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FACED WITH COVID-19, IS THERE A MARKET FAILURE IN PUBLIC HEALTH, AND SHOULD THE GOVERNMENT ADOPT A FREE TREATMENT POLICY? ----EVIDENCE FROM CHINA

Abstract. *This paper uses text mining to model 21,403 Chinese news items related to the free treatment of the new coronavirus disease (COVID-19) and constructs China's free treatment policy index, which overcomes the difficulty a short data time span poses to in-depth analysis on the economic impact of public health emergencies. In addition, the causal network model is selected to study 52 listed companies in the health industry to test whether there is market failure in the field of public health and the effect of intervention measures. The study found that if the government only relies on market regulation and monetary policy (such as interest rate policy and exchange rate policy), market failure will emerge in the public health sector, yielding an increase in the number of infected people. Therefore, on the basis of market self-regulation, the government should use not only monetary policy but also free treatment policy to make up for the market failure in the public health sector, control the spread of COVID-19 and promote the development of the health industry.*

Keywords*: new coronavirus; free treatment; monetary policy; fiscal policy; causal network.*

JEL Classification: C81; H41; H51; I11; I18

1. Introduction

Since the outbreak of the new coronavirus disease (COVID-19), there have been more than 10 million confirmed cases and more than 500,000 deaths worldwide. COVID-19 has become a large-scale public health incident across the world, causing people to worry about the upcoming economic crisis and recession (Wang et al., 2020). In general, the government have implemented macro interventions to compensate for market failures, for instance, countercyclical adjustments mainly based on monetary and fiscal policies, by increasing government input to boost the effective demand and promote economic recovery.

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However, public policies, such as social distance, self-isolation, and travel restrictions, have led to a reduction in the labor force in all economic sectors and caused the loss of many jobs (Maria et al., 2020).

Market failure means that the optimal allocation of resources cannot be achieved through market allocation. The literature on market failure can be divided into the following categories. First, some scholars believe that the market failure of agriculture is due to consumption externalities and production misallocation (Shenoy, 2017). Second, many scholars believe that capital market failures arising because of informational and institutional frictions prevent individuals and economies from reaching their full potential and can lead to poverty traps (Aney et al., 2016). Third, it is believed that the market failure regarding energy and the environment is due to imperfect information, coordination failure in complementary markets and the improper crafting of environmental policy (Shi and Variam, 2017). Fourth, some scholars provide a theoretical background that justifies government intervention or patronage in innovation. Government subsidies can successfully address market failure in private research and development (Choi and Lee, 2017). Many scholars believe that the market failure of innovation is due to negative externalities (Frank, 2016; Chen, 2016; Cherry et al., 2017; Lorenczik, 2019).

In the early literature investigating the economic impact of public emergencies, such as natural disasters, major disasters, and public health events, scholars often used intervention models, case study methods, event research methods, natural experiment methods and other methods due to the difficulty of obtaining macroeconomic data statistics and the low sample frequency. Ragin and Halek (2016) find that catastrophic impact is expected to increase industry's net income, and the most direct beneficiaries are securities companies. Deryugina et al. (2018) found that Hurricane Katrina had a great and lasting impact on people's lives but had little impact on employment and income. Boehm et al. (2019) used enterprise-level micro data to discuss the 2011 Tōhoku earthquake as an exogenous shock and explore its impact on the international trade industry chain. Lanfear et al. (2019) studied the strong anomalous effects of hurricanes landing in the United States on stock returns and illiquidity and found that the returns to high-momentum stocks suffer a negative impact that is one order of magnitude greater than the impact on other stocks. Mirza et al. (2020) found that at various stages of the development of COVID-19, most European investment funds faced pressure. Goodell and Huynh (2020) evaluated the reactions of various industries in the United States to COVID-19-related breaking news announcements and analyzed the degree of investor attention to COVID-19. Hsiang et al. (2020) found that if no policy action is taken, the early infection of COVID-19 shows an exponential growth rate, and anti-infection policies greatly slow this growth.

