Hindawi
Indoor Air
Volume 2023, Article ID 6031225, 12 pages
https://doi.org/10.1155/2023/6031225

Research Article

A Novel Approach towards Assessing the Impact of Air Quality and Major Public Health Emergencies on Light Industry: A Multiscale Investigation towards Improving the Risk Prevention System

Fang Su,[1] Nini Song,[2] Haiyang Shang,[3] and Shah Fahad[4]

[1]School of Economics and Management, Northwest University, Xi'an, Shaanxi, China
[2]School of Economics, Xian University of Finance and Economics, Xi'an, China
[3]School of Business, Northwest University of Political Science and Law, Xi'an, China
[4]School of Management, Hainan University, Haikou 570228, China

Correspondence should be addressed to Shah Fahad; shah.fahad@xjtu.edu.cn

Received 31 August 2023; Revised 9 November 2023; Accepted 16 November 2023; Published 30 November 2023

Academic Editor: Orish Ebere Orisakwe

Measuring the systemic impact of major public health emergencies on the light industry and preventing various uncertain future external risks have become the key challenges to ensuring the stability of the light industry. This paper takes the occurrence of major public health emergencies as the background and focuses on environmental issues such as air pollution and indoor air quality degradation during emergencies. And to explore the multiscale impact of major public health emergencies on the light industry, typical light industry subsectors, and light industry enterprises. The findings of our study reveal that major public health emergencies have a negative impact on the light industry, particularly in the form of a short-term decline in exports, which tends to converge in the long run. Further, it is also revealed that there is heterogeneity in the impact on environmentally sensitive industries, labor-intensive industries, and others. At the microfirm level, major public health emergencies have shown a negative effect, especially the recent pandemic, which has a longer duration and a wider reach. Through multiscale research, this paper provides policy suggestions to improve the macrogovernance mechanism and risk prevention system for the light industry.

1. Introduction

Since the 21st century, major public emergencies have erupted around the world, for example, the September 11 attacks in 2001, the SARS epidemic in 2003, the Indonesia tsunami in 2004, the Wenchuan earthquake in 2008, the Fukushima Daiichi Nuclear Disaster in 2011, the Ebola virus outbreak in West Africa in 2014, and the recent outbreak of COVID-19. These public emergencies, including social security, public health events, natural disasters, and accidents, pose a great challenge to global development [1].

In terms of social development, countries and regions affected by major public health emergencies usually face the loss of national property and residents' safety. In particular, the spread of the virus in the air poses a great threat to the life and health of the population. In terms of economic operation, it always has a severe impact on economic systems, squeezing both the demand and supply sides. The continuous negative impact on a country or the global economy further intensifies the risk of uncertainty in the macroeconomic internal and external environment and is highly likely to lead to a vicious circle. In terms of the ecological environment, to a certain extent, the widespread shutdown of work and production and the reduction of travel after an emergency may lead to an improvement in air quality. But more than that, the environmental problems arising from such emergencies and follow-ups are a serious threat to the stable development of a country or region.

Looking at all kinds of emergencies that have occurred in the world, the impact of public health emergencies on economic development is particularly prominent, which causes various industries to generally have a large shock [2]. Generally speaking, global and regional supply chains, industrial chains, and demand chains are at risk of disruption, especially those enterprises or industries at the end of the value chain [3]. Overall, under the impact of major public health emergencies in the past, the performance of the "light industry" is particularly complex [4]. Specifically, due to the risk of viruses spreading in the air, some light subindustries related to protective products, such as chemical product manufacturing and mask manufacturing, maintained a strong operating trend. Some industries with rigid support, such as food manufacturing, were less affected. While leather manufacturing, household appliance manufacturing, or other traditional industries tend to downturn development. In this context, how to respond effectively to sudden external shocks and prevent various uncertain external risks in the future has become the key to ensuring the smooth operation of the industry.

With the active response of governments, major public health emergencies can always be controlled in the short or long term [5], but this does not mean that research on the economic impact of major public health emergencies has lost value. Since the scale of economic development, market environment, and industrial structure of countries are vastly different from before, they may still face a variety of emergent risks in the future. And the economic impact and response measures of past emergencies can provide important reference values for similar situations [6]. In view of this, this paper takes China's case as an example to sort out the impact of major public health emergencies on the light industry at different levels. Then, the path of the multiscale impact of major public health emergencies on the light industry is systematically decoupled.

The contributions of this study are as follows: (1) This paper focuses on the light industry, a traditionally advantaged industry and important livelihood industry in China, and the light industry is more prominently affected by major public health emergencies. (2) In the context of complex and variable real systems, multiscale science is central to the problem of coherent nonlinearity and complexity. This paper systematically analyzes the multiscale impact of major public health emergencies on the light industry, based on the light industry, typical industry sectors, and microenterprises. (3) In terms of methodology, this paper adopts the time-varying parameter-stochastic volatility-vector autoregression (TVP-SV-VAR) model, which can take into account the sudden change characteristics of the light industry under external shocks, to quantify the overall impact of major public health emergencies on the light industry. And, in quantifying the impact of major public health emergencies on a typical subsector, this paper uses an improved hypothesis extraction method (HEM) to measure the general impact of exogenous shocks. In addition, to quantify the impact of major public health emergencies on firms, this paper uses the occurrence of major public health emergencies as an exogenous intervention and empirically tests the net effect using a difference-in-differences model (DID).

The remainder of this paper is organized as follows: Section 2 presents the literature review and theoretical background. Section 3 describes the methods and data sources. Section 4 reports the empirical results and the discussion. Section 5 concludes the research and offers suggestions for industry in response to emergency shocks.

2. Literature Review and Theoretical Analysis

2.1. Literature Review

2.1.1. Research on the Macroeconomic Impact of Major Public Health Emergencies. Major public health emergencies have received particular academic attention due to their complexity, devastation, and persistent effects [7]. On the other hand, based on the general rules of macroeconomic fluctuation theory, it is known that the occurrence of major public health emergencies often leads to lower output, reduced consumption, lower investment, restricted foreign trade, and impaired industrial development from both the supply and demand sides [8]. However, major public health emergencies have a high potential for secondary shocks to the economy as a result of intercountry transactions [9]. That is, when a major public health emergency occurs in a country or region, it first causes a shock to the national or regional economic system. Then, its impact on the production chain will be transmitted upstream and downstream through the global production network [10].

2.1.2. Research on the Industrial Impact of Major Public Health Emergencies. Some scholars have mainly focused on industry chain shocks during major public health emergencies [11]. The results show that major public health emergencies have a negative impact on the industry chain and stimulate the restructuring of global and regional value chains [12]. Then, the impact of major public health emergencies on the tourism, entertainment, accommodation, and catering industries was analyzed using the event study methodology (ESM) [13, 14]. Through a comparison of selected economic parameters before and after, it was found that there are two sides to the industrial impact of major public health emergencies. On the one hand, the light industry is a major polluter; the higher the share of the light industry in CDP, the more significant the improvement effect on air quality after emergencies [15]. On the other hand, since the occurrence of major public health emergencies is often accompanied by air pollution and the spread of viruses, especially in indoor air, the impact is greater [16]. Many sectors of the light industry are environmentally sensitive and labor-intensive and often bear the brunt of negative impacts [17]. Furthermore, major public health emergencies have a differential impact on the industry in terms of degree and scope [18].

