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The impact of COVID-19 on industry-related characteristics and risk contagion

Zhong-fei Li\textsuperscript{a,b}, Qi Zhou\textsuperscript{a,b}, Ming Chen\textsuperscript{a,b}, Qian Liu\textsuperscript{c,d,*}

\textsuperscript{a} Business School, Sun Yat-sen University, Guangzhou, China
\textsuperscript{b} Center for Financial Engineering and Risk Management, Sun Yat-sen University, Guangzhou, China
\textsuperscript{c} School of Finance, Guangdong University of Foreign Studies, Guangdong, China
\textsuperscript{d} Southern China Institute of Fortune Management Research; Guangdong University of Foreign Studies, Guangdong, China

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\textbf{ABSTRACT}

We use the cutting-edge causal forest algorithm to analyze the heterogeneous treatment effects of the COVID-19 outbreak on China’s industry indexes. The variable importance index is used with the causal forest and complex network methods to analyze the characteristics of industrial relations and the types of industry risk contagion before and after the COVID-19 outbreak. The results show that the heterogeneity of industries was significantly weakened during the COVID-19 outbreak. In addition, the COVID-19 outbreak changed the original structure of the industry-related network, which shifted to a star network structure with leisure services at the core. It also changed the type of risk contagion between industries, from the original middleman risk type to the input risk type.

1. Introduction

At the time of writing, it has been more than nine months since the outbreak of COVID-19 in early 2020. As of 24:00 EST, September 15, 2020, 29,576,191 infections and 935,124 deaths worldwide had been caused by COVID-19. The outbreak of COVID-19 in China coincided with a traditional Chinese festival, the Spring Festival, significantly affecting the economy of the tertiary sector, especially the offline service industry. In China, the structure of industrial relations has certain important characteristics, with the risks of a certain industry quickly spreading to its upstream supply chain and downstream clients. For example, after the catering service industry suffered the direct effect of the epidemic, its demand for consumer goods and agricultural products fell directly, affecting the supply of manufacturing firms in the secondary industry and that of agriculture and animal husbandry in the primary industry. At the same time, to prevent cross infection caused by population flows during the epidemic period, many cities restricted traffic flows, directly affecting the transportation industry. Transportation risk leads to overstock and risks associated with the circulation of agricultural products. Based on the above cases, the motive of our study is to explore whether COVID-19 changes the original structure of industrial relations and break the ecological balance of the original industry system. In addition, the network structure among some industries may change during the pandemic compared with that before. Based on the above motivation, we propose three research questions: (1) Does COVID-19 have heterogeneous impacts on different industries? (2) Does COVID-19 change the existing industry-related structure? (3) Does COVID-19 change the original type of industrial risk contagion?

Based on this background, this paper first investigates the industry structure and risk contagion under the impact of COVID-19.
Specifically, we use the cutting-edge causal forest model proposed by Wager and Athey (2018) to test the heterogeneous effects of COVID-19 on different industries. Second, we analyze the impact of other industries on a given industry when affected by the epidemic. Unlike research on spillover effects between industries based on Vector Autoregression models, this study focuses on the industrial relations under the heterogeneous effects of COVID-19 as an exogenous event. Finally, a directed weighted network (Benson et al., 2018) is constructed based on the above-mentioned industrial associations to calculate the clustering coefficient of different industries and analyze the types of risk contagion between industries.

Unlike other nonparametric estimation methods for heterogeneous processing effects (e.g., approximate matching, the kernel method), the causal forest algorithm does not suffer from the “digit curse” problem. In addition, according to the literature, the causal forest algorithm proposed by Wager and Athey (2018) was the first algorithm to open the “black box” in the field of machine learning, providing important economic implications for the results of machine learning calculations.

