade module: The total domestic output is divided into goods produced domestically and sold domestically and export goods, and the goods sold in

the domestic market include the goods produced in the domestic market and the import goods. Producers optimize the combination of domestic sales and exports when selling products to maximize revenue. Consumers will also optimize the combination of domestic and imported goods when purchasing goods. Therefore, the model follows the Armington assumption (Armington, 1969) and the inlet equation is described by CES function, and the outlet equation is characterized by Constant Elasticity of Transformation (CET) (Armington, 1969).

$$Q_{\mathrm{i}} = AQ_i[\delta Q_i D_i{}^{\rho Q_i} + (1 - \delta Q_i) M_i{}^{\rho Q_i}]^{1/\rho Q_i}, \quad (4)$$

$$X_{\mathrm{i}} = AT_i[\delta T_i D_i{}^{\rho T_i} + (1 - \delta T_i) E_i{}^{\rho T_i}]^{1/\rho T_i}. \quad (5)$$

In the equation, Q_i represents the total supply of commodities; D_i, M_i, and E_i, respectively represent goods produced domestically and sold domestically, import commodities, and export commodities; AQ_i and AT_i represent the scale parameters of the import commodity equation and the export commodity equation respectively; δQ_i and δT_i represent the share parameters of import commodity equation and export commodity equation, respectively; $\rho Q_i$and ρT_i represent the elastic parameter coefficients of the import commodity equation and export commodity equation, respectively.

(3) Revenue and expenditure module: In this module, the main economic entities are residents, enterprises, and government. Residents' income come from labor, capital gains, and transfer payments from the government and enterprises (Equation (6)). The income of the enterprise come from capital gains (Equation (7)). The government's revenue comes from indirect tax revenue, resident income tax, enterprise income tax, and import and export tariff (Equation (8)).

$$YH = WL \times LS + \beta^H \times WK \times KS + GTP + EPT \quad (6)$$

$$YE = \beta^E \times WK \times KS \quad (7)$$

$$YG = \sum (PQ_i \times \mathrm{t}_i \times X_{\mathrm{i}} + th_i \times YH + te_i \times YE) + \sum (\mathrm{tm}_i \times pwm_{\mathrm{i}} \times M_i \times EXR). \quad (8)$$

In the equation, YH, YE, and YG represent resident income, enterprise income, and government income, respectively; LS and KS, respectively represent the supply of labor and the supply of capital; GTP and ETP represent the transfer payments from the government and enterprises to residents; β^H and β^E represent the share of capital income distributed to residents and enterprises; WL, WK, and PQ_i represent labor factor price, capital factor price, and commodity price, respectively; pwm_{i} and EXR respectively represent the international prices and exchange rates of import goods; th_i, t_i, te_i and tm_i represent individual income tax rate, indirect tax rate, enterprise income tax rate and import tax rate, respectively.

(4) Macro closure module: All prices are completely elastic and determined endogenously by the model. Full employment of the total social investment is endogenously determined by savings and real exchange rates are endogenous. The foreign savings are assumed to be exogenous to the modeled economy. The labor factor is also determined by the factor endowment given by the exogenous. In the end, the clearing of the commodity market, the clearing of the labor market, the clearing of the capital market, the balance of payments, and the balance of savings and investment are realized.

3.3. Basic Data

Social Accounting Matrix (SAM) is the data basis of the CGE model. The data needed to compile the SAM table includes China's input and output table for 2017, China statistical yearbook (2001–2018), government financial final accounts data for 2018, tax statistics data for 2018, capital flow statement for 2018, among others. After collecting, summarizing, and analyzing the above data, the simultaneous nonlinear equations are established according to the general equilibrium theory to describe various equilibrium relationships in the economic system. Activities, commodities, labor, capital, residents, enterprises, government, fixed assets, inventory, and other parts of the world are set up in the macro SAM table, and the specific values are shown in Table I.

In the research of the CGE model, in addition to using the SAM table as the basic data, it is also necessary to set the elastic parameters of production function and trade function. These elastic parameters are generally gathered from the literature. Because key parameters are often not appropriately selected, the CGE model is often subject to criticism (Yamazaki, Koike, & Sone, 2018). Depending on the time scales for evaluation, the CGE model can be classified as static and dynamic. Therefore, the static CGE model and the dynamic CGE model are different in the selection of elastic parameters. In this article, we refer

Table I. China Macro Social Matrix in 2017 (hundred million dollar)

	Activities	Commodities	Labor	Capital	Residents	Enterprises	Government	The Capital Account	Inventory Movement	ROW
Activities		310,123								24,267
Commodities	212,465				47,458		18,328	53,193	1,230	
Labor	62,690									
Capital	45,169									
Residents			62,690	4,536		2,030	4,574			
Enterprises				41,093						
Government	14067	444			1,772	4,757				
The capital account					24,600	34,306	−1,862			−2,620
Inventory movement								1,230		
ROW		22,108		−461						

to studies that adopt the static CGE model to carry out analysis research, including Shi, Jin, and Seeland (2015) and Okiyama and Tokunaga (2017). The settings are shown in Table II.