2.1.3. Research on the Impact of Major Public Health Emergencies on Enterprises. Scholars have focused primarily on the impact of "economic crises" or "financial crises" on business behavior [19]. Additionally, the impact of external shocks on enterprises is studied specifically in the context of major public health emergencies [20]. On the one hand,

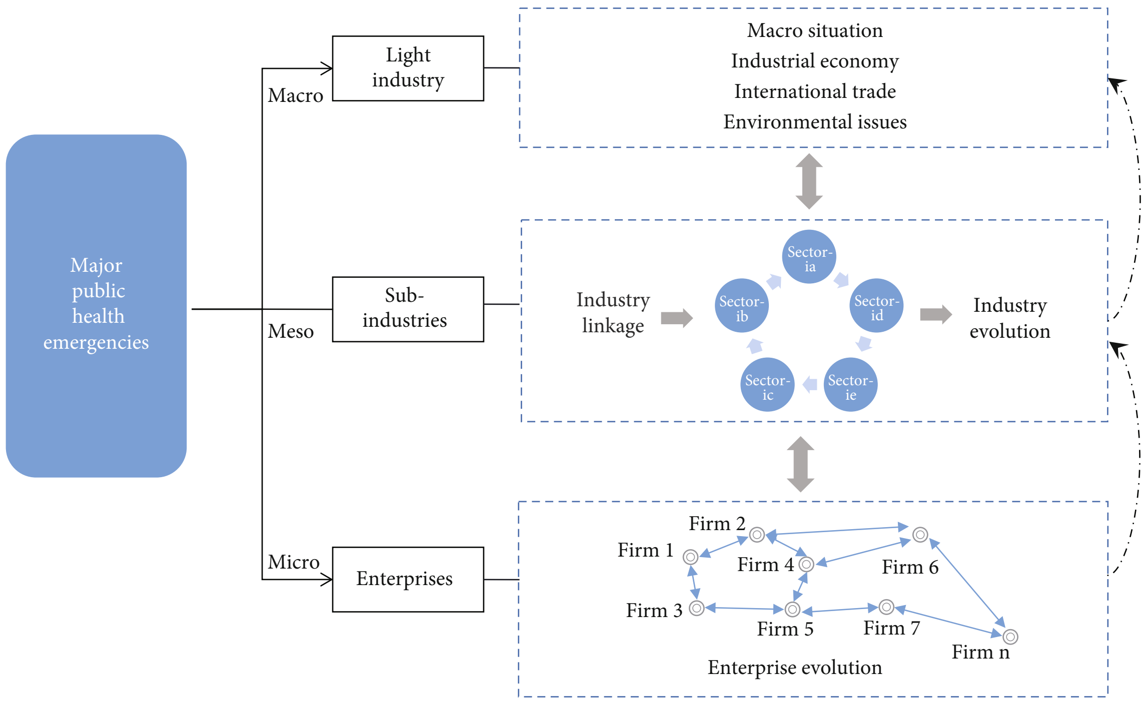


Figure 1: Transmission path of major public health emergencies on the industry system.

using descriptive statistical analysis, Bressan et al. review the operational dilemmas faced by firms when major public health emergencies occur [21]. Rubio-Andrés et al. analyzed firms' performance under COVID-19 by treating COVID-19 as a high-intensity external shock [22]. On the other hand, Zhu et al. used the questionnaire survey method to interview operators to summarize the difficulties faced by enterprises and policy demands at the time of major public health emergencies [23]. In summary, most current research focuses on the impact of shocks such as financial crises, and less research has been conducted on the impact of major public health emergencies on enterprises. The impact of major public health emergencies on firms, as a typical shock originating from outside the economic system, should also be focused on. In addition, descriptive statistical analysis is mostly used to analyze the impact of unexpected shocks on enterprises. Fewer studies have quantified the impact of major public health emergencies on enterprises.

2.2. Theoretical Analysis. From the above three levels of analysis, it is clear that a major public health emergency is a sudden external shock to the industry system. The combined effect of the firm and industry levels is that the external shock of a major public health emergency will change the existing supply-demand relationship. And after the initial impact, the change in firm behavior will cause structural changes in the industrial sector. Moreover, interindustry linkages allow direct losses to certain industries to cause indirect changes in the output of all related industries. This will lead to a reflow of capital between industries, which in turn will lead to changes in the composition of capital and ultimately cause an overall restructuring of the industry [24]. Under the influence of multiple factors, such as the macroenvironment and international trade, the structural adjustment of industry will eventually have a complex systemic impact on the industry sector. In this paper, the shock process and the research content are integrated to construct a basic theoretical analysis framework. Under this broad, comprehensive theoretical framework, the impact of a major public health emergency on the economy is transmitted at three levels: macro, meso, and micro. Both short-term shocks and long-term effects are observed.

From the perspective of evolutionary theory [25], the economic impact of major public health emergencies consists of three layers. The first is the microlevel (firm evolution). Second, the mesolevel, interfirm interactions constitute individual industry evolution. The third is the macrolevel; interindustry evolution constitutes the light industry system. Among them, the mesolevel is the logical link that describes the industrial phenomenon, and the macrolevel is the result of the interaction between the microlevels. This paper considers "major public health emergencies" as the driving force of macroevolution and the actor that creates uncertainty and breaks equilibrium. Based on the above theoretical analysis, the transmission path of the impact of major public health emergencies on the light industry is summarized (as shown in Figure 1).

In Figure 1, first, major public health emergencies have an impact on microfirms. Firms under pressure to survive will transform to adapt to new environments or exit new markets. Second, an industry is made up of numerous firms that are partly homogeneous and necessarily heterogeneous. When facing a major public health emergency, the results of firms' own choices will lead to a "spiral change" in the industry as a whole. Further, due to the spillover effects of industry linkages, the evolution of an industry may lead to the transformation of its upstream or downstream components, ultimately causing a complex systemic impact on the entire light industry. Therefore, this paper constructs a theoretical framework for the impact of major public health emergencies on the light industry at three levels: the light industry as a whole, subsectors, and enterprises. This contributes to a comprehensive and in-depth understanding of the impacts on different subjects in the light industry.

3. Methodology and Data

3.1. Methods

3.1.1. Time-Varying Parameter-Stochastic Volatility-Vector Autoregression (TVP-SV-VAR) Model. Compared with traditional regression analysis, the TVP-SV-VAR model can effectively overcome the "curse of dimensionality" problem of too many categories of macrodata and a too short sample period [26]. Thus, it can accurately portray the impact of emergencies on the macroeconomy [27]. Therefore, at the overall level of the light industry, vector autoregressive models with time-varying parameters and stochastic fluctuations are constructed in this paper [28]. This model is used to quantify the impact of major public health emergencies on the light industry and to assess the isointerval impulse response.

