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The real economic costs of COVID-19: Insights from electricity consumption data in Hunan Province, China

Hongshan Ai a,b, Tenglong Zhong c, Zhengqing Zhou a,*

a School of Economics and Trade, Hunan University, Changsha 410081, Hunan, China
b Hunan Key Laboratory of Energy Internet Supply-demand and Operation, Changsha 410004, China
c School of International Trade and Economics, Central University of Finance and Economics, Beijing 102206, China

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ABSTRACT

The COVID-19 pandemic has caused extreme economic fluctuations. However, the magnitude of the economic cost of this extreme event remains challenging to quantify. The impact of the COVID-19 pandemic on the economy is estimated through firm-level electricity consumption data from Hunan province, China. Specifically, a difference-in-differences (DID) model was employed to estimate the real economic costs. The results indicate that electricity consumption in Hunan Province dropped by 27.8% during the early stage of the COVID-19 pandemic. Manufacturing and the transportation industry suffered the most severe declines. Electricity consumption began to recover after the virus was controlled. We suggest that government departments should take full measures to prevent and control COVID-19 outbreaks and associated economic impacts, in conjunction with preparing for economic recovery, deploying targeted measures to support different industries in response to the heterogeneity COVID-19 pandemic impacts. The COVID-19 has changed people’s living habits and brought a new direction, the Internet industry, of economic growth. Hunan Province needs to accelerate the digital empowerment of traditional industries, develop the Internet, 5G technology, and new digital infrastructure to offset the negative impact of the COVID-19 pandemic. Electricity consumption is an applicable index in estimate the real economic cost of extreme events.

1. Introduction

In early 2020, the COVID-19 pandemic caused widespread public health impacts and disruptions to the economy. To stop the spread of the virus, the Chinese government implemented strict public health measures, e.g., locking down entire regions and urging people to quarantine in their homes, and these measures affected the real economy. Importantly, factories stopped production on the supply side. National Bureau of Statistics of the People’s Republic of China (NBS) reported that the gross domestic product (GDP) growth rate of China in the first quarter of 2020 dropped by 10% from the previous month. However, the GDP cannot measure the whole picture of economic activities, especially in developing countries (Chen and Nordhaus, 2011; Henderson et al., 2012). This study aimed to estimate the impacts of COVID-19 on the real economy by using daily electricity consumption data of Hunan province China.

Electricity consumption is the most fundamental barometer of the economy. Specifically, reductions in electricity consumption are related to production stagnation, the closure of production facilities, and increased difficulty in accessing credit lines. Moreover, electricity consumption opens the door for study daily real economic growth. However, given the extraordinary nature of the current issue, there is no established quantitative methodology to link electricity consumption with the impacts of COVID-19, even though such an index could be crucial for reviving a fluctuating economy.

This study relates to the following two major avenues of research in the literature. The first set of literature involves the study of economic performance and electricity consumption during the COVID-19 pandemic. Since the initial outbreak leading up to the COVID-19 pandemic, a large number of papers have been published. Extensive studies focused on the economic impacts of the COVID-19 pandemic. Altig et al. (2020) measured US and UK economic uncertainty indicators...
before and during the COVID-19 pandemic. Kong and Prinz (2020) studied the effect of non-pharmaceutical interventions in the US with an event study framework using Google search data during the pandemic. Meanwhile, some studies focused on the shocks to specific markets and sectors, such as crude oil (Salisu and Adediran, 2020), financial (Zhang et al., 2020), commodity market (Chen et al., 2021), international trade (Iyke, 2020; Vidya and Prabheesh, 2020), tourism (Gossling et al., 2020), and environmental protection (He et al., 2020; Magazzino et al., 2020; Ming et al., 2020).