With the continuous development of modern econometric methods, scholars have continued to propose new methods to analyze the impact of public emergencies on the economy.

Aruník and Křehlík (2018) introduced a framework based on the variance decomposition spectrum to measure the connectivity between financial variables. They found that when connectivity is at a high frequency, shocks have an impact in the short term. Galariotis et al. (2018) constructed an expectation/sentiment indicator. They found that the conventional monetary policy of the European Central Bank has a positive and significant impact on the economic expectations of the core countries of the euro area. Bai et al. (2019) found that embedding disasters in a general equilibrium model with heterogeneous firms would result in strong nonlinearity in the pricing kernel, which would help explain the failure of consumer capital asset pricing model . Runge et al. (2019) combined complex networks with causal analysis to propose a causal network model (PCMCI), which combines the linear or nonlinear conditional independence test with the causal discovery algorithm to estimate causal networks and quantifies their strength from large-scale time series data sets.

To control the spread of COVID-19, in addition to the above public policies, China has implemented free treatment of COVID-19 using fiscal policy. Therefore, in the context of the rapid global spread of COVID-19, it is of great academic value and practical significance to investigate the impact of public policy on COVID-19. That is, from the perspective of economics, we study the impact size and transmission path of public policies in the prevention of the spread of COVID-19 and the development of the health industry to test whether there is market failure in the field of public health and to observe the effect of adopting these public policies.

The rest of the paper is organized as follows. The methods is introduced in Section 2. We present the empirical results in Section 3. Section 4 concludes the paper. The discussion are described in Section 5.

2. Methods

In addition to inferring the directionality between two time series, the causal network model can distinguish the direct and indirect dependencies between multiple time series as well as the common driving factors, including inferring the causal network with time delay from multivariate time series. Runge et al. (2019) consider a complex system $Z_t = \left(Z_t^1, \ldots, Z_t^N\right)$ with time dependence, which can be expressed by the following equation:

$$Z_t^j = f_j\left(P\left(Z_t^j\right), \xi_t^j\right) \tag{1}$$

where f_j indicates that there are some potential nonlinear functional dependencies, and ξ_t^j indicates independent dynamic noise. The nodes Z_t^j in the time series represent variables with different lag times, and

$P\left(Z_t^j\right) \subset Z_t^- = \left(Z_{t-1}, Z_{t-2}, \ldots\right)$ represent the causal parents of the variables Z_t^j in the past for all N variables. If $Z_{t-\tau}^i \in P\left(Z_t^j\right)$, there is a causal relationship $Z_{t-\tau}^i \to Z_t^j$. Another way to define links is that $Z_{t-\tau}^i$ has nothing to do with the past of all variables Z_t^j without given conditions. This is defined as $Z_{t-\tau}^i \forall Z_t^j \left| Z_t^- \setminus \left\{Z_{t-\tau}^i\right\}\right.$, where $\forall$ indicates that there is no conditional independence. The goal of causal discovery is to estimate causal parents from time series data.

The causal network model (PCMCI) is also based on a conditionally independent framework $Z_t^j = \hat{P}^\alpha\left(Z_t^j\right)\beta$ and adapted to highly interdependent time series situations. The model includes two stages. The first stage is the PC1 conditional selection algorithm to identify the relevant conditions $\hat{P}\left(Z_t^j\right)$ of all time series variables $Z_t^j \in \left\{Z_t^1, \ldots, Z_t^N\right\}$. The second stage is the instantaneous conditional independence test (MCI) to test whether $Z_{t-\tau}^i \to Z_t^j$ has the following relationship:

$$MCI : Z_{t-\tau}^i \forall Z_t^j \left| \hat{P}\left(Z_t^j\right) \setminus \left\{Z_{t-\tau}^i\right\}, \hat{P}\left(Z_{t-\tau}^i\right)\right. \tag{2}$$

Therefore, the MCI condition includes the time condition changes for the parents of Z_t^j and the parents of $Z_{t-\tau}^i$. Two-stage detection has the following purpose: PC1 is a Markov set discovery algorithm based on the PC stabilization algorithm, which removes the irrelevant conditions for each of the N variables through an iterative independence test. Then, the MCI test solves the problem of false positive control in the case of highly correlated time series.