4. SCENARIO SETTING

According to statistics released by Chinese government agencies, the COVID-19 epidemic has seriously affected the output of several sectors seriously. In addition, the outbreak of this disaster aggravates the downside risks to the world economy and significantly increases the uncertainties faced by international trade. Furthermore, the disaster would further affect China's economy through the reduced working hours of the labor force. Therefore, in the scenario setting, the disaster impact coefficients (DIC) of the seriously affected sectors, international trade, and labor force affected by the epidemic disaster are calculated, indicating the degree of impact on relevant variables, which are used to evaluate the ripple effect of COVID-19 epidemic on China's economic system. The value of DIC is the ratio of the direct losses of the epidemic to related variables in 2020. From the perspective of direction, if the coefficient is a positive sign, it represents a positive promoting effect; if the coefficient is a negative sign, it represents a negative inhibiting effect.

4.1. Direct Impact on the Output of Sectors

In terms of the transportation sector, most of China's cities are sealed off with poor traffic, and there is less demand for public travel. In addition, from the perspective of the international situation, with the announcement of WHO's classification of COVID-19 as PHEIC, many countries have canceled flights to and from China. Also, most domestic travel plans and outdoor leisure activities have been canceled due to the public fear of virus infection. From the perspective of the disaster impact on the service sectors, the impact of the epidemic is serious, especially for tourism, wholesale and retail trade, accommodation, and catering sector. Not only that, but the epidemic also affects labor employment, which will cause short-term production declines in various sectors. According to statistics released by Chinese government agencies, four sectors suffered the most direct losses in the epidemic, including wholesale and retail sector, transportation sector, accommodation and catering sector, and leasing and business services sector.

Table II. Elastic Parameter Setting of the Model

Industrial Sector	The Elasticity of Added Value and Intermediate Input	Capital and Labor Factor Elasticity	Armington elasticity	CET elasticity
Agriculture	1.05	0.9	2.45	2.55
The mining sector	1.05	1.2*	2.2*	2.55
Manufacturing sector	1.05	1.25	3.2	2.55
Production and supply of electricity, gas and water	1.05	1.25	2.5	2.55
Construction sector	1.05	1.3	2.05	2.55
Transportation sector	1.05	1.45	2.05	2.55
Wholesale and retail trade	1.05	1.25	2.05	2.55
Accommodation and catering sector	1.05	1.25	2.05	2.55
Finance	1.05	1.25	2.05	2.55
Real estate	1.05	1.25	2.05	2.55
Information transfer, software and information technology services	1.05	1.25	2.05	2.55
Leasing and business services	1.05	1.25	2.05	2.55
Scientific research and technical services	1.05	1.25	2.05	2.55
Citizen services, repairs and other services	1.05	1.25	2.05	2.55
Water, environment and public facilities management	1.05	1.25	2.05	2.55
Education	1.05	1.25	2.05	2.55
Health and social work	1.05	1.25	2.05	2.55
Culture, sports and entertainment	1.05	1.25	2.05	2.55
Public administration, social security and social organization	1.05	1.25	2.05	2.55

Note: (1) Elasticity of value added and intermediate input, elasticity of capital and labor factors, Armington elasticity and CET elasticity are set according to the average value of Shi et al. (2015) and Okiyama and Tokunaga (2017). (2) * represents the parameter selection is based on Shi et al. (2015) due to missing data in Okiyama and Tokunaga (2017).