3.1.2. Hypothesis Extraction Method (HEM). In the subsector within the light industry, the severity of major public health emergencies is incorporated as a weight in the traditional hypothetical extraction model [29]. The improved hypothetical weight extraction method is used to measure the direct impact of major public health emergencies on different subsectors and to measure the indirect losses due to industry-linked effects. The improved hypothetical weight extraction model is constructed as follows:

Set the weight matrix as an $n \times 1$ matrix to represent the degree of loss caused by industry n after being hit by a major public health emergency. The specific calculation formula is as follows:

$$w_i = \left[\sqrt[yt-y0+1]{\frac{V_{y_t}}{V_{y_0-1}}} \times 100\% - 100\% \right] - \left(\frac{\mathrm{IV}_1 - \mathrm{IV}_0}{\mathrm{IV}_0} \right) \times 100\%. \tag{1}$$

In formula (1), w_i reflects the extent to which industry i is affected by the major public health emergencies. The industry value added reflects the difference between the total monetary value created by the production of all goods or services in an industry and the total monetary value consumed by it. And the sum of the value added by each industry constitutes the GDP. Therefore, this paper uses the difference between the expected and actual year-over-year growth rate of industry value added as a measure of how the industry would be affected under a major public health emergency. In addition, y_t denotes the ending year of the study period, and y_0 denotes the beginning year of the study period. V_{yt} is used to measure the value added of the industry at the end of year t, IV_1 denotes the value added of industry i in the current period, and IV_0 denotes the value added of industry i in the same period last year. When w_i is greater than 0, it means that the impact of industry i under the impact of major public health emergencies is negative. Otherwise, it is the reverse.

To measure the degree of loss caused by the industry linkage effect, three aspects are measured: the loss of the total linkage effect, the forward linkage effect, and the backward linkage effect [30]. The total linkage effect represents the impact of a single sector on the entire economic system or other industry sectors. It can be divided into forward and backward linkages. Taking the calculation process of the total linkage effect as an example, let there be n sectors in a region and divide the intermediate input technology coefficient A^D into two groups. The first group is the industry i that is to be calculated, and the second group is the remaining n-1 sectors. Then, the Leontief model can be expressed as follows:

$$\begin{bmatrix} X_1 \\ X_2 \end{bmatrix} = \begin{bmatrix} A_{11}^D & A_{12}^D \\ A_{21}^D & A_{22}^D \end{bmatrix} \times \begin{bmatrix} X_1 \\ X_2 \end{bmatrix} + \begin{bmatrix} F_1^D \\ F_2^D \end{bmatrix}. \tag{2}$$

In formula (2), F^D indicates the final demand for a product in a particular sector. Taking a negative shock as an example, it is assumed that an external shock from a major public health emergency reduces the input-output of industry i between related industries by w_i. And the reductions in output and input to other industry sectors are denoted as w_1 and w_2, respectively. Then, the output of the economic system under the shock of a major public health emergency can be expressed as follows:

$$\begin{aligned} \begin{bmatrix} X_1' \\ X_2' \end{bmatrix} &= \begin{bmatrix} A_{11}^D(1-w_1) & A_{12}^D(1-w_1) \\ A_{21}^D(1-w_2) & A_{22}^D \end{bmatrix} \times \begin{bmatrix} X_1 \\ X_2 \end{bmatrix} + \begin{bmatrix} F_1^D \\ F_2^D \end{bmatrix} \\ &= \begin{bmatrix} \left(\mathrm{I}-\mathrm{A}_{11}^{\mathrm{D}}\right)^{-1}(1-w_1) & \left(I-A_{12}^D\right)^{-1}(1-w_1) \\ \left(I-A_{21}^D\right)^{-1}(1-w_2) & \left(I-A_{22}^D\right)^{-1} \end{bmatrix} \times \begin{bmatrix} F_1^D \\ F_2^D \end{bmatrix}. \end{aligned} \tag{3}$$

The difference between equation (2) and equation (3) is the amount of loss suffered by the industry under the total linkage effect.

3.1.3. Difference-in-Difference (DID) Model. Taking the typical COVID-19 as an example, for enterprises in the light industry, the generalized DID model is used to examine the impact of major public health emergencies on microenterprises [31]. In a quasinatural experiment with COVID-19, the sample is selected from a panel of Chinese A-share listed companies. The outbreak of COVID-19 was almost all-encompassing in all provinces of China. All regions were hit by this emergency, and the severity of the event is what makes the difference, rather than the occurrence of the event. Therefore, it is difficult to estimate the parameters of the COVID-19 sample using the traditional DID model. On the contrary, the generalized DID model can incorporate the characteristics of exogenous interventions with sample

Table 1: Setting and definition of all variables in the DID model.

Variables	Variable definition
Y	Enterprise performance: to measure the operating condition of the enterprise, reflecting its profitability, asset operation level, solvency and subsequent development ability, etc.
Age	Years of enterprise operation.
Labor	Total number of employees in the enterprise at the end of the year.
Capital	Total fixed assets: reflects the enterprise's investment in fixed assets, the production scale and equipment level, etc.
ITR	Inventory turnover ratio: the ratio of an enterprise's operating costs to its average inventory balance. A comprehensive indicator used to measure a company's input production, inventory management level, and sales recovery ability.
ROA	Debt ratio: a comprehensive indicator of the company's level of indebtedness.
Asset	Total assets: all assets owned or controlled by the company.
DTL	Combined leverage: the role played by operating and financial leverage together. Used to measure the extent to which changes in sales volume affect changes in earnings per common share.
Nature	Nature of ownership: state-owned enterprises = 1, nonstate-owned enterprises (private enterprises, foreign joint ventures, and other enterprises) = 0.
Scale	Enterprise scale: large-scale enterprises = 1, other enterprises (medium – sized, small, and microenterprises) = 0.
Overseas	Overseas income: whether the enterprise has overseas business income in the current year. Yes = 1, no = 0.
Industry	Industry nature: industry dummy variable.

individuals at the same time into the model processing. And it can reflect the differential effects of exogenous interventions on the sample individuals. Therefore, this paper adopts the generalized DID model to verify the effect on enterprises. The generalized DID model is set as follows:

$$Y_{\text{it}} = \alpha + \delta_2 \text{TREAT}_i \times \text{POST}_t + \beta Z_{\text{it}} + \mu_i + \lambda_t + \varepsilon_{\text{it}}. \quad (4)$$

Among them, Y_{it} denotes the firm's performance indicator. i denotes a firm's code, and t denotes a time series in quarters. TREAT_i is a dummy variable indicating whether the sample is a "treatment group" or not. POST_t is also a dummy variable to describe whether the sample is in the "treatment period" or not. Z_{it} denotes a set of other control variables. μ_i and λ_t denote individual fixed effects and time fixed effects, respectively, and ε_{it} denotes a random error term. In addition, considering the heterogeneity of enterprise characteristics, further subdivision of enterprise types is required. In this paper, heterogeneity is analyzed by the characteristics of enterprises (X_i) such as equity nature, enterprise size, overseas business, and industry attributes. At this point, the assumption of individual fixed effects needs to be released, and the empirical model is extended to a triple difference model (Equation (5)). All the variables are set in Table 1.