The literature on the impact of COVID-19 on the economy can be divided into two branches. First, regarding the impact of COVID-19 on the entire economic system, Fernandes (2020) found that countries with a larger proportion of service industries were more severely affected by the pandemic. The impact of this crisis was also transmitted through supply chain networks, leading many industry sectors to shut down their operations due to a lack of parts. Baldwin and Weder di Mauro (2020) noted that the disruption of global supply chains and transportation restrictions slowed global economic activity. While the tertiary sector was hit in all affected countries, the manufacturing industry was usually the most severely affected. For instance, Al-Awadhi et al. (2020) analyzed the Chinese stock market and found that all stock returns were significantly negatively affected by the COVID-19 outbreak. Second, in terms of the impact of COVID-19 on individual industries, Goodell and Huynh (2020) analyzed the abnormal returns of 49 industry sectors in the United States and found that 30% had negative abnormal returns on the day the first domestic case was diagnosed. Goodell (2020) summarized the impact of the pandemic on the financial industry, suggesting that COVID-19 has had a destructive economic impact globally, with potential non-performing bank loans and even bank runs in extreme cases. In addition, Norouzi et al. (2020) analyzed China’s electricity and oil demand and found that the oil industry was more vulnerable to the global crisis than the power industry was. Del Rio-Chanona et al. (2020) found that the output of the transportation industry was affected by demand shocks, that industries related to manufacturing, extractive, and services were affected by supply shocks, and that entertainment, restaurants, and tourism were significantly affected by both supply and demand shocks. In the literature on the economic impact of COVID-19, the impact on individual industries has been mainly analyzed from the perspective of a given industry, using relatively outdated analysis methods. Moreover, the interaction between industries has rarely been considered.

Based on this literature review, the main contributions of this paper are as follows. (1) This paper combines the latest causal forest algorithm in machine learning field with the complex network method to study the correlations among industries under heterogeneous impacts of COVID-19. (2) The industrial relations are considered on the premise that exogenous events or shocks have heterogeneous treatment effects on industries. (3) Changes of industrial risk contagion types before and after COVID-19 were investigated. Unlike research on spillover effects between industries based on Vector Autoregression models, this study focuses on the industrial relations under the heterogeneous effects of COVID-19 as an exogenous event. Finally, a directed weighted network (Benson et al., 2018) is constructed based on the above-mentioned industrial associations to calculate the clustering coefficient of different industries and analyze the types of risk contagion between industries.

The rest of this paper is organized as follows. Section 2 introduces the causal forest and complex network methods. Section 3 presents the data and empirical analysis. Finally, Section 4 summarizes the findings of the study.

2. Research methods

2.1. Causal forest inference

This paper uses the causal forest method proposed by Wager and Athey (2018) to calculate the treatment effect, which seeks to generate multiple causal trees and to average the estimated treatment effect of each tree to obtain the final prediction. Based on the data to estimate the treatment effect ($X_i, W_i, Y_i$), let $X_i$ be a vector of covariates for industry $i$. $W_i$ is the treatment assignment, and $W_i \in \{0, 1\}$ indicates two treatments. $Y_i$ is the response variable and $Y_i(1) - Y_i(0)$ indicates the potential outcome if industry $i$ is assigned to the treatment (control) group. The causal effect of the treatment on industry $i$ is therefore $Y_i(1) - Y_i(0)$.

The principle of a single regression tree is as follows:

$$
\min_{j,s} \left[ \sum_{x \in R_1(j,s)} (y_i - \bar{y}_1(j,s))^2 + \sum_{x \in R_2(j,s)} (y_i - \bar{y}_2(j,s))^2 \right],
$$

in which $x_i$ is the splitting criterion, and $s$ is a split point. $R_1(j,s) = \{X_i | X_i \leq s\}$, $R_2(j,s) = \{X_i | X_i > s\}$, and $\bar{y}_1(j,s)$ and $\bar{y}_2(j,s)$ are the industrial average treatment effects of $R_1(j,s)$ and $R_2(j,s)$, respectively.