Especially, some important research focuses on the electricity market performance during the COVID-19. Bahmanyar et al. (2020) construct a Demand Variation Index to compare the electricity consumption variation in Europe during the COVID-19 period. They compare the index in European countries and find that the decrease in electricity consumption was higher in countries with severe restrictive measures. The COVID-19 pandemic caused a reduction of electricity consumption up to 37% compared to the same time as the previous year in Italy (Ghiani et al., 2020). Abu-Rayash and Dincer (2020) compare the electricity consumption between April 2019 and April 2020. They find a decrease of 14% in Ontario province Canada. Carvalho et al. (2021) apply the joinpoint model to measure the heterogeneous regional impact of COVID-19 on the electricity market in Brazil. They find electricity consumption in Southeast-Midwest, South, and North-Northeast of Brazil decreased 20%, 18%, 14%, respectively. In Spain, electricity consumption has decreased by 13.49% from March 14 to April 30, compared to the average value of five previous years (Santiago et al., 2021). Ceylan (2021) borrows the machine-learning approach to estimate the impact of COVID-19 on the electricity demand of Turkey in May 2020. Specifically, demand decreased approximately 17% compared to 2019 levels. The decrease in electricity consumption is mainly concentrated in the commerce and manufacture industry (Madurai Elavarasan et al., 2020; García et al., 2021).

This kind of literature point out the negative impact of COVID-19 on electricity is approximately 10% ~ 40%. Furthermore, A small part of the literature pointed out that the decrease in electricity consumption can be used to assess the economic cost of COVID-19 (Fezzi and Fanghella, 2020; Beyer et al., 2021). Nevertheless, their research is not based on a counterfactual framework, ignoring the potential growth trend in 2020, resulting in an understimation of economic costs. A key contribution of this study is the description of a methodology to investigate the economic costs of the COVID-19 pandemic within the counterfactual framework, which is a useful complement to the ongoing research in this field.

The second avenue of research in the literature related to this study pertains to studies on the relationship between electricity consumption and economic growth. Research on energy consumption and economic growth began with Kraft and Kraft (1978). As technology has advanced and the electronics industry has continued to grow, human demand for electricity has risen considerably. Meanwhile, the relationship between electricity consumption and economic growth has been drawing increasing attention from several researchers. These types of studies can be divided into two parts, as discussed in the subsequent sections.

Many scholars have focused on the link between electricity consumption and GDP. Ferguson et al. (2000) showed the connections between economic growth and electricity consumption. In most countries, the correlation between electricity consumption and GDP is close to one. Nowadays, relevant global research is increasing. Shi and Lam (2004) pointed out that an increase in electricity consumption supports GDP growth in China. Yoo (2005) finds that an increase in electricity consumption directly affects economic growth and that economic growth also stimulates further electricity consumption. Kumar Narayan and Singh (2007) examined the causality between electricity consumption and economic growth for Fuji islands. They find unidirectional causality running from electricity consumption to GDP in the long run and a bidirectional causality running from GDP to labor force in the short run. A Granger causality relationship was found between electricity consumption and GDP in Malaysia (Tang and Tan, 2013). Ozturk (2010) finds that most studies support the causality is running from electricity consumption to economic growth. Beyer et al. (2021) find that electricity consumption increased by 0.95% for each percent additional economic activity. This type of literature has demonstrated a strong correlation between electricity consumption and GDP.

Another part of the literature is devoted to the measurement of the shadow economy. Kaliberda and Kaufmann (1996) proposed that electricity consumption is a reasonable yardstick to measure the level of economic activity. They measured the informal economic activity growth level in 16 countries and regions (mainly in Ukraine). According to their approach, the difference between the growth rate of registered GDP and the growth rate of total electricity consumption can be attributed to hidden economic growth. Lackó (2000) added strength to the opinions of Kaliberda and Kaufmann. They developed a methodology to measure the hidden economy using real electricity inputs. They then measured the hidden economy of 20 post-socialist countries. In addition, with the maturity of remote sensing technology, many scholars have used night landscape lighting data to correct the GDP (Chen and Nordhaus, 2011; Henderson et al., 2012; Egger et al., 2017). Therefore, electricity consumption can be a precise indicator of the level of economic growth (Feige and Urban, 2008). This study uses decreases in electricity consumption to measure the economic costs of the COVID-19 pandemic.

This study has three main innovations. First, there is still no clear methodology for measuring the economic costs of COVID-19 in the existing literature. A convenient and precise approach is provided for measuring the direct economic losses from extreme events. Specifically, this paper used daily data on electricity consumption and DID model to measure daily economic growth. Second, during the COVID-19 pandemic, most of the firms in the secondary industry department shut down. In addition, the tertiary industry department was also seriously hit by the restriction policy. Therefore, electricity consumption can be a precise indicator of the level of economic growth (Feige and Urban, 2008). This study uses decreases in electricity consumption to measure the economic costs of the COVID-19 pandemic.