In order to quantitatively analyze the direct impact of the epidemic on China's seriously affected sectors in 2020, it is necessary to predict the counterfactual output of these sectors, assuming that the COVID-19 epidemic did not occur. Thus, based on the historical output value of these sectors from 2000 to 2019, the autoregressive moving average model (hereinafter referred to as ARMA model) is constructed to predict the output value of these sectors in 2020 under normal circumstances without the epidemic.[1] And, the augmented Dickey–Fuller test (ADF) is used to test the stationarity of the annual series of data. Subsequently, according to the actual output value in China in 2020 released by government agencies, the output difference of these seriously affected sectors can be determined. Finally, the output difference between the predicted value and the actual value can be adopted to calculate the disaster impact coefficients. The calculation formula for disaster impact coefficients of seriously affected sectors are as follows:

$$\mathrm{DIC}_{\mathrm{sec},k} = \frac{\mathrm{SEC}_k - \mathrm{FSEC}_k}{\mathrm{FSEC}_k} \times 100\%. \tag{9}$$

In the formula, $\mathrm{DIC}_{\mathrm{sec},k}$ represents the percentage change in the output value of the seriously affected sectors when they are affected by the epidemic, including wholesale and retail sector, transportation sector, accommodation and catering sector, and leasing and business services sector; SEC_k represents the actual output value of the seriously affected sectors in 2020; FSEC_k represents the predicted output value of the seriously affected sectors in 2020 if the epidemic did not occur. It can be calculated that when affected by the COVID-19 epidemic, the percentage changes of the output value of wholesale and retail sector, transportation sector, accommodation and catering sector, and leasing and business services sector are −12.87 %, −11.5%, −20.16 %, and −20.30 %, respectively.

4.2. Impact on Labor Force

The epidemic can also lead to a decrease in labor supply and labor force participation. First, by 0:00 am on December 31, 2020, in China, there were 87,071 confirmed cases, 279 suspected cases, and 4,634 deaths, with a mortality rate of 5.3%. Second, the time of returning to work has been delayed throughout the country, and most enterprises delaying for one week and the time of returning to work of some blockaded cities are to be determined. Since the deaths of the epidemic are distributed in different time periods in 2020, the time of reduction in labor force participation they cause is generally not a full year, thus we assume that the average lost time caused by death is half a year. And, we assume that half of the suspected cases will be confirmed, the mortality rate of confirmed cases is 5.3%. The remaining cases, which did not result in death but required treatment or isolation, are assumed to be one month late for work. In addition, the national labor supply time is reduced by one week.

In this article, the cumulative time of the labor force affected by or delayed by the epidemic not being able to work is used as the basis for calculating the impact coefficient of the labor force. First, based on the number of employed populations in China from 2000 to 2019, the ARMA model is constructed to predict the total employed population in China in 2020 under normal circumstances of no epidemic[2]. Second, the total working hours of the labor force and the employment situation of the labor force affected by the outbreak are calculated, including death, treatment and delay. Finally, the percentage of the labor force affected by the outbreak is calculated based on the simulation results. The equation is as follows:

$$\mathrm{DIC}_{\mathrm{ls}} = \frac{\sum \mathrm{LS}^{\mathrm{affect},k} \times \mathrm{Time}^{\mathrm{affect},k}}{\mathrm{LS}^{\mathrm{total}} \times \mathrm{FT}} \times 100\%. \tag{10}$$

In the equation, $\mathrm{DIC}_{\mathrm{ls}}$ represents the percentage of the labor force affected by the epidemic, $\mathrm{LS}^{\mathrm{affect,k}}$ represents the population affected by the epidemic, $\mathrm{LS}_t{}^{\mathrm{total}}$ represents the total number of labor force, $\mathrm{Time}_t{}^{\mathrm{affect},k}$ represents the number of days that labor cannot participate in work due to the epidemic, and FT represents the total working days in a year. Through calculation, it can be obtained that by 00:00 am on December 31, 2020, the time of decreased labor force participation caused by the death of patients is $(87{,}071 + 279 \div 2) \times 5.3\% \times 0.5 \times (52 \times 5)$, that is, 600,800 days; The time for reduction of labor force participation due to patient rehabilitation or isolation is $(87{,}071 + 279 \div 2) \times 94.7\% \times (4 \times 5)$, that is, 1,651,767 days; The time of reduction in labor force participation caused by the delay in resuming work is $(508{,}628{,}900 - 77{,}041) \times (1 \times 5)$, that is,

[1]Data sources: the website of the National Bureau of Statistics of China. https://data.stats.gov.cn/easyquery.htm?cn=B01

[2]Data sources: the website of the National Bureau of Statistics of China. https://data.stats.gov.cn/easyquery.htm?cn=C01

2,542,759,295 days. Therefore, the impact coefficient of the epidemic on the labor force is set at −1.85%.