The estimated values of heterogeneous treatment effects are as follows:

$$
\hat{\tau}(x) = \frac{1}{|\{i : W_i = 1, X_i \in L\}|} \sum_{i \in \{i : W_i = 1, X_i \in L\}} Y_i - \frac{1}{|\{i : W_i = 0, X_i \in L\}|} \sum_{i \in \{i : W_i = 0, X_i \in L\}} Y_i,
$$

in which $L$ is a leaf node, and $\hat{\tau}(x)$ is the consistent estimator of the treatment effect $\tau(x) = E[Y_i(1) - Y_i(0) | X_i = x]$. The first half represents the mean value of the response variable $Y_i$ of the individual, with the treatment assignment $W_i$ equal to one in leaf L, and the second half represents the mean value of the response variable $Y_i$ of the individual, with the treatment assignment $W_i$ equal to zero in leaf L. The forest generates the final predicted value by averaging the predicted value of each tree.
COVID-19 epidemic as an exogenous event on various industries in the Chinese securities market. The input data for the causal forest method consist of three parts (3.2. Heterogeneous impact of COVID-19 on different industries). The sampling period is from January 20, 2020 to February 7, 2020. The sample consists of stocks belonging to classified industries. The descriptive statistics of the data are shown in Table 1.

Table 1 Descriptive statistics of data.

|                | Min   | Mean  | Max   | Variance | Kurtosis | Skewness |
|----------------|-------|-------|-------|----------|----------|----------|
| 2020.01.20     | -10.0432 | 0.9234 | 21.3881 | 7.3231 | 8.3418 | 0.8561 |
| 2020.01.21     | -12.0329 | -1.1673 | 19.5929 | 8.1374 | 7.8780 | 1.3406 |
| 2020.01.22     | -12.6518 | 0.0680 | 20.0040 | 7.6365 | 8.0606 | 0.6579 |
| 2020.01.23     | -10.1322 | -3.4017 | 16.4216 | 8.0974 | 8.3443 | 1.3023 |
| 2020.02.03     | -20.0197 | -8.8642 | 20 | 16.6320 | 16.2623 | 3.1997 |
| 2020.02.04     | -10.0649 | -0.5445 | 20 | 25.5230 | 3.0094 | 0.6794 |
| 2020.02.05     | -6.9027  | 2.7123 | 20.0096 | 7.9928 | 5.0481 | 1.1278 |
| 2020.02.06     | -10      | 2.6191 | 19.9976 | 8.4548 | 5.1759 | 1.3239 |
| 2020.02.07     | -10.0087 | 1.2038 | 20 | 11.0047 | 4.8642 | 0.8225 |

2.2. Complex network method

Fagiolo (2007) defined four types of clustering coefficients (cycle, middleman, input, and output, abbreviated as Cyc, Mid, In and Out) based on different morphological characteristics of triples in directed networks. The undirected network clustering coefficient defined by Watts has been directly used for risk measurements (Schwaab et al., 2017). In this paper, Fagiolo’s (2007) idea is introduced in the field of financial risk management, and the clustering coefficients are used to measure the types of risk contagion. The specific definitions of these clustering coefficients are defined in the paper of Fagiolo (2007).

3. Data and empirical analysis

3.1. Data

When using the causal forest method, the research samples for the treatment and control groups should be determined first. In the medical field, we can accurately distinguish the research samples for two groups using artificial experiments. In economic and financial studies, we usually determine the group samples through event research. The first step of our study is to ascertain the time of occurrence of the event. Therefore, this study examines the contagion timeline of the COVID-19 epidemic in China. The impact of this incident did not spread to the stock market until January 23, 2020. On that day, the Shanghai Composite Index fell by 2.75% and the Shenzhen Component Index fell by 3.52%. Therefore, this paper selects January 23, 2020 as the first day of the impact of the new epidemic on all industries in the securities market (Ambros et al., 2020; Schell et al., 2020). As a result, all data before January 23, 2020 are used for the control group and all data after January 23 are used for the treatment group.