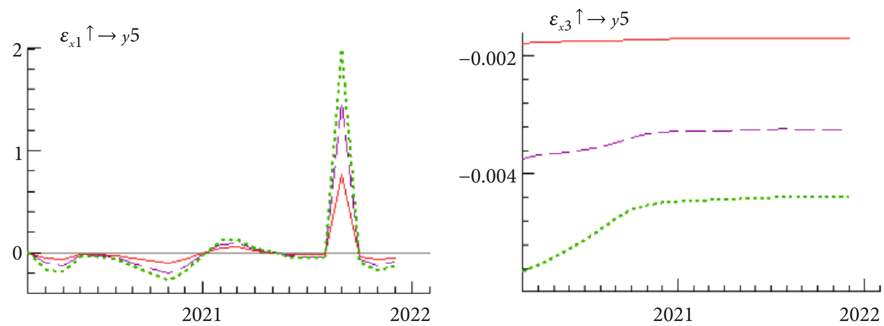
$$Y_{\text{it}} = \alpha + \delta_2 \text{TREAT}_i \times \text{POST}_t \times X_i + \beta Z_{\text{it}} + \lambda_t + \varepsilon_{\text{it}}. \quad (5)$$

3.2. Data Source

3.2.1. Data Sources and Processing in the Light Industry. In the TVP-SV-VAR model, first, it is necessary to identify exogenous shock variables that represent major public health emergencies and endogenous variables that represent the shocked side of the light industry. In terms of the choice of representative major public health emergencies, this paper selects COVID-19, which is the window period to observe the impact of shocks on the light industry. The second is the quantification of exogenous variables. Data on COVID-19 were obtained from the database "Public Health Emergency of International Concern." Finally, the third is the quantification of the endogenous variables. The China Light Industry Information Center (CLIC) publishes the monthly comprehensive index "China Light Prosperity Index" and subindexes "main business income prosperity index, export prosperity index, asset prosperity index, and profit prosperity index." It is used to measure the economic performance of the light industry.

3.2.2. Data Sources and Processing of the Subsector in the Light Industry. In the HEM, calculations need to be performed using input-output tables and a hypothetical weight matrix. First, this paper regroups the input-output tables of the light industry. Second, a hypothetical weight matrix is constructed to measure the extent of losses caused by external shocks to the light industry subsectors. The values of the hypothetical weight matrix are calculated based on the industrial value added. The data on the added industrial value are obtained from the China Light Industry Statistical Yearbook and the China Industrial Economic Statistical Yearbook.

3.2.3. Data Sources and Processing for Enterprises. At the firm level, a multicombination DID model is used in this paper. First, the data of all A-share listed enterprises are obtained from the China Stock Market and Accounting Research Database (CSMAR). And the listed companies with special treatment are excluded. Secondly, the data of the enterprises in the light industry were obtained by manual filtering. Finally, the total assets net profit ratio of enterprises, as well as the age of enterprises, number of employees, gearing ratio, inventory turnover, and other data, are collated. After excluding the severely missing data, a total



(a) China data

(b) Global data

Figure 2: Equal interval impulse response results for light industry prosperity.

of 14109 observations for the sample period were obtained. To improve the smoothness of the data, continuous data at the firm level were subjected to 1% tailing and logarithmic processing.

4. Results and Discussion

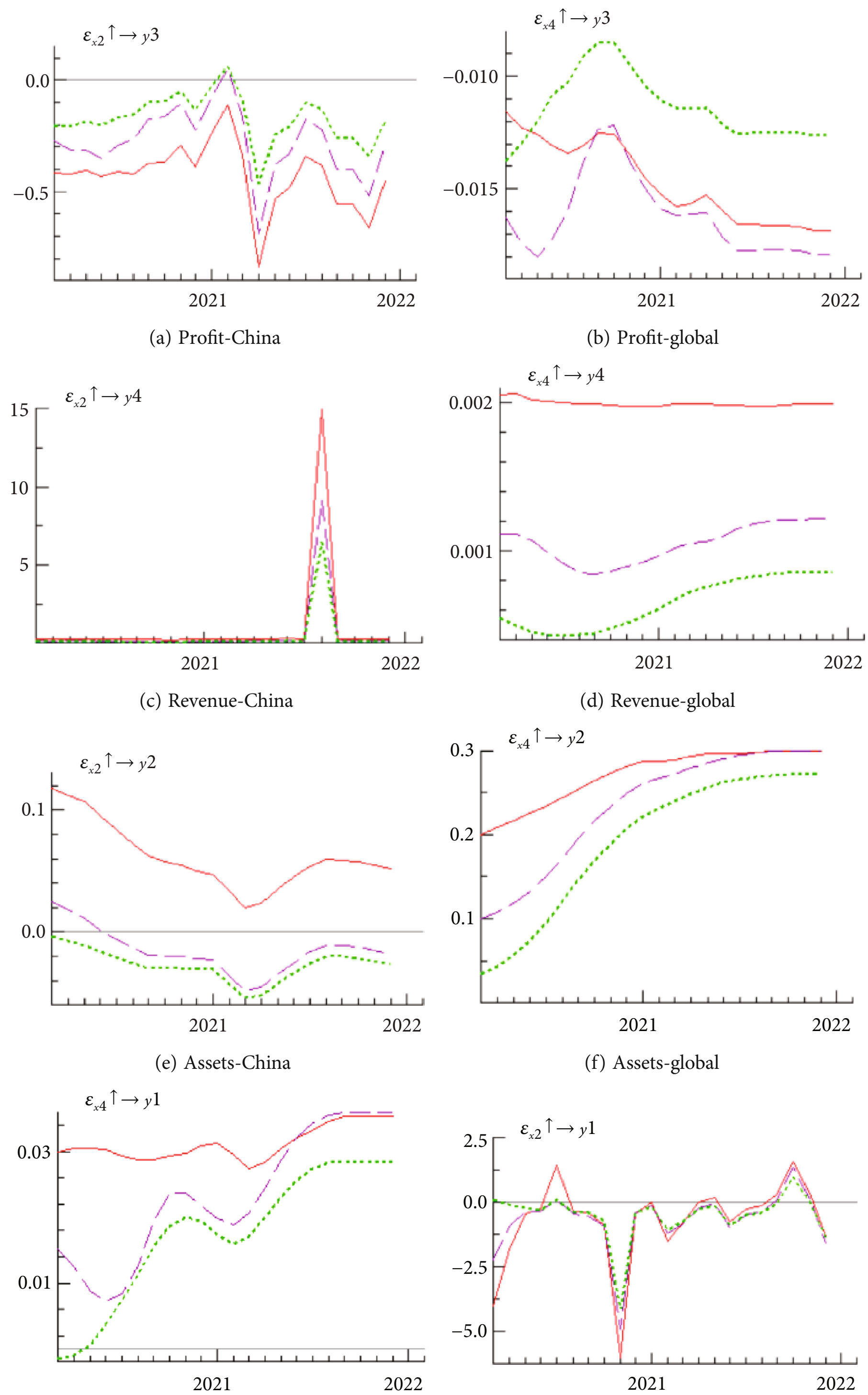
4.1. The Impact of Major Public Health Emergencies on the Light Industry. In this paper, the TVP-SV-VAR model is used to analyze the short-, medium-, and long-term effects of major public health emergencies on China's light industry by setting different lags. The typical time-varying characteristics of the shock response intensity are also examined. Usually, the impulse response fluctuations are most significant around 4 lags. The impulse response fluctuation has been more obvious around lag 8. The impulse response tends to converge around lag 12. Therefore, the lags of 4, 8, and 12 months are set as short-, medium-, and long-term. The response of a light industrial boom state to the shock of a major public health emergency is simulated. The short- and long-term effects of the impact of a major public health emergency on the light industry are also examined. The simulation results of the equal interval impulse response function are shown in Figures 2 and 3, respectively.