4.3. Impact on International Trade

The goods of China's imports and exports mainly involve the agriculture sector, mining sector, and manufacturing sector. To focus on the loss assessment of the COVID-19 epidemic, we assume that China's economy follows the historical trend between 2000 and 2019, and the trade disturbance is mainly caused by the disaster. Specifically, the calculation of disaster impact coefficients in imports and exports is as follows. First, the ARMA model is conducted on the trade data from 2000 to 2019 to predict the counterfactual volumes of imports and exports in various sectors in China in 2020, assuming that the COVID-19 epidemic did not occur[3]. Second, the difference between the real trade value and the counterfactual value of imports and exports can be obtained. Finally, the difference of various sectors can be adopted to calculate the disaster impact coefficients in imports and exports. The calculation formulas of disaster impact coefficients in imports and exports are as follows:

$$\mathrm{DIC}_{\mathrm{im},k} = \frac{\mathrm{IM}_k - \mathrm{FIM}_k}{\mathrm{FIM}_k} \times 100\%, \tag{11}$$

$$\mathrm{DIC}_{\mathrm{ex},k} = \frac{\mathrm{EX}_k - \mathrm{FEX}_k}{\mathrm{FEX}_k} \times 100\%. \tag{12}$$

In the equation, $\mathrm{DIC}_{\mathrm{im},k}$ and $\mathrm{DIC}_{\mathrm{ex},k}$ are the percentage change in the imports and exports of various sectors when they are affected by disasters; IM_k and EX_k are actual imports and exports of various sectors in 2020; FIM_k and FEX_k are the predicted imports and exports when the disaster does not occur. It can be calculated that when affected by COVID-19 epidemic, the percentage changes of imports are −9.36% in agriculture sector, −25.20% in mining sector, and −6.15% in manufacturing sector. And also, the percentage changes of exports are −7.67% in agriculture sector, −28.04% in a mining sector, and 2.31% in manufacturing sector. It can be seen that under the influence of the epidemic, China's manufacturing exports in 2020 have increased compared with normal economic conditions. This is mainly because the global epidemic is still spreading. China has become the world's largest supplier of antiepidemic materials. The increase in global demand for pharmaceutical products in the short term has driven the increase in China's manufacturing exports. The results of ADF test are shown in Table III. The regression results of ARMA model are shown in Table IV.

[3]Data sources: the website of General Administration of Customs of the People's Republic of China. http://www.customs.gov.cn/customs/302249/zfxxgk/2799825/302274/302277/3227050/index.html

5. ANALYSIS OF SIMULATION RESULTS

5.1. The Impact of the COVID-19 Epidemic on Industrial Sectors and Economic System of China

Through the development of the SAM Table in China in 2017, the CGE model is adopted to simulate the impact of the COVID-19 epidemic on China's economic system. When the epidemic disaster occurs, the economic system is unbalanced, and the production and consumption activities of economic entities as well as the supply and demand of economic elements will change. In addition, the disturbance effect of the epidemic spreads downstream along the supply chain to various sectors; on the other hand, it also causes the abnormal demand of the upstream economic entities (Haimes et al., 2005; Rose, 2004). According to the above assumptions and the model designed in the third part, and the calculation results of the fourth part, the GAMES programming is used to calculate the disaster loss rate and loss value of each industry sector, as shown in Table V below.

In the CGE model, labor input is allocated according to the input–output relationship between sectors, and the labor losses caused by the epidemic reduced the labor input of each production sector. The COVID-19 epidemic has a certain impact on the labor force and consumer demand in various sectors of China's economic system, and further causes the economic indicators of the whole region to change to different degrees through the correlation effect among various sectors. According to the simulation results, the output value of each industrial sector and the socioeconomic system is declining.

In terms of total output, in 2020, the COVID-19 epidemic has caused losses of \$75.8713 billion, \$1354.534 billion, \$101.2378 billion, \$125.0099 billion, and \$ −751.7825 billion in China's agriculture, industry, construction, transportation and service industries, respectively. The loss of the social total output value is \$ −2408.4355 billion, and the loss rate of the total output of China in 2020 is −8.534%, accounting for 19.45% of the GDP in 2019. From the