The remainder of this paper is organized as follows. The second section introduces the background and the empirical design. The third section introduces the data sources and provides a descriptive statistical analysis of the data. In the fourth section, this paper reports on the main estimation results, address potential empirical model limitations, and perform extensive robustness checks. The fifth section presents an analysis of the heterogeneity among each industry and the economic costs of COVID-19. The conclusions are presented in the sixth section.

2. Research background and research design

2.1. Background research

In early 2020, the COVID-19 pandemic broke out in Wuhan, and the virus spread around the world over the following months. The COVID-19 pandemic is an unprecedented global epidemic that precipitated widespread and deep impacts on the world economy. As of September 24, 2021, in terms of public health, there were only 12 countries and regions with no confirmed cases of COVID-19, whereas a total of 230,418,451 confirmed cases and 4,724,876 deaths were recorded elsewhere. In
addition, the COVID-19 virus has a strong mutation ability. The new mutant strains Delta and Lambda have more vital transmission ability and more severe symptoms among the many existing mutant viruses, remarkably raising the prevention difficulties. The COVID-19 pandemic has far outpaced SARS and Middle East Respiratory Syndrome (WHO, 2021) in terms of the speed of transmission, scope of influence, ability of mutation, and number of infections. On the economic front, the International Monetary Fund predicted that the global economy is projected to grow 5.5% in 2021 and 4.2% in 2022. Many countries fell into a recession (IMF, 2021). Furthermore, the World Trade Organization estimated that the volume of world merchandise trade would decline by 9.2% and this could lead to the worst recession since the Great Depression (WTO, 2020). On the employment side, the International Labor Organization (ILO) reported that Global unemployment increased by 33 million in 2020, with the unemployment rate rising by 1.1 percentage points to 6.5% (ILO, 2021). Therefore, it is necessary to conduct in-depth analyses of the full socioeconomic impacts of the COVID-19 pandemic.

In late December 2019, patients presenting with novel coronaviruses were first reported in Wuhan, China, and the disease spread quickly (Zhu et al., 2020). The Chinese government adopted a lockdown policy to prevent the further spread of the COVID-19 pandemic. Wuhan announced its lockdown on January 23, 2020. Subsequently, the bus, subway, ferry, and long-distance transportation services in the city were temporarily suspended. Additionally, the airport, railway station, and other channels for leaving Wuhan were temporarly closed. Local governments in China also implemented policies to lockdown their cities to prevent the spread of COVID-19. The central government called on citizens to reduce travel and quarantine at home. However, these policies were implemented at the cost of less travel and less economic activity.

Hunan Province is conveniently located and is the largest province in central China. In 2019, the total population of Hunan Province was 66.4 million, ranking seventh among all provinces in China, with a GDP of 3989.41 billion yuan ranking ninth. The economic situation of Hunan Province is in the middle position in China, close to the average level of all provinces in China, which reflects the average economic cost of COVID-19 of provinces in China. In Hunan Province, heavy industry is the leading industry. Meanwhile, in the tertiary industry department, the transportation and tourism industry are also the pillars of economic growth because of the geographic advantages. In 2019, the electricity consumption of Hunan Province was 186.432 billion kWh and ranked 17th in the country. Among them, the electricity consumption of the primary industry department was 1.656 billion kWh, the secondary industry department 98.757 billion kWh, the tertiary industry department 35.068 billion kWh, residents 50.951 billion kWh. During COVID-19, the production of enterprises was restricted, especially in the secondary and tertiary industry departments. Therefore, taking Hunan Province as an example to study the economic cost of COVID-19 has important reference significance for the secondary industry department-led economy to fight against COVID-19. Besides, Hunan Province is adjacent to Hubei Province, which suffered greatly from the pandemic. The trade-off between the restriction policy and economic performance occurs in the regions around the harder-hit epidemic area. Thus, the experiences in Hunan Province can potentially serve as a precious resource to other cities engaged in pandemic prevention.

Estimating the impacts of the COVID-19 pandemic on the economy requires a comparative analysis. The lockdown policy implemented by the Chinese government provided a quasi-experimental setting to identify the impacts of the COVID-19 pandemic on electricity consumption. Based on the construction concept of the difference-in-differences (DID) model, this paper used samples in 2020 as the treatment group and samples with the same lunar calendar date to the treatment group in 2019 as the control group. The losses caused by COVID-19 were measured by estimating the differences between the treatment and the counterfactual of treatment groups after implementing the lockdown policy of the Chinese government.