For the prosperity index of the Chinese light industry (Figures 2(a) and 2(b), COVID-19 has a negative impact on it in January 2020-January 2021. However, the shock has been oscillating slightly below the value of 0. This indicates that the shock effect is not very strong. Until after July 2021, the positive shock of major public health emergencies increased abruptly. However, the duration is not long. That is, the subsequent shocks are somewhat less dynamic. Due to the different lags in the impulse response, the fluctuation trends of the three curves are more consistent. The impulse responses of lag 12 are slightly larger than those of lag 4 and lag 8, both in the early negative shock phase and in the later positive shock phase. This indicates that the impact of major public health emergencies on light industry prosperity has a certain time lag. However, in terms of the final presentation of the three curves, all curves eventually converge to a value of 0. In other words, although the light industry is hit by fluctuations at the beginning, the light industry system will eventually reach a new stable state due to various factors, such as national macroeconomic regulation and economic cycles. This finding is also verified in the impulse response results of the global data. Unlike the case of China, the impact of global COVID-19 on the sentiment of the light industry shows a significant negative effect. The impulse response fluctuates from -0.001 to -0.005, and the duration of the negative shock is longer.

For the degree of profit boom (Figures 3(a) and 3(b)), the impulse response results from the Chinese data show that the profit prosperity in the light industry is subject to a continuous negative shock. The peak of the shock reaches -0.9. Looking at the different lags, the three curves show consistent fluctuations. The impulse response of lag 4 is greater than that of lag 8. That is, the shock-to-profit sentiment is most significant in the short run, and there is no significant time lag. From the impulse response results of the global data, similarly, the light industry profit prosperity is subject to a negative shock. Unlike China's results, the impact of global COVID-19 on the profitability of the Chinese light industry is most significant with lag 8. That is, the impact of the global case on the profit sentiment of the Chinese light industry has a time lag. It is worth noting that the impulse impact of global COVID-19 has not yet converged to a zero value. In other words, there is still uncertainty about the persistence of the impact.

From the prosperity of the main business income (Figures 3(c) and 3(d)), there is no significant shock in the early stage. The impulse responses of different lags show consistent results. It is noteworthy that the demand for the main business of the light industry was stimulated in the late stage of the emergency. This led to a rebound in their prosperity, especially in the short term. This finding is also confirmed in the global data. The impulse response curve of the global data on the light industry's main business income shows a weak upward trend. And the impact is much smaller than that of China's data. However, the results of the impulse response with different lags show that the main boom in business income is hit by an upward trend.

In terms of asset sentiment in the light industry (Figures 3(e) and 3(f)), the impact of major public health emergencies on asset sentiment shows a decreasing trend. With different lags, the impact on asset sentiment exhibits dynamic, time-varying characteristics. Specifically, in the short run, it does not show a significant negative trend in



(a) Profit-China (b) Profit-global

(c) Revenue-China (d) Revenue-global

(e) Assets-China (f) Assets-global

(g) Exports-China (h) Exports-global

FIGURE 3: Equal interval impulse response results for subindices of prosperity.

asset sentiment. However, the negative impact starts to appear in lags 8 and 12, especially in lag 12. This indicates that the occurrence of major public health emergencies has a time-lagged impact on light industry asset sentiment. A good sign is that the medium-term and long-term impulse response results gradually converge to zero values. In other words, the negative impact gradually weakens and tends to stabilize. This suggests that the outbreak of COVID-19 has not changed the scale of development of the light industry. However, the impact of the global case on China's light industry asset sentiment is still on an upward trend, and the impact is still very significant. Therefore, the major impact of the global public health emergencies on China's light industry still needs to be alerted.

Table 2: Measurements of industrial linkage loss based on improved HEM.

Sectors	Forward linkage	Backward linkage	Total linkage	Forward linkage	Backward linkage	Total linkage
		1st quarter			2nd quarter	
Agricultural and sideline food processing	0.378	0.540	0.895	0.285	0.408	0.698
Food manufacturing	0.065	0.487	0.234	0.044	0.329	0.166
Beverage manufacturing	0.122	0.138	0.251	0.083	0.094	0.174
Leather industry	0.085	0.160	0.193	0.071	0.134	0.162
Wood processing	0.198	0.159	0.295	0.148	0.119	0.221
Furniture manufacturing	0.033	0.116	0.148	0.026	0.093	0.118
Paper industry	0.179	0.133	0.263	0.118	0.088	0.175
Chemical industry	0.774	0.574	1.099	0.570	0.423	0.809
Rubber and plastics industry	0.378	0.334	0.654	0.230	0.203	0.411
Equipment manufacturing	0.187	0.312	0.445	0.083	0.139	0.199
		3rd quarter			4th quarter	
Agricultural and sideline food processing	0.263	0.376	0.574	0.234	0.335	0.512
Food manufacturing	0.040	0.301	0.155	0.038	0.286	0.148
Beverage manufacturing	0.075	0.085	0.158	0.068	0.077	0.144
Leather industry	0.067	0.126	0.152	0.063	0.118	0.142
Wood processing	0.138	0.111	0.205	0.126	0.101	0.188
Furniture manufacturing	0.022	0.077	0.098	0.019	0.066	0.085
Paper industry	0.102	0.076	0.151	0.091	0.067	0.133
Chemical industry	0.482	0.358	0.684	0.415	0.308	0.589
Rubber and plastics industry	0.185	0.164	0.309	0.154	0.136	0.286
Equipment manufacturing	0.069	0.116	0.181	0.062	0.103	0.163

For the light industry export boom, it is more important to measure the global shock. According to the impulse response results (Figures 3(g) and 3(h)), overall, the occurrence of global COVID-19 has a significant negative shock on China's export sentiment. The shock peaks at -6.25, with the largest negative shock occurring in the fourth quarter of 2020. Subsequently, the shock effect diminishes but remains in the negative range. Impulse response curves are consistent across lags. That is, there is no significant time-lag effect. Combined with the development history of COVID-19, after the initial negative impact of the embargo on light industry exports, the demand for epidemic prevention products such as masks, protective clothing, and respirators increased. This made China's light industry export demand to rise. However, due to the "embargo" policy of various countries, the export of light industry products still has a greater impact, so the export prosperity shows a volatile trend.