Table III. Results of Series Stationarity Test

Series	ADF Test	*p*-Value	Result	Series	ADF Test	*p*-Value	Result
ln(wholesale and retail sector)	−2.4912	0.3276	Nonstationary	dln(wholesale and retail sector)	−5.5335	0.0000	Stationary
ln(transportation sector)	−2.4912	0.3276	Nonstationary	dln(transportation sector)	−4.7051	0.0094	Stationary
ln(accommodation and catering sector)	−1.6937	0.7117	Nonstationary	dln (accommodation and catering sector)	−4.3790	0.0153	Stationary
ln(leasing and business services)	−2.4176	0.1559	Nonstationary	dln (leasing and business services)	−8.1179	0.0000	Stationary
ln(labor force)	−1.4411	0.5405	Nonstationary	dln(labor force)	−3.7170	0.0133	Stationary
ln(exports of agriculture)	−1.4604	0.5311	Nonstationary	dln(exports of agriculture)	−4.0541	0.0067	Stationary
ln(exports of mining sector)	−1.6265	0.4504	Nonstationary	dln(exports of mining sector)	−5.2680	0.0006	Stationary
ln(exports of manufacturing sector)	−2.7132	0.0901	Nonstationary	dln(exports of manufacturing sector)	−2.9652	0.0576	Stationary
imports of agriculture	0.7266	0.9894	Nonstationary	ln(imports of agriculture)	−3.0721	0.0494	Stationary
ln(imports of mining sector)	−1.5233	0.5005	Nonstationary	dln(imports of mining sector)	−3.4942	0.0207	Stationary
imports of manufacturing sector	−1.6876	0.4212	Nonstationary	ln(imports of manufacturing sector)	−3.0478	0.0483	Stationary

perspective of comprehensive loss rates in the output of sectors, leasing and business services (−13.3393%), finance (−13.0763%), production and supply of electricity, gas and water (−11.1546%), the mining sector (−10.8399%), accommodation and catering sector (−10.4060%), real estate (−10.3329%), health and social work (−10.2400%), transportation sector (−9.7518%), manufacturing sector (−9.4566%), and education (−8.3670%) are the 10 most affected sectors.

From the perspective of comprehensive losses, manufacturing sector ($1192.5745 billion), finance ($154.2031 billion), wholesale and retail trade ($125.0099 billion), leasing and business services ($119.7293 billion), construction sector ($101.2378 billion), real estate ($101.0719 billion), production and supply of electricity, gas and water ($88.5377 billion), transportation sector ($83.6274 billion), agriculture ($75.8713 billion), and the mining sector ($73.4218 billion) are the 10 most affected industries, and the total losses of these ten sectors are $2115.2848 billion, account for 87.8282% of the total output losses.

Both in terms of comprehensive economic loss rates and absolute economic losses, manufacturing sector (−9.4566%, $1192.5745 billion), finance (−13.0763%, $154.2031 billion), leasing and business services (−13.3393%, $119.7293 billion), real estate (−10.3329%, $101.0719 billion), production and supply of electricity, gas and water (−11.1546%, $88.5377 billion), transportation sector (−9.7518%, $83.6274 billion), and mining sector (−10.8399%, $73.4218 billion) are ranked in the top 10. This indicates that these sectors rely on basic elements such as transportation and labor to a greater degree, and are deeply affected by the epidemic.

In addition, the impact of the epidemic on China's GDP growth rate is also one of the important issues of concern. Given that China's GDP growth rate is 6.1% in 2019, assuming that China's GDP growth rate in 2020 is likely to be 4–8% in the absence of COVID-19 shocks. Then, according to the economic loss calculated in Table V, the counterfactual GDP growth rate and GDP in 2020 can be forecasted in Table VI.

From Table VI, for the COVID-19, the predicted GDP growth rate in our paper in 2020 will be −8.7678 to −12.7678%. There is no doubt that this is the first negative growth since China's reform and opening-up era (1978). Of course, this is only a static forecast without considering the retaliatory economic growth after the COVID-19. In addition, China's economic