PCMCI can correctly detect the causal transmission structure with direction in the causal network, and the MCI test statistics give the causal strength and P value of each edge in the network. Therefore, we can accurately calculate the impact of a free treatment policy on the containment of COVID-19 and the development of the health industry.

The experimental data included the Shanghai Interbank Offered Rate (SHIBOR) and the Chinese Yuan to United States dollar exchange rate (CNYUSD) in the CSMAR database from January 16, 2020, to June 11, 2020, to reflect China's monetary policy. There are 52 listed companies in the health industry (industry code Q83) in the CSMAR database. Return on equity (ROE) is the ratio of the company's after tax profit divided by its net assets. This indicator reflects the level of return on shareholder equity and is used to measure the efficiency of a company's use of its own capital. The industry's ROE (ROE83) in this paper is used to evaluate the investment return of the industry. The higher the index value is, the higher the profit brought by industry investment. The total number of COVID-19 cases in China every day is selected from the Chinese Center for Disease Control and Prevention.

To obtain China's free treatment policy index, 21,403 Chinese news items related to the free treatment of COVID-19 were selected from the China InfoBank Database. We use a LDA model where each article is treated as a combination of topics, and each topic is treated as a combination of words. The LDA model is one of the most popular topic models in the natural language processing (NLP) literature because of its simplicity and because it has proven to classify text in much the same manner as humans would (Larsen et al., 2021).

First, for each day, the frequency with which each topic is represented in the newspaper that day is calculated. Let the corpus consist of N distinct documents, where $W = \sum_{n=1}^{N} W_n$ is the total number of words in all documents. R denotes the total number of latent topics, and V denotes the size of the vocabulary. Each document consists of a repeated choice of topics $Z_{\mathrm{n,w}}$ and words $K_{n,w}$. Let t be a term in V, and denote $P(\mathrm{t}|z=r)$ the mixture component, one for each topic, by $\Phi = \{\varphi_r\}_{r=1}^{R}$. Finally, let $P(z|d=n)$ define the topic mixture proportion for document n, with one proportion for each document $\Theta = \{\theta_n\}_{n=1}^{N}$. The goal of the algorithm is then to approximate the distribution:

$$P(Z|K;\alpha,\beta) = \frac{P(K,Z;\alpha,\beta)}{P(K;\alpha,\beta)} \tag{3}$$

using Gibbs simulations (Griffiths and Steyvers, 2004), where α and β are the (hyper) parameters controlling for the prior conjugate Dirichlet distributions for θ_n and φ_r, respectively.

Second, to determine whether the news is positive or negative, this paper constructs a symbol recognition data set based on the number of positive and negative words in the text. Through the mapping, the positive/negative words in the article are recognized in an external word list, the BosonNLP_sentiment_score Dictionary. The count process provides two statistics for each article, including the number of positive words and the number of negative words. Then, these statistics are normalized so that the observation of each article reflects the scores of positive and negative words.

$$Pos_{t,w^a} = \frac{positivewords}{totalwords} \qquad Neg_{t,w^a} = \frac{negativewords}{totalwords} \tag{4}$$

The overall mood of the article w^a, for $w^a = 1,\ldots,W_t^a$ at day t, is defined as:

$$Z_{t,w^a} = Pos_{t,w^a} - Neg_{t,w^a} \tag{5}$$

Using the Z_{t,w^a} statistic and the topic article described above, so we can get China's free treatment policy index (FTP). Free treatment policy include early detection, early diagnosis, early reporting, early isolation and early treatment. Figure 1 shows the daily changes of China's free treatment policy index.