4.2. The Impact of Major Public Health Emergencies on Subsectors. A modified hypothetical weight extraction method was used to measure the losses suffered by industry-linked effects during major public health emergencies. Reviewing the major public health emergencies that occurred in the past, it is found that the major public health emergencies have the basic characteristic of evolving over time [32]. In view of this, this paper assigns different weight matrices to industry loss values in different quarters. According to the input-output table of the light industry sector reassembled in this paper, it focuses on analyzing the industry-related loss degree of the light industry subsectors (Table 2).

From the results of the calculation of the first quarter, first, the loss of total linkage effect in the manufacturing industry of chemical raw materials and products is particularly prominent. This is followed by the agricultural and sideline food processing and rubber and plastics industries. This indicates that the above sectors have a greater impact on the overall output of the national economy when they are hit by major public health emergencies. Second, the results of the forward linkage loss measure show the same three sectors, namely, agricultural and sideline food processing, chemical industry, and rubber and plastics industries. These are higher forward linkage losses compared to other sectors. In other words, the loss of forward linkage is higher in the agricultural and sideline food processing industries than in the other sectors when they are hit by emergencies. Third, the results of the backward linkage loss measure indicate that the loss rate of agricultural and sideline food processing, food manufacturing, chemical industry, rubber and plastics industries, and equipment manufacturing is higher. This indicates that the transmission effect of the industry linkage effect makes the pulling effect of sectors, such as

Table 3: Regression results for the effects of major public health emergencies on enterprises.

	Model 1	Model 2	Model 3	Model 4	Model 5
$TREAT_i^*POST_t$	-0.008** (0.039)	-0.012 (0.039)	-0.011 (0.039)	-0.015 (0.039)	0.008 (0.001)
$TREAT_i^*POST_t^*W_i$		0.009*** (0.002)	0.010*** (0.003)	0.013*** (0.002)	0.007*** (0.002)
Scale		-0.011*** (0.002)			
Nature			-0.006** (0.002)		
Overseas				-0.009** (0.023)	
Industry					0.005*** (0.001)
Age	-0.009*** (0.002)	-0.009*** (0.002)	-0.009*** (0.002)	-0.009*** (0.002)	-0.009*** (0.002)
Labor	0.014*** (0.006)	0.016*** (0.001)	0.014*** (0.001)	0.014*** (0.001)	0.014*** (0.006)
Capital	-0.003*** (0.009)	-0.003*** (0.001)	-0.003*** (0.001)	-0.002*** (0.001)	-0.003*** (0.009)
ITR	-0.013(0.014)	-0.009(0.013)	-0.015(0.014)	-0.009(0.013)	-0.003(0.001)
ROA	-0.157*** (0.003)	-0.157*** (0.003)	-0.156*** (0.003)	-0.157*** (0.003)	-0.155*** (0.003)
Asset	0.003*** (0.006)	0.003*** (0.006)	0.003*** (0.001)	0.n(0.001)	0.003*** (0.006)
DTL	-0.001** (0.007)	-0.002** (0.001)	-0.002** (0.001)	-0.018** (0.007)	-0.002** (0.007)
Constants	0.072*** (0.005)	0.065*** (0.006)	0.072*** (0.006)	0.075*** (0.005)	0.068*** (0.005)
Observations	13936	13936	13936	13936	13936
R^2	0.1794	0.1814	0.1807	0.1821	0.1836

Note: *, **, and *** denote 10%, 5%, and 1% levels of significance, respectively.

the agricultural and sideline food processing industry on itself and its upstream industries, also affected by spillover.

Comparing the results of the first quarter with those of the other quarters, it is found that the total linkage effect, backward linkage effect, and forward linkage effect loss rankings are more consistent across sectors. In other words, the sectors that were more hit by major public health emergencies in the first quarter will continue to be affected in subsequent periods. However, in general, there is a clear downward trend in the loss of total sectoral correlation effects for the four time periods in 2020. That is, aggregate losses in the first quarter are effectively controlled in subsequent periods.

4.3. The Impact of Major Public Health Emergencies on Enterprises. In this paper, the differences-in-differences model is used for firm-level empirical testing. After passing a series of hypothesis tests of the model, the impact of major public health emergencies on firms is simulated and tested. The basic regression results and heterogeneity results are shown in Table 3. As can be seen from Table 3 in model 1, the results of the basic model simulation for the COVID-19 sample indicate that the impact of major public health emergencies on firm operational performance is negative. And the simulation results passed the significance test at the 5% confidence level. The regression results of the control variables indicate that the stronger the firm's previous operating capability, the better the firm can maintain normal operation under an emergency shock.

Specifically, the regression coefficients of employees and total assets on firm performance are positive. This indicates that human investment and asset size have a significant positive effect on firm performance. The regression result of gearing on firm operating performance is significantly negative, with a regression coefficient of -0.157. That is, the unhealthier the firm's past asset-to-liability ratio is, the more likely it is to be overly indebted and fall into a business crisis when a sudden shock occurs. Unlike previous studies [33], this study found that the age of the firm has a negative effect on its operation. This suggests that the older the firm, it does not mean that it is better able to cope with an unexpected shock. To some extent, the older the firm is in business means that the firm may have experienced similar sudden shocks in the past (for example, SARS). However, compared to COVID-19, the impact of SARS on enterprises in certain areas is localized [34, 35]. The above findings remained reliable after a series of robustness tests, such as the placebo test, changing the sample size, and variable measure replacement.

A triple difference model was used to examine the impact of a major public health emergency on enterprises, and the simulation results are presented in Table 3, model 2. The study concludes that the interaction term coefficient is significantly positive, which indicates that major public health emergencies have a greater impact on MSMEs compared to large-scale enterprises. That is when faced with a major public health emergency, large enterprises can rely on endogenous dynamics to withstand and recover from the shock, but MSMEs need to rely more on government forces to withstand external shocks and resume business operations. It should be noted that although the sample of listed companies selected in this paper involves small, medium, and microenterprises only in comparison with large enterprises in terms of scale, it can be inferred that the negative impact of emergencies should be more prominent for MSMEs whose production and operation scale is much smaller in reality.

The above analysis shows the differences between large and small, medium, and microenterprises that affect firms under a major public health emergency shock. Further, in general, the level of support received by firms varies by their attributes. Therefore, based on the heterogeneity of equity properties, this paper divides the total sample of enterprises into subsamples of different properties. In Table 3, model 3 gives the estimation results for the sample of SOEs and non-SOEs. The results show that major public health emergencies have a greater impact on nonstate-owned enterprises compared to state-owned enterprises. In other words, state-owned enterprises are less affected when major public health emergencies occur, and state-owned enterprises are able to achieve business recovery more quickly. In addition, other key factors affecting the operation of nonstate-owned enterprises are total corporate assets, net fixed assets, etc.