Table IV. Regression Results of the ARMA Model

Variable	d(log(Y)) Wholesale and Retail Sector	d(log(Y)) Transportation Sector	d(log(Y)) Accommodation and Catering Industry Sector	d(log(Y)) Leasing and Business Services	d(log(Y)) Labor Force	d(log(Y)) Exports of Agriculture	d(log(Y)) Exports of Mining Sector	d(log(Y)) Exports of Manufacturing Sector	log(Y) Imports of Agriculture	d(log(Y)) Imports of Mining Sector	log(Y) Imports of Manufacturing Sector
AR(1)	0.471	0.1803	0.5621*	−0.4972**	−0.46	−0.5759**	0.4349*	−0.8725***	0.9422***	0.1789	0.5027**
	(0.121)	(0.5900)	(0.0928)	(0.0308)	(0.119)	(0.0280)	(0.0829)	(0.0000)	(0.0000)	(0.5528)	(0.0192)
AR(2)	−0.748***	−0.0632	0.0223	−0.6434***	−0.682**					−0.4618	
	(0.003)	(0.7628)	(0.9269)	(0.0030)	(0.015)					(0.1106)	
AR(3)	0.286				0.161						
	(0.283)				(0.548)						
MA(1)	−0.407***	−0.9538***	−0.9997***	0.7810***	0.959***	0.9245***	−0.9587***	1.2729***		−0.2095	−0.4814*
	(0.008)	(0.0000)	(0.0027)	(0.0086)	(0.001)	(0.0000)	(0.0000)	(0.0009)		(0.3183)	(0.0630)
MA(2)	0.937***	−0.9761***			0.947***			0.2967		0.9226***	−0.5178**
	(0.000)	(0.0002)			(0.000)			(0.3308)		(0.0000)	(0.0428)
MA(3)		0.9542***									
		(0.0000)									
Constant	0.119***	0.0766***	0.0796***	0.1549***	−0.021***	0.0561***	0.0368***	0.0791*	9.7071***	0.1324	0.0274
	(0.000)	(0.0000)	(0.0000)	(0.0000)	(0.008)	(0.0087)	(0.0254)	(0.0758)	(0.0000)	(0.1378)	(0.1657)
N	20	20	20	20	19	20	20	20	20	20	20
F	1.965	8.8649	2.3962	9.7394	2.503	1.1770	2.8473	0.9254	338.5291	1.1972	6.9619
R^2_a	0.243	0.7239	0.2183	0.6860	0.349	0.0204	0.1785	0.1655	0.9493	0.0470	0.5127

Note: (1) The expression of the AR(p) model is: $Y_t = \beta_1 Y_{t-1} + \beta_2 Y_{t-2} + \cdots + \beta_p Y_{t-p} + \varepsilon_t$, and p is the order of the AR model, $\beta_i (i = 1, 2, \ldots, p)$ is the undetermined coefficient of the model, ε_t is the error, and Y_t is the stationary sequence. (2) The expression of the MA(q) model is: $Y_t = \varepsilon_t + \alpha_1 \varepsilon_{t-1} + \alpha_2 \varepsilon_{t-2} + \cdots + \alpha_q \varepsilon_{t-q}$, and q is the order of the MA model, $\alpha_i (i = 1, 2, \ldots, q)$is the undetermined coefficient of the model, ε_t is the error, and Y_t is the stationary sequence. (3) Select the optimal lag order by comparing AIC and SC criteria. (4) All the residual sequences of the model have passed the white noise test. (5) Time sequence is from 2000 to 2018; (6) *, ** and *** represent significance levels of 10%, 5%, and 1% respectively.

Table V. Impact of COVID-19 on Various Sectors in China in 2020

Industrial Sector	Loss Rate (%)	Loss Value (Billion dollar)
Agriculture	−5.5117%	−75.8713
Mining sector	−10.8399%	−73.4218
Manufacturing sector	−9.4566%	−1192.5745
Production and supply of electricity, gas and water	−11.1546%	−88.5377
Construction sector	−3.54%	−101.2378
Transportation sector	−5.7727%	−83.6274
Wholesale and retail sector	−9.7518%	−125.0099
Accommodation and catering sector	−10.406%	−49.5106
Financial sector	−13.0763%	−154.2031
Real estate	−10.3329%	−101.0719
Information transfer, software and information technology services	−7.3393%	−51.8595
Leasing and business services	−13.3393%	−119.7293
Scientific research and technical services	−3.9025%	−24.9009
Citizen services, repairs and other services	−6.5377%	−22.0313
Water, environment and public facilities management	−4.3519%	−5.0334
Education	−8.367%	−38.4536
Health and social work	−10.24%	−53.1432
Culture, sports and entertainment	−5.3014%	−9.0854
Public administration, social security and social organization	−5.634%	−39.1328
Total output	−8.534%	−2408.4355

Note: (1) The loss rate in the table is loss value calculated based on CGE divided by the total output value of each sector in the annual input-output table in 2017. (2) In this table, 1$ = 7 RMB.

growth in 2020 has already shown a positive growth situation in reality, it is due to the strong control measures taken by the Chinese government, which have basically controlled the spread of the epidemic.

5.2. Uncertainty Discussion

In this article, the CGE model is used to quantitatively evaluate the economic losses caused by COVID-19 in China, and there are still some uncertainties in the study that merit further discussion, as follows:

(1) Uncertainty due to incomplete data collection. In the case study, because the epidemic is still developing, the data epidemic in various sectors is incomplete, and can only be observed through the official data. If the data of each industry sector are sufficient, and the direct impact of disasters on all aspects are included in the model for comprehensive assessment, the simulation results will be completer and more accurate.