### 2.2. Empirical model

Causality rather than correlation unveils the fact between the dependent variables and independent variables. DID strategy is first adopted by Ashenfelter (1978). DID strategy base on the quasi-experiment, and it helps find causality and policy evaluation (Arat sov and Black, 2020; Gu et al., 2021; Huang and Zhang, 2021). The principle of the DID model is to construct the counterfactual results of the treatment group with the help of the control group to estimate the causal effect of exogenous shocks. Specifically, The basic did model can be written as eq. (1).

$$Y = \beta_0 + \beta_1 \text{treat} + \beta_2 \text{post} + \beta_3 \text{treat,post} + e$$

The counterfactual framework helps to eliminate the potential growth trend of the treatment group and estimate the clean treatment effect. The treatment effect is the treatment group minus the counterfactual of the treatment group, which means the potential outcome that the treatment group has not been treated. However, The counterfactual of the treatment group can not be observed directly. Therefore, the control group is needed to estimate the potential outcome of the treatment group after the treatment. The control group captures the trend of the treatment group applied to construct the potential outcome of treatment. From the eq. (1), $\beta_3$ captures the treatment effect. Twice differentiation is needed to obtain the clean treatment effect. The first difference is based on the time of treatment. The treatment group after treatment minus the treatment group before treatment to obtain the difference before and after treatment. The same method is used in the control group to obtain the difference before and after the potential treatment. The second difference uses the difference before and after treatment in the treatment group minus the difference before and after treatment in the control group to obtain the treatment effect. Table 1 lists the principle of DID strategy. The first difference is used to obtain $\Delta Y_t$ and $\Delta Y_0$. The second difference eliminates the potential growth trend of the treatment group and captures the treatment effect.

In the empirical analysis, DID strategy is employed and used the Wuhan lockdown date (January 23, 2020) to start the treatment. Thus, the treatment group is the samples in 2020. DID strategy implies an assumption that the control group trends the same before the treatment. In addition, the seasonal variation in electricity consumption was related to the Chinese New Year (CNY). This research follows the idea of Chen et al. (2021) used the same data sample from the Chinese lunar calendar in 2019 as the control group. The CNY effect of the treatment groups can be offset by the CNY effect of the control group, which excludes the impact of the CNY effect on the research paper. The model is as follow:

$$Y_{i,j} = \alpha + \delta_i + \gamma_j + \lambda_{ij} + \beta^* \text{dd}_{ij} + \pi + \epsilon_{i,j}$$

where $Y_{i,j}$ represents the electricity consumption of company $i$ on day $j$

| Table 1 | The principle of DID model. |
|---------|----------------------------|
| Before treatment | After treatment | Difference |
| Treatment group | $\beta_0 + \beta_1$ | $\beta_0 + \beta_1 + \beta_2 + \beta_3$ | $\Delta Y_t - \beta_2 + \beta_3$ |
| Control group | $\beta_0$ | $\beta_0 + \beta_2$ | $\Delta Y_0 - \beta_2$ |
| Difference | $\Delta Y_t$ | $\Delta Y_0$ |

1. For convenience, the basic form is used to explain the principle of DID model. The same result is the same in general DID form, which is adopted in this paper.
in year $c$, $d_{i,c,j}$ is the core estimation variable constructed in this study, which equals 1 if the sample is company $i$ after the date of the COVID-19 outbreak in Wuhan and 0 if the sample is company $i$ before the COVID-19 outbreak in Wuhan. $\alpha$ is the city fixed effect, $\gamma_i$ is the year fixed effect, $\gamma_j$ is the daily fixed effect, $\lambda_{ic}$ is the individual fixed effect, $\xi$ is the industry fixed effect, and $\epsilon_{ic,j}$ is the residual. $\beta$ is the impact coefficient of COVID-19 on the economy. The city fixed effect controls the time-invariant city characteristics, for example, the minerals, climate, population, customs of the city. The industry fixed effect controls the industry characteristic that is invariant over time, such as the electricity consumption customs of industry. The year fixed effect captures the year characteristics of the sample. The daily fixed effect included accounting for the common patterns of electricity consumption. During the estimation, the robustness is verified through a stepwise regression approach. If $\beta$ is negative, this indicates that COVID-19 is having a negative impact on the economy. If $\beta$ is positive, this indicates that COVID-19 is promoting the economy.