Combined with the above study, it is found that light industry export performance is more negatively affected by shocks when major public health emergency shocks occur. Therefore, at the firm level, this paper further verifies whether firms involved in overseas business are more affected by emergency shocks. The presence or absence of “overseas income” is used as a measure of whether an enterprise is involved in overseas business. The sample enterprises are divided into two groups accordingly. Among the light industry sample enterprises, those with overseas revenue accounted for about 60% of the total sample enterprises. The results of model 4 show that major public health emergencies have a greater impact on enterprises with overseas business compared to those without overseas business.

Section 4.2 concluded that the industry impact of major public health emergencies is heterogeneous, and the direct and indirect impacts on key industries in the industry network are particularly prominent. Based on this, this paper uses the industry association measurement results for each industry in the light industry in Table 2 as a benchmark and divides the enterprises into strong industry association groups and weak industry association groups. The results of model 5 show that enterprises downstream of the industry chain are more affected by major public health emergencies than those in strongly related industries. When a major public health emergency occurs, enterprises downstream of the chain are subject to greater tail shocks to their operating performance.

5. Conclusions and Policy Implications

5.1. Conclusions. This paper explores the general common features of the impact of major public health emergencies on light industry, subindustries, and enterprises. The main conclusions are drawn as follows.

(i) The analysis of the equal-interval impulse response reveals that the development status of the light industry tends to deteriorate in the early stage of major public health emergencies with a negative impact. In particular, the negative impact on exports is particularly obvious. Then, the development status of the light industry fluctuates slightly, but the shock effect gradually decreases in the 8th and 12th lag periods. Finally, a new system equilibrium will be achieved

(ii) For the subsector in the light industry, the negative impact is greater in the initial stage of a major public health emergency. However, different subsectors are affected in different ways. For example, the food industry is less affected by the negative impact. The leather industry, furniture manufacturing, household appliance manufacturing, and other traditional export-advantaged enterprises are more negatively impacted. And it still takes a long time for the industry to recover. Due to threats such as virus spreading and air pollution, the medical instrument and equipment manufacturing industry and the daily chemical products manufacturing industry are outstanding under the impact of the major public health emergency

(iii) For light industry enterprises, the occurrence of major public health emergencies has a negative impact. And the scales of previous development of the enterprises are also crucial to whether the enterprises can maintain operation under emergencies. Additionally, differences in the nature of property rights, the strength of industrial affiliation, and overseas operations lead to heterogeneous effects of major public health emergencies on enterprise operations

5.2. Policy Implications. Finally, some additional considerations can be made.

(i) First of all, it is necessary to establish an early warning system for industrial security and formulate corresponding safeguard measures for export-oriented industries to prevent international trade friction, geopolitical risks, and global epidemic tail effects on the impact of light industry. Secondly, on the basis of safeguarding the industrial security of the light industry, it should also actively integrate into the global industrial system and continue to encourage the light industry to “go global,” guide the light industry industrial chain and supply chain to establish a diversified layout, and finally, in the new globalization process to achieve high-quality development of the light industry

(ii) Combining the empirical tests of this paper with the realistic characteristics of the development of the light industry, it is concluded that the global demand for light industry products such as food, daily chemical products, and other medical equipment and instruments will surge when major public health emergencies occur. For such key industries, more attention should be paid to the quality and efficiency of the industry. On the one hand, to promote the enhancement of its ability to meet global demand and to protect consumer demand as a strategic base point, special projects for technical reform and green development are necessary. Through technological innovation, production process improvement, production, and marketing linkage, all kinds of light industry products can meet multilevel consumption demand. On the other hand, the government should support the improvement of key industrial chains to promote the transformation and upgrading of key sectors, focus on strengthening the weak links of the industry chain and short-board technology to achieve technological independence in high-end industries such as medical instrument and equipment manufacturing, consolidate the industrial base, and promote the modernization of industrial chains by improving the quality and efficiency of key industries

(iii) At the beginning of emergencies, it was difficult for enterprises in almost all regions and industries to "stand aloof," although the government always takes a series of positive macroregulation in response. However, while receiving various preferential policies from the government, enterprises should take major public health emergencies as an opportunity to improve their endogenous capacity to cope with similar impacts in the future. In essence, in the past major public health emergencies, enterprises were hit hard because of their small scale, lack of capital, and weak risk resistance. Therefore, it is necessary to further improve the enterprise management model and establish crisis plans. In addition, enterprises should think about long-term development and combine their own characteristics to innovate business models. For example, the Midea Group began to explore live commerce and emerging sales channels. And it also focuses on the development of automated systems, accelerating the speed of product development iteration and expanding sales channels to meet multiple challenges in the post-COVID era. In summary, large enterprises must cultivate autonomy, and small and medium enterprises must focus on improving innovation capability and specialization. Finally, the resilience of the system from enterprises, subsectors, and light industry to cope with the impact of external contingencies will be established

5.3. Limitations. This paper specifies the general common impact characteristics of major public health emergencies on light industries, subindustries, and enterprises. However, there is still much room for empirical analysis. As the global economy is facing various uncertainties, the analysis of the economic impact of different types of emergencies is a direction that should be studied in depth in the future. In addition, due to the limitation of data acquisition, this paper uses "enterprise above designated size" as an example. It is inferred that the negative shocks suffered by small and medium enterprises (SMEs) may be greater due to their relatively weaker resistance to risk. The next step will be to fully obtain a sample of SMEs through questionnaires to fully grasp the situation of SMEs under major public health emergencies.

Data Availability

Data will be available upon reasonable request from the corresponding author.

Conflicts of Interest

The authors declared that they have no conflicts of interest in this work.

Authors' Contributions

Fang Su and Nini Song provided substantial contributions to the conceptualization, data curation, and formal analysis. Haiyang Shang was in charge of funding acquisition and investigation. Shah Fahad and Nini Song were responsible for the methodology, project administration, resources, software, supervision, validation, and visualization. Fang Su contributed to the writing—original draft and writing—review and editing.

Acknowledgments

This work was supported by the National Natural Science Foundation of China (grant numbers 42171281 and 72034007) and the Shaanxi Innovation Research Team for Science and Technology (grant number 2021TD-35).

References

[1] Z. Yang, Y. Chen, and P. Zhang, "Macroeconomic shock, financial risk transmission and governance response to major public emergencies," *Journal of Management World*, vol. 36, no. 5, 2020.

[2] A. Gamal, M. Abdel-Basset, and R. K. Chakrabortty, "Intelligent model for contemporary supply chain barriers in manufacturing sectors under the impact of the COVID-19 pandemic," *Expert Systems with Applications*, vol. 205, article 117711, 2022.

[3] D. Ivanov, "Predicting the impacts of epidemic outbreaks on global supply chains: a simulation-based analysis on the coronavirus outbreak (COVID-19/SARS-CoV-2) case," *Transportation Research Part E: Logistics and Transportation Review*, vol. 136, article 101922, 2020.

[4] Y. Jiang, "Thorns ahead: new challenge, new trend, and new momentum (2023 world economic analysis report)," *World Economy Studies*, vol. 347, no. 1, 2023.

[5] D. Guan, D. Wang, S. Hallegatte et al., "Global supply-chain effects of COVID-19 control measures," *Nature Human Behaviour*, vol. 4, no. 6, pp. 577–587, 2020.