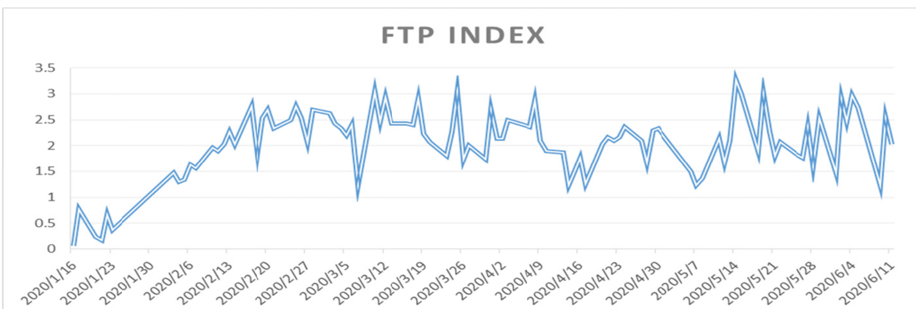

Figure 1. China's free treatment policy index during 2020.1.16-2020.6.11

3. Experimental results

In the experimental part, the causal network of the health industry is comparatively analyzed. The cause and effect of the market on the number of new coronavirus infections (COVID-19) and the health industry is tested first without the free treatment policy (FTP) and then with the free treatment policy.

3.1 Analysis of the market's impact on the health industry without the FTP

The purpose of this part is to conduct a causal network analysis of the health industry without the FTP to test whether there is market failure in the public health sector, if so, and to analyze the reasons for the failure. Table 1 shows the statistical results of the strength of the causality without the FTP.

Table 1. The results of Causal Network for ROE83 without the FTP

Test for COVID-19	H_0:CNYUSD(6) does not cause COVID-19(0)			
	Causality strength	*p*-values		
	0.255**	0.024		
Test for SHIBOR	H0: ROE83(5) does not cause SHIBOR(0)		H0: ROE83(6) does not cause SHIBOR(0)	
	Causality strength	*p*-values	Causality strength	*p*-values
	-0.609***	0.000	0.248**	0.029
Test for CNYUSD	H0: SHIBOR(6) does not cause CNYUSD(0)			
	Causality strength	*p*-values		
	-0.239**	0.035		

Note: ***, ** and * indicate significance at the 1%, 5% and 10% levels, respectively. The null hypothesis is that no causal relationship exists between the variables. Numbers in brackets indicate the number of lag periods.