In addition, to avoid data quality problems for the treatment and control groups caused by endogeneity, it is necessary to intercept short enough data samples, but this would certainly lead to data shortage. Therefore, our solution is to select data on individual stocks from all industries in the securities market three days before and six days after the outbreak as research samples. Specifically, this paper uses the return index of Shenyin Wanguo (an authoritative database from China)’s 28 first class industries and the returns of 3,901 stocks belonging to classified industries. The sampling period is from January 20, 2020 to February 7, 2020. The sample consists of 3,743 stocks, after excluding all stocks without data for this period. The descriptive statistics of the data are shown in Table 1.

3.2. Heterogeneous impact of COVID-19 on different industries

This section uses the causal forest method proposed by Wagier and Athey (2018) to analyze the influence (treatment effect) of the COVID-19 epidemic as an exogenous event on various industries in the Chinese securities market. The input data for the causal forest method consist of three parts \(Y_i, X_i, W_i\). The specific structure is as follows. 1. Response variable \(Y_i\): we use an industry’s individual stock return data three days before January 23, 2020 to choose \(Y_i\) for the control group and use individual stock return data six days after January 23 through February 7 (No data for weekends and holidays) to choose \(Y_i\) for the treatment group. 2. Treatment assignment \(W_i\): if \(Y_i\) is from the control group, then the corresponding \(W_i\) is equal to zero, and \(W_i\) is equal to one if the corresponding \(Y_i\) is from the treatment group. 3. Covariate \(X_i\): this paper considers the heterogeneous treatment effects of COVID-19 on different industries. We select 28 industry indexes with a one-day lag as the covariate variable (to calculate the industry index for a particular stock, we subtract the weighted value of that stock from the Shenyin Wanguo industry index). For a six-day period from January 23, 2020 to February 7, 2020, the daily heterogeneous impact (treatment effects) of the novel coronavirus epidemic on various industries are shown in Table 2.

Table 2 shows that on January 23 and February 3, the heterogeneous treatment effects of COVID-19 on the 28 industries all passed the significance t-test; that is, COVID-19 had a significant effect on all 28 industries. However, the treatment effects were significantly greater on February 3 than on January 23 and were negative across all industries; that is, COVID-19 had a negative impact on all 28 industries. The severity of COVID-19 increased during the 10-day stock market shutdown that started on January 24, the first day of the Chinese New Year vacation, which only appeared in market information on February 3. The outbreak of the epidemic coincided with the Chinese Spring Festival, when the leisure industry, such as catering and tourism, and the media industry, such as movies, were in peak season. Therefore, on February 3, leisure services was the industry most affected by the epidemic. Table 3 presents an industry classification according to the heterogeneous treatment effects of the epidemic. So far, the pandemic is still not over. In the future,
heterogeneous effects of COVID-19 on different industries may still change with the pandemic, which may not disappear until the universal use of COVID-19 vaccines.

### 3.3. Industry-related network

When analyzing the heterogeneous effects of the epidemic on each industry, we can obtain the degree of influence for each industry, then we call this index Variable Importance (VI), and its expression is shown in Formula (3).

\[
\text{VI} = \frac{\text{Effect on Industry} - \text{Baseline Effect}}{\text{Max Effect} - \text{Min Effect}}
\]

Where 
- \(\text{Effect on Industry}\) is the effect of the epidemic on a specific industry.
- \(\text{Baseline Effect}\) is the baseline effect before the epidemic.
- \(\text{Max Effect}\) and \(\text{Min Effect}\) are the maximum and minimum effects across all industries.