[6] A. Giurca, N. Befort, and A. Taylor, "Exploring transformative policy imaginaries for a sustainable post-COVID society," *Journal of Cleaner Production*, vol. 344, article 131053, 2022.

[7] C. M. Junior, D. M. Ribeiro, and A. B. N. Viana, "Public health in times of crisis: an overlooked variable in city management theories?," *Sustainable Cities and Society*, vol. 66, article 102671, 2021.

[8] Y. Zhang and S. Hamori, "Do news sentiment and the economic uncertainty caused by public health events impact macroeconomic indicators? Evidence from a TVP-VAR decomposition approach," *The Quarterly Review of Economics and Finance*, vol. 82, pp. 145–162, 2021.

[9] H. Zhang, P. Li, Z. Zhang et al., "Epidemic versus economic performances of the COVID-19 lockdown: a big data driven analysis," *Cities*, vol. 120, article 103502, 2022.

[10] M. I. Mostafiz, M. Musteen, A. Saiyed, and M. Ahsan, “COVID-19 and the global value chain: immediate dynamics and long-term restructuring in the garment industry,” *Journal of Business Research*, vol. 139, pp. 1588–1603, 2022.

[11] M. Lenzen, M. Li, A. Malik et al., “Global socio-economic losses and environmental gains from the coronavirus pandemic,” *PLoS One*, vol. 15, no. 7, article e0235654, 2020.

[12] J. Zhou, S. Chen, W. Shi, M. Kanrak, and J. Ge, “The impacts of COVID-19 on the cruise industry based on an empirical study in China,” *Marine Policy*, vol. 153, article 105631, 2023.

[13] E. Yang and J. W. Smith, “The spatial and temporal resilience of the tourism and outdoor recreation industries in the United States throughout the COVID-19 pandemic,” *Tourism Management*, vol. 95, article 104661, 2023.

[14] D. Carter, S. Mazumder, B. Simkins, and E. Sisneros, “The stock price reaction of the COVID-19 pandemic on the airline, hotel, and tourism industries,” *Finance Research Letters*, vol. 44, article 102047, 2022.

[15] X. Wang and R. Zhang, “How did air pollution change during the COVID-19 outbreak in China?,” *Bulletin of the American Meteorological Society*, vol. 101, no. 10, pp. E1645–E1652, 2020.

[16] A. Riccardo, P. Giovanni, and G. Andrea, “A Monte Carlo assessment of the effect of different ventilation strategies to mitigate the COVID-19 contagion risk in educational buildings,” *Indoor Air*, vol. 2023, Article ID 9977685, 24 pages, 2023.

[17] H. Sakawa and N. Watanabel, “The impact of the COVID-19 outbreak on Japanese shipping industry: an event study approach,” *Transport Policy*, vol. 130, pp. 130–140, 2023.

[18] D. Gavalas, T. Syriopoulos, and M. Tsatsaronis, “COVID-19 impact on the shipping industry: an event study approach,” *Transport Policy*, vol. 116, pp. 157–164, 2022.

[19] M. K. Pazir, A. Ahmadi, and P. H. Khezri, “The effect of COVID-19 pandemic on the shrimp industry of Iran,” *Marine Policy*, vol. 136, article 104900, 2022.

[20] T. T. Hordofa, L. Song, N. Mughal, A. Arif, H. M. Vu, and P. Kaur, “Natural resources rents and economic performance: post-COVID-19 era for G7 countries,” *Resources Policy*, vol. 75, article 102441, 2022.

[21] A. Bressan, A. D. Alonso, and O. T. K. Vu, “Business-community relations under COVID-19: a study of micro and small firms,” *Journal of Business Research*, vol. 155, article 113441, 2023.

[22] M. Rubio-Andrés, M. D. M. Ramos-González, M. Á. Sastre-Castillo, and S. Gutiérrez-Broncano, “Stakeholder pressure and innovation capacity of SMEs in the COVID-19 pandemic: mediating and multigroup analysis,” *Technological Forecasting and Social Change*, vol. 190, article 122432, 2023.

[23] W. Zhu, P. Zhang, P. Li, and Z. Wang, “Firm crisis, government support and policy efficiency under the epidemic shock: evidence from two waves of questionnaire on SMEs,” *Journal of Management World*, vol. 36, no. 4, pp. 3–26, 2020.

[24] S. Liu, Y. Han, and D. Wang, “An impact path analysis of COVID-19 outbreak in China and policy response,” *Journal of Management World*, vol. 36, no. 5, 2020.

[25] G. B. Benitez, N. F. Ayala, and A. G. Frank, “Industry 4.0 innovation ecosystems: an evolutionary perspective on value cocreation,” *International Journal of Production Economics*, vol. 228, article 107735, 2020.

[26] A. Jiménez, G. Rodríguez, and M. A. Arellano, “Time-varying impact of fiscal shocks over GDP growth in Peru: an empirical application using hybrid TVP-VAR-SV models,” *Structural Change and Economic Dynamics*, vol. 64, pp. 314–332, 2023.

[27] S. Lin and S. Chen, “Dynamic connectedness of major financial markets in China and America,” *International Review of Economics & Finance*, vol. 75, pp. 646–656, 2021.

[28] C. Yang, Z. Niu, and W. Gao, “The time-varying effects of trade policy uncertainty and geopolitical risks shocks on the commodity market prices: evidence from the TVP-VAR-SV approach,” *Resource Policy*, vol. 76, article 102600, 2022.

[29] G. Mao, Y. Luo, Y. Wang, W. He, and H. Liu, “Analysis on industry emission reduction of air pollutants based on HEM and price transmission influence coefficient,” *China Environmental Science*, vol. 38, no. 4, pp. 1561–1569, 2018.

[30] M. L. Lahr and R. E. Miller, *Regional Science Perspectives in Economic Analysis (Contributions to Economic Analysis)*, Emerald Publishing Limited, London, UK, 1st edition, 2001.

[31] D. Yu, S. Li, and T. Zhou, “Industrial structure effect of China’s urban air quality improvement: a natural experiment of COVID-19,” *Journal of Finance Economics*, vol. 47, no. 3, pp. 19–34, 2021.

[32] I. Chakraborty and P. Maity, “COVID-19 outbreak: migration, effects on society, global environment and prevention,” *Science of The Total Environment*, vol. 728, article 138882, 2020.

[33] X. Ren, Y. Li, M. Shahbaz, K. Dong, and Z. Lu, “Climate risk and corporate environmental performance: empirical evidence from China,” *Sustainable Production and Consumption*, vol. 30, pp. 467–477, 2022.

[34] M. Umar, F. Shahzad, I. Ullah, and F. Tong, “A comparative analysis of cryptocurrency returns and economic policy uncertainty pre- and post-Covid-19,” *Research in International Business Finance*, vol. 65, article 101965, 2023.

[35] Y. Wu, Z. Chen, and J. Chen, “Historical memory and resident’s suffering consciousness: the long-term impact of SARS on preventing COVID-19,” *Review of International Economics*, vol. 44, no. 3, pp. 19–33, 2021.