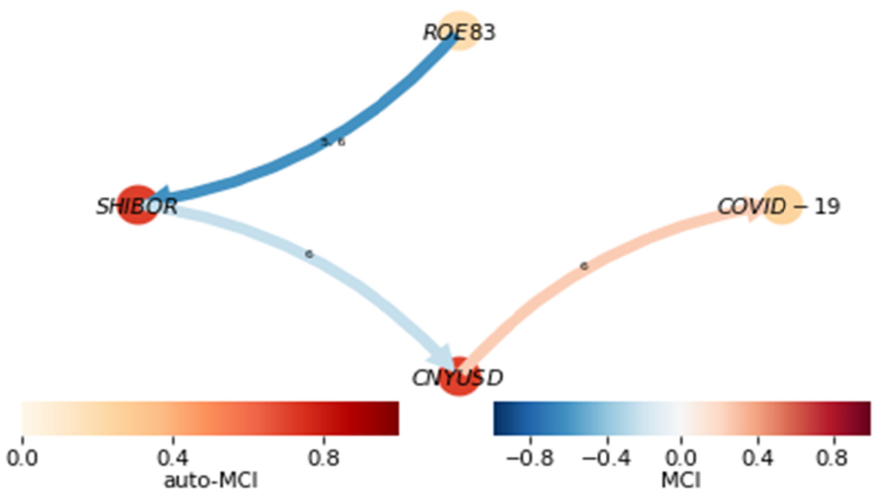

Figure2. ROE83 causal network without the FTP during 2020.1.16-2020.6.11

Figure 2 shows the causal network of the health industry ROE83 without the FTP from January 16, 2020, to June 11, 2020. The bar auto-MCI under the graph shows the influence of the midpoint in the causal network. MCI represents the strength of the causal effect of the edge in the causal network. The redder the color is, the stronger the positive causal effect is. The bluer the color is, the stronger the negative causal effect is. Combining the statistical results of causality strength in Table 1, we found that in the absence of the FTP, the health industry (ROE83) has no direct causal impact on COVID-19, and its direct causality strength is 0. When the exchange rate policy (CNYUSD) lags by six periods, it has a positive direct causal effect on COVID-19, and the causality strength is 0.255, indicating that the exchange rate policy can lead to the spread of COVID-19.

ROE83 has an indirect causal effect on COVID-19 through the interest rate policy (SHIBOR) and CNYUSD. When ROE83 lags 5 periods and 6 periods, there are positive and negative direct causal effects on SHIBOR, and the causality strength is -0.609 and 0.248, respectively. Overall, ROE83 has a greater negative causal effect on SHIBOR. When SHIBOR lags 6 periods, it has a negative direct causal effect on CNYUSD, and the causality strength is -0.239. When CNYUSD lags 6 periods, it has a positive direct causal effect on COVID-19, and the causality strength is 0.255. Because there are both positive and negative causal effects in its causal transmission path, the indirect causal effect of ROE83 inhibiting the spread of COVID-19 is greatly weakened. The experimental results show that the market cannot effectively allocate resources to control COVID-19 by itself, and market failure has occurred in the public health sector.

3.2 Analysis of the impact of the market on the health industry with the FTP

The purpose of this part is to analyze the causal network of the health industry with the FTP and to test whether the FTP can make up for the market failure in public health. Table 2 shows the statistical results of causality strength with the FTP.

Table 2. The results of Causal Network for ROE83 with the FTP

Test for COVID-19	H_0: FTP(5) does not cause COVID-19(0)		H_0: CNYUSD(3) does not cause COVID-19(0)	
	Causality strength	*p*-values	Causality strength	*p*-values
	-0.228**	0.047	-0.203*	0.076
	H_0: CNYUSD(6) does not cause COVID19-(0)			
	Causality strength	*p*-values		
	0.199*	0.083		

Test for FTP	H_0: SHIBOR(0) does not cause FTP(0)			
	Causality strength	*p*-values		
	0.249**	0.027		
Test for SHIBOR	H0: ROE83(5) does not cause SHIBOR(0)		H0: ROE83(6) does not cause SHIBOR(0)	
	Causality strength	*p*-values	Causality strength	*p*-values
	-0.609***	0.000	0.248**	0.029
	H0: FTP(0) does not cause SHIBOR(0)			
	Causality strength	*p*-values		
	0.249**	0.027		
Test for CNYUSD	H0: SHIBOR(6) does not cause CNYUSD(0)			
	Causality strength	*p*-values		
	-0.216*	0.056		

Note: ***, ** and * indicate significance at the 1%, 5% and 10% levels, respectively. The null hypothesis is that no causal relationship exists between the variables. Numbers in brackets indicate the number of lag periods.