The larger the VI, the greater the impact of the epidemic on the industry. This provides insights into which industries are most affected by the pandemic.
\[ V_{\phi} = \left( \frac{\sum_{\text{all trees}} \sum_{\text{all trees}} \text{numberdepthsplitsonx} \cdot k^2}{\sum_{\text{all trees}} \text{totalnumberdepthsplitsonx}} \right) / \left( \sum_{k=1}^{4} k^2 \right) \] (3)

As each of the 28 industries has a set of variable importance rankings for each day from January 23 to February 7, this paper only shows the variable importance rankings of the five most concerned industries in the securities markets, namely real estate, non-bank financial, agriculture & farming, media, and bank on January 23 and February 4, as shown in the appendix. The results for January 23 and February 4 are chosen because these two days were respectively the day before and the day after the COVID-19 outbreak as measured in this study, showing a sharp contrast.

Fig. 1 shows the change in the industry-related network based on the variable importance in the causal forest analysis over four days from January 23 to February 5. On January 23, when the epidemic broke out, the securities market had not yet reacted to the COVID-19 outbreak. By February 5, the network had changed significantly, indicating the impact of the outbreak on the industry-related relationships.
outbreak. The whole network showed a diffusion structure, with some nodes in the secondary industry, such as bank, non-bank financial, steel and extractive, as the network center. On February 3, after experiencing an influx of information during the Spring Festival vacation, the stock market fully responded to the epidemic. The whole network structure became a star network structure with leisure services at the core. According to Zareei (2019), a star network structure is the riskiest of all network structures. On February 4, although the network structure was gradually being restored, the central node of the network shifted to leisure services, transportation, and agriculture & farming, which were seriously affected by the epidemic. On February 5, the characteristics of the industry-related network gradually returned to those of January 23. In addition, a possible explanation for the change of industrial structure is that Chinese investors were likely to have herding behavior while responding to non-fundamental information more frequently during the crisis, which might make the industrial risk contagion spread from leisure services and transportation to other industries on February 3 (Ju, 2019). Then, the herd effect has gradually disappeared, and the industrial risk contagion structure has begun to return to its original type (while some changes have taken place in the central industries). Another possible explanation is that some investors had a pessimistic forecast on the fluctuation trend of the securities market, and sold the stocks of leisure services and transportation in these industries. As a result, COVID-19 had heterogeneous effects on these industries, which caused diffusion effects on other industries. Finally, the structure of industrial risk contagion changed (Goodell and Huynh, 2020). The pandemic not only has a great impact on various industries, but also changes the related structure among some industries. In the late stage of the pandemic or after COVID-19 vaccines come out, the risk contagion structure among industries may still change.

3.4. Types of industry risk contagion

Based on Fagiolo (2007), we calculate different types of industry clustering risks on January 23, February 3, and February 4, then determine the types of risk contagion for all 28 industries. The rule for determining the type of risk contagion for each industry is as follows: calculate four types of clustering risks for each industry and take the greatest value of the four as the type of clustering risk for a given industry. The results are shown in Table 4. Table 4 shows that on January 23, the main types of risk contagion for the 28 industries were the middleman type and the input type, representing respectively 50% and 39.29%. However, on February 3, when COVID-19 broke out, the types of risk contagion changed considerably, with the input type accounting for 71.43%. The reason is that leisure services and transportation were directly and most severely affected by the epidemic. The risk contagion type for leisure services and transportation is the diffusion type, while that for other industries is the input type. On February 4, the situation gradually improved and the proportion of input risk type industries decreased to 53.57%. In addition, from January 23 to February 4, there were no cyclic risk type industries in the Chinese securities market. The main reason for this phenomenon is not directly related to the epidemic: the supply chain structure in China and even the world is generally an upstream and downstream structure, rarely forming a