(2) Uncertainty caused by the structural characteristics of the CGE model. Although the CGE model can take into account postdisaster production elasticity, price elasticity, and other issues, reflecting the resilience of the economy (Koks et al., 2016). However, the CGE model itself also has some inevitable defects, such as the assumption of optimal behavior of economic subjects in the model construction and the elastic setting in the model equation, which often leads to extreme changes in price and quantity, and the comprehensive impact of disasters on the economy may be underestimated (Rose, 2004).

(3) Uncertainty caused by not including restoration measures. In the face of the severe impact of COVID-19, in order to promote economic development, government departments adopted some policy measures to protect severely damaged sectors, used equipment, or means to update production technology and strengthened the regulation or protection of production resources. If those measures for promoting the recovery of sectors can be taken into account in the analysis, the model constructed will be more in line with reality.

5.3. Sensitivity Analysis

Since the CGE model needs to set many parameters, some of which need to be assumed based on empirical judgment, which may affect the reliability of CGE model results, it is necessary to conduct a

Table VI. Forecasted Economic Growth Rate in 2020

Expected Growth Rate in 2020	GDP in 2019 (Billion dollar) (1)	Expected GDP in 2020 (Billion dollar) (2)	Evaluated Economic Loss in 2020 (Billion dollar) (3)	Forecasted GDP in 2020 (Billion dollar) (4)	Forecasted GDP Growth Rate in 2020 (5)
0.04	14,363.4848	14,938.02419	2,408.4355	12,529.5887	−0.127677659
0.05	14,363.4848	15,081.65904	2,408.4355	12,673.2235	−0.117677659
0.06	14,363.4848	15,225.29389	2,408.4355	12,816.8584	−0.107677659
0.07	14,363.4848	15,368.92874	2,408.4355	12,960.4932	−0.097677659
0.08	14,363.4848	15,512.56358	2,408.4355	13,104.1281	−0.087677659
Average	14,363.4848	15,512.56358	2,408.4355	12,816.8584	−0.107677659

Note: (1) In 2019, 1\$ = 6.8985 RMB. (2) Expected GDP in 2020 = GDP in 2019 × (1+Expected GDP Growth rate in 2020). (3) Evaluated economic loss in 2020 come from last row of Table V. (4) Forecasted GDP in 2020 = Expected GDP in 2020–Evaluated economic loss in 2020. (5) Forecasted GDP Growth Rate in 2020 = (Forecasted GDP in 2020- GDP in 2019) / GDP in 2019.

sensitivity analysis of these parameters of the model. This article refers to the method of Mahmood and Marpaung (2014) to change the elastic parameters of the production function of the model and conduct sensitivity analysis. The relevant elastic parameters are respectively set as high elasticity (increase by 30%) and low elasticity (decrease by 30%), and the new elasticity value is used for simulation to obtain the change rate of economic indicators. The sensitivity test results showed that the fluctuation of elastic parameters by 30% had an acceptable effect on the loss, the direction of the variables was the same as before. That is, the difference in the research results was not significant. Therefore, the simulation results of the model are highly reliable. The sensitivity assessment results are shown in table VII.

6. CONCLUSION AND PROSPECT

In this article, we used the CGE model to analyze the disaster scenario and assess the comprehensive economic losses of the COVID-19 epidemic in China based on the available data. The direct impact, comprehensive economic loss rates, and absolute economic losses of industries are calculated and the GDP growth rate in 2020 is also predicted. In addition, the theoretical framework and scenario setting of loss assessment, and calculation procedures based on the CGE model constructed in this article also can be applied to related economic fluctuations (e.g., stock market crash), cultural shocks (e.g., after the reform and opening up, China or Vietnam suffered from the culture shock from developed countries), and policy comparison (e.g., tax laws and rate changes) studies. According to current calculations, China's GDP growth rate in 2020 may be negative without any emergency measures or recovery strategies. To reduce the negative impact further caused by the COVID-19 epidemic disaster, we propose the following suggestions:

(1) Disaster recovery for key sectors such as the labor force, transportation industry, and service industry should be enhanced. Employment, transport, and services are the sectors directly impacted by the COVID-19 disaster, and the direct impact on these sectors can be transmitted to other sectors, resulting in a huge negative impact. Employment and service sectors are related to people's livelihood and the transportation industry is the major artery of the economic system. These