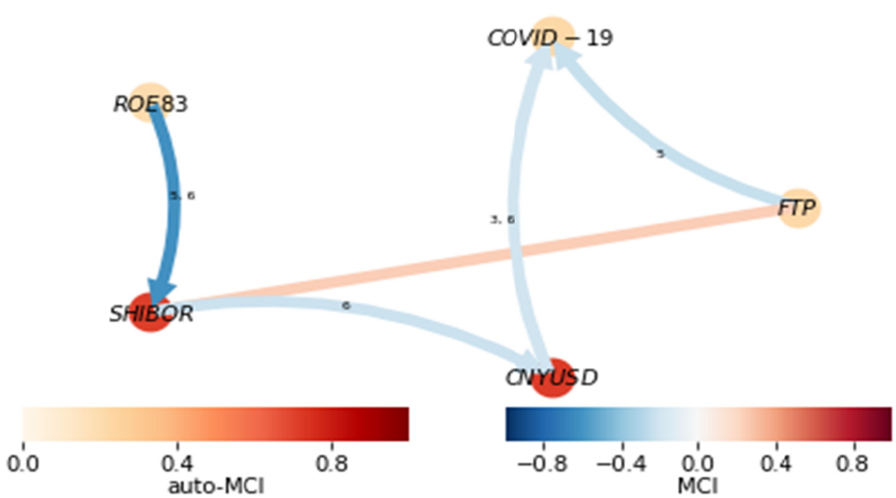

Figure3. ROE83 causal network with the FTP during 2020.1.16-2020.6.11

Figure 3 shows the causal network of the health industry ROE83 with the FTP from January 16, 2020, to June 11, 2020. Combined with the statistical results of causality strength in Table 2, we find that when the FTP lags for 5 periods, it has a direct negative causal effect on COVID-19, and its causality strength is -0.228. When CNYUSD lags by 3 periods and by 6 periods, there are positive and negative direct causal effects on COVID-19, and their causality strengths are -0.203 and 0.199, respectively. Overall, CNYUSD has a negative causal effect on COVID-19.

ROE83 has an indirect causal effect on COVID-19 through SHIBOR and CNYUSD. When ROE83 lags 5 periods and 6 periods, there are positive and negative direct causal effects on SHIBOR, and their causality strengths are -0.609 and 0.248, respectively. Overall, ROE83 has a greater negative causal effect on SHIBOR. When SHIBOR lags 6 periods, it has a negative direct causal effect on CNYUSD, and its causality strength is -0.216. CNYUSD has a greater negative direct causal effect on COVID-19. Therefore, in this causal path, ROE83 has a strong inhibitory effect on COVID-19. In the same way, SHIBOR also has a strong inhibitory effect on COVID-19 through this causal path.

ROE83 also has an indirect causal effect on COVID-19 through SHIBOR and the FTP. ROE83 has a direct negative causal effect on SHIBOR. For SHIBOR in period 0, there is a positive direct causal effect on the FTP, and the causality strength is 0.249. The FTP has a direct negative causal effect on COVID-19. Therefore, through this causal path, ROE83 has a strong inhibitory effect on the spread of COVID-19. For the same reason, SHIBOR also has a strong inhibitory effect on COVID-19 through this causal path.

The results show that the free treatment policy can make up for the market failure in the field of public health. The free treatment policy, with the cooperation of interest rate policy and exchange rate policy, has a strong inhibitory effect on COVID-19 in the short term and can effectively prevent the spread of COVID-19. Moreover, the implementation of the free treatment policy has no causal effect on the health industry, so there is no impact on the development of the health industry.

4. Conclusion

This paper uses the most recent causal network model to study the impact and transmission mechanism of China's free treatment policy on preventing the spread of COVID-19. This method overcomes the shortcomings of existing research methods (e.g., intervention model, case study method, event research method and natural experiment method) that analyze the economic impact of emergencies only before and after the event (Boehm et al., 2019). Based on 21,403 daily Chinese news items related to free treatment for COVID-19 from January 16, 2020, to June 11, 2020, a free treatment policy index was constructed by the LDA model, which overcomes the difficulty a short time span of data poses for the comprehensive analysis of economic shocks caused by public health emergencies (Galariotis et al.,2018). The study found that in the face of COVID-19, when only market regulation and monetary policy measures are adopted, market failure emerges in the field of public health. However, the implementation of a free treatment policy can inhibit the spread of COVID-19. Therefore, on the basis of market self-regulation, the government should use not only monetary policy but also fiscal policy to provide free treatment in order to make up for the market failure in the field of public health and control the spread of COVID-19 while promoting the development of the health industry.