| Industry Type          | 01.23  | 02.03  | 02.04  | 01.23  | 02.03  | 02.04  |
|------------------------|--------|--------|--------|--------|--------|--------|
| Extractive             | Mid    | In     | In     | In     | Out    | In     |
| Media                  | in     | In     | In     | In     | Building materials | Out    | In     |
| Electrical equipment   | in     | In     | In     | In     | Agriculture & Farming | Mid    | In     |
| Electron               | Mid    | In     | In     | In     | Mid    | In     |
| Real estate            | In     | In     | Out    | Automobile | In     |
| Textile & garment      | in     | In     | In     | In     | Light manufacturing | Mid    | In     |
| Non-bank financial     | Mid    | In     | In     | In     | Commercial trade | Mid    | Out    |
| Steel                  | Out    | In     | In     | In     | Food & beverage | Mid    |
| Public utility         | Mid    | Mid    | Out    | Communication | Mid    |
| National defense & military | Mid | In     | mid    | Leisure Services | In   | Mid    |
| Chemical               | Mid    | In     | Out    | Medical biology | In     |
| Mechanical equipment   | Mid    | In     | Mid    | Bank | Out    | Mid    |
| Computer               | In     | Mid    | Out    | Nonferrous metals | In   |
| Household appliances   | Mid    | In     | mid    | Sum | Mid    |

Note: “Mid” indicates the middleman risk type; “in” indicates the input risk type; “Out” indicates the output risk type.
Fig. 2. Variable Importance ranking of covariates.
closed-loop structure. In order to further investigate types of industrial risk contagion from January 23 to February 4, this paper conducts correlation analysis of the measurements of industrial risk contagion types on January 23, February 3 and February 4. It can be seen from Table 5 that the correlation is very weak, indicating that industrial risk contagion types fluctuated greatly during this period. The results of t-test on January 24 and February 4 show that the industrial risk contagion type on February 4 was slowly returning to that on January 23.

4. Conclusion

The main conclusions of this study are as follows:

1. Due to the strong coincidence of COVID-19 and the Chinese Spring Festival, it had a great impact on the leisure services, transportation, and media industries, and the heterogeneity of industries was weakened during the outbreak. Government support policy should focus more on the leisure, transportation, and media industries, as helping these industries can not only directly generate economic benefits for these industries but also indirectly radiate to other industries, resulting in indirect economic benefits.

2. The COVID-19 outbreak changed the original structure of the industry-related network, shifting to a star network structure with leisure services at the core. According to Zareei (2019), a star network structure is the riskiest of all network structures.

3. The COVID-19 outbreak changed the type of industry risk contagion, which shifted from the original middleman risk type to the input risk type. However, over time, the risk contagion type slowly began to return to its original characteristics.

We have to realize that, COVID-19 has not been over, and some countries have encountered the second wave of COVID-19. In the future, the impacts of the COVID-19 on various industries may still change with the pandemic, some of which may be irreversible, such as teleworking. In the late stage of the pandemic or after the universal use of COVID-19 vaccines, the association structure among industries may also change further.

In addition, due to the short period of the research data and the use of daily data, the research conclusion has certain limitations. Intraday data is suggested to be used to study the heterogeneous effects of COVID-19 on different industries and the impact on the industrial association structure from the micro perspective in the future.

Authors’ statement

We confirm that our work has not been published previously, that it is not under consideration for publication elsewhere, that its publication is approved by all authors and tacitly or explicitly by the responsible authorities where the work was carried out, and that, if accepted, it will not be published elsewhere in the same form, in English or in any other language, including electronically without the written consent of the copyright-holder.

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Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.frl.2021.101931.

Appendix. variable importance ranking of covariates

It can be seen from Fig. 2 that compared to January 23, concentration ratio of variable importance is higher on February 3 when analyzing heterogeneous treatment effect on real estate, non-bank financial, agriculture & farming, medical biology and bank. Among all the covariates, leisure services and transportation were the most important during the outbreak, having greater impact on other industries on February 3. On the day before the outbreak, heterogeneous treatment effect on real estate and non-bank financial showed that bank was the most important covariate, while real estate is the most important covariate when analyzing treatment effect on bank. Results show that in the early stage of the outbreak, bank and real estate were interdependent, but in the later stage of the outbreak, the structure of industrial relations changed as leisure services and transportation are the most important covariates.

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