Table VII. Sensitivity Test of Elastic Parameters of Production Function

Industrial Sector	Elastic Parameters of the Model		
	Original Elasticity Parameter Value	High Elasticity (Increase by 30%)	Low Elasticity (Decrease by 30%)
Agriculture	−5.5117%	−5.543%	−5.1986%
Mining sector	−10.8399%	−11.2877%	−10.5844%
Manufacturing sector	−9.4566%	−9.653%	−9.3466%
Production and supply of electricity, gas and water	−11.1546%	−12.705%	−10.8546%
Construction sector	−3.54%	−3.7230%	−3.1830%
Transportation sector	−5.7727%	−5.9300%	−5.3515%
Wholesale and retail sector	−9.7518%	−10.2352%	−9.4493%
Accommodation and catering sector	−10.406%	−11.0499%	−10.1467%
Financial sector	−13.0763%	−13.3028%	−12.6763%
Real estate	−10.3329%	−10.5233%	−10.1421%
Information transfer, software and information technology services	−7.3393%	−7.7163%	−7.2526%
Leasing and business services	−13.3393%	−13.9213%	−12.5809%
Scientific research and technical services	−3.9025%	−4.2161%	−3.4530%
Citizen services, repairs and other services	−6.5377%	−6.7103%	−6.2776%
Water, environment and public facilities management	−4.3519%	−4.4208%	−4.1017%
Education	−8.367%	−8.8252%	−8.6183%
Health and social work	−10.24%	−10.4076%	−9.7363%
Culture, sports and entertainment	−5.3014%	−5.3918%	−5.1466%
Public administration, social security and social organization	−5.634%	−5.7522%	−5.2057%
Total output	−8.534%	−8.8045%	−8.2985%

industries play an extremely important role in ensuring life safety, maintaining economic stability, and promoting people's livelihood. Therefore, the current important work is to cut off the "fuse" of the disaster impact as soon as possible and reduce the comprehensive economic losses as far as possible. For example, take multiple measures to help the labor force return to work as soon as possible. In major epidemic areas and megacities, we should explore flexible working mechanisms, shift peak commuting, develop online and intelligent offices, avoid cross-infection of people, resume production as soon as possible, and reduce the negative impact of disasters on the economic system. Second, strengthen countercyclical regulations. For urban agglomerations in the metropolitan area where the population flows into, appropriate infrastructure construction can be carried out, and investment in basic industries such as transportation, education, and medical care can be increased to stimulate demand, stabilize employment, improve infrastructure, and improve the potential economic growth.

(2) Disaster emergency rescue work in highly sensitive sectors should be carried out. In this article, we show that sectors such as the manufacturing sector, finance, leasing and business services, real estate, production and supply of electricity, gas and water, transportation sector, and mining sector are the most affected sectors. In such a special period, on the one hand, the government can optimize the way of tax reduction and fee reduction, shift from the current VAT tax reduction pattern to lower social security rates and corporate income tax rates, so as to help enterprises quickly resume production, especially to reduce the survival pressure of small and medium-sized enterprises.

(3) In the long run, precise measures to strengthen the refined management of disaster risk with big data resources and means should be taken. The supporting role of informatization should be fully utilized, and technologies such as the Internet of Things, cloud computing, and big data computing platforms should also be fully applied to find the source of disasters and susceptible individuals, and form a state of unified dispatch of regional epidemic prevention and control (Wu, Cao, Tan, & Xu, 2020). For example, in the case of the severe shortage of medical resources, the production capacity, output, and inventory of various key material companies could be collected, statistics and unified scheduling and these resources should be supplied to the severely affected areas preferentially. Also, in the emergency process, the optimal treatment plan should be matched in time according to the medical resource conditions and traffic conditions, including the dispatch of ambulances, the extraction of patients' personal information, and the selection of medical resources to avoid cross-infection and delays in treatment.

Finally, some uncertainties exist in this article, which we should note and conduct further investigations in the future. First, there is incomplete data collection about direct losses. In fact, this epidemic disaster has caused a huge negative impact on China's various sectors, especially the psychological damage caused by the disaster is even more incalculable. In addition, 19 sectors are divided in the paper, and the industry sectors are very aggregated. In the future, methods such as investigation and interview, case analysis and cost-benefit analysis can be used to evaluate these direct economic losses. Second, from the perspective of model construction, this paper only adopts the static CGE model because of the rapid outbreak and short time of the epidemic. As the epidemic disaster continues, the dynamic multi-region CGE model can be used to study the negative effects in different periods and regions (Giesecke et al., 2012). Third, it is difficult to accurately separate the influence of other factors, although there are many factors affecting the social and economic system in China during the outbreak of COVID-19 in 2020, including the impact of COVID-19 in other countries on China, the background of the global economic slowdown, and the periodicity of economic activity, etc.

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