5. Discussion

In the research in the field of public emergencies, there are three main questions that need to be answered. First, due to the short duration of such events and the relatively short time span of macro data, most of the existing literature analyzes the economic impact of natural disasters, such as earthquakes and hurricanes, but pays less attention to major public health events (Marcellino and Sivec, 2016). Traditional methods often cannot comprehensively analyze economic shocks due to data constraints (Galariotis et al., 2018). Thus, how to use text mining to transform unstructured data into time series data to compensate for the lack of macro data is the first question.

Second, when analyzing the economic impact of public emergencies, most studies only perform comparative analysis before and after the event, and there is little comprehensive analysis on the economic impact of the emergency itself (Boehm et al., 2019). Did the COVID-19 epidemic cause market failure in the public health sector? That is, whether the market itself can control the spread of the virus is the second question.

Third, if the public's understanding of policy actions is increasing, such as through news reports, then such communications should be seen as a way for policies to change the growth of infections, and these potential impacts represent an important issue for investigation (Hsiang et al., 2020). If there is a market failure in the field of public health, whether monetary and fiscal policies communicated through news reports can make up for market failures is the third question.

This article offers three innovations in response to the above questions. First, this paper uses the latent Dirichlet allocation (LDA) model to extract the topic of free treatment for COVID-19 from daily relevant Chinese news to construct a free treatment policy index for China. This index overcomes the difficulty the short data time span typically poses for in-depth analysis of the economic impact of public health emergencies. The economic significance of the index lies in the quantitative measurement of China's free treatment policy to test the effect of free treatment policy on COVID-19.

Second, we use the causal network model (PCMCI) to estimate the causal network from large-scale time series data sets and quantify its strength. Runge et al.'s (2019) experimental results show that the PCMCI exhibits more powerful causal detection capabilities than existing time series causal test methods, such as Lasso, PC algorithm or Granger causality and other nonlinear methods. It can better evaluate the interaction between the information set and multiple specific variables at the same time. Therefore, the causal network model is used to test whether there is market failure in the field of public health and the effect of remedial measures.

Third, due to data and methodological challenges, the existing literature rarely analyzes the effect of free treatment policy on the spread of COVID-19 and its impact on the health industry. This paper uses text mining and causal networks to overcome these problems and analyzes the impact and transmission mechanism of China's free treatment policy on the containment of COVID-19 and the development of the health industry. The study found that if we simply relied on market regulation and monetary policies (e.g., interest rate policy and exchange rate policy), market failure would occur in the field of public health, and the number of infections would increase. Therefore, on the basis of market self-regulation, in addition to monetary policies, the government needs to employ a free treatment policy to compensate for the market failure in the field of public health.

The root cause of the market failure in public health is due to the sector's attributes of public goods or quasi-public goods. Public goods refer to nonexclusive and noncompetitive products in the consumption process. Nonexclusivity means that once goods are produced, the producer cannot prevent those who do not pay from consuming the goods. While the health sector can technically do this kind of exclusion, the costs of such exclusion are higher than the benefits. Noncompetitiveness means that for the producer, one more or one less consumer does not affect the production cost; that is, the marginal consumption cost is zero. For consumers, as long as there is no congestion or overcrowding in the consumption of the public good, their consumption level will remain stable. Essentially, the production of public goods goes against market forces. Under purely market forces, producers will not actively produce public goods, resulting in an insufficient supply of public goods. In this way, the contradiction between the lag of public goods production and the needs of society and economic development is very strong. Therefore, market failure occurs in public health, and the market itself cannot control COVID-19 but will lead to an increase in COVID-19 cases.

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