3. Data analysis

3.1. Data source

The impact of COVID-19 on the economy is examined via electricity consumption data. This study used the daily electricity consumption data of Hunan Province, China, from December 1, 2019, to March 31, 2020. This dataset was obtained from a 0.1% sample of electricity consumers in Hunan Province and contained daily electricity consumption data from 322 representative enterprises. In this dataset, State Grid Hunan Electric Power Company provides the electricity consumption, the main product, firm id, and category type for each sample. It allows us to identify the firm-level information, such as the category or department of firms.

This dataset was chosen for three reasons. First, because of the insufficient statistical frequency of macroeconomic variables such as the GDP, the feasibility that use these general variables to estimate the immediate response of the economy is low. However, electricity consumption provided an opportunity to estimate the typical macroeconomic influence caused by COVID-19. Second, electricity is an essential element in economic activities (Fezzi and Fanghella, 2020). Therefore, fluctuations in the economy are represented by electricity consumption. Third, the data of Hunan province is representativeness. Hunan province has advantages in the secondary industry department, transportation, and tourism. Besides, During the COVID-19 pandemic, Hunan province suffers tremendous pressure to prevent the COVID-19 virus. In China, it is one of the representatives in the fight against the COVID-19 pandemic. The experience in Hunan is of reference significance for regions that leading industry is in the secondary industry department, transportation, and tourism. Because of the official data shortages in real-time and integrity, and the representative characteristics of Hunan Province, such as the epidemic affected the situation, industrial structure, and geographical conditions. Therefore, this article chooses the electricity consumption of Hunan Province to measure the economic cost of the COVID-19 pandemic.

3.2. Data description

In this paper, the treatment group is the samples in 2020, and the control group is the samples in 2019 with the same lunar calendar date to the treatment group. The external event shock is the Wuhan lockdown. The underlying assumption of the DID model is that the treatment and control groups showed consistent trends before treatment. The electricity consumption in 2020 should have a common trend with 2019, before the Wuhan lockdown. This study tested this assumption by plotting the temporal trends of the treatment and control groups. As shown in Fig. 1, the control group fits the prior trend of the treatment group well. There was almost no difference between the treatment and control groups before the Wuhan lockdown. However, the difference between them rapidly increased after the Wuhan lockdown. Because of the CNY effect, most of the firms are on holiday break. A decrease has been observed both in the treatment group and control group. After an approximately one-week holiday break, the electricity consumption in the control group starts to increase and quickly recover to the normal level. The electricity consumption in the treatment group is maintained at a low level. The restrictive policy for COVID-19 has caused a delay in production recovery and allowing us to estimate the direct impact of the pandemic. The electricity consumption level of the treatment group did not return to the level of the same period of 2019 until the ten weeks after Wuhan lockdown.

Table 2 presents the descriptive statistics for the samples. Panel A describes the statistics for the entire sample. Panel B shows the descriptive statistics of the control group. Panel C shows the statistics for the treatment group. This study collected 66,976 electricity consumption observations. These samples consist of two groups. The first group is the treatment group which contains 322 firms, 22 days before Wuhan lockdown, to 81 days after Wuhan lockdown. The second group is the control group which consists of the same firms and the same lunar calendar date samples with the treatment group in 2019. It can be seen that the mean electricity consumption in the control group was greater than that in the treatment group.

Table 3 shows the mean differences between the treatment and control groups. Panel A depicts the mean difference before and after the COVID-19 outbreak in the treatment and control groups. The mean differences in the treatment groups were minor, but the mean differences were massive in the control group. It means that the COVID-19 pandemic entails a decrease in electricity consumption.

4. Empirical results

4.1. Main result

The Chinese government adopted a lockdown policy to fight the

![Fig. 1. Electricity consumption trends for the treatment and control groups. This figure shows a comparison of the electricity consumption trends for the treatment and control groups. The vertical axis shows the mean electricity consumption expressed on a logarithmic basis. The horizontal axis indicates the distance to the day of the Wuhan lockdown. The red reference line represents the date of the Wuhan lockdown. The green reference line represents the date that the end of Wuhan’s lockdown. Dates before the Wuhan lockdown is defined as negative values.](image-url)
COVID-19 pandemic. Consequently, the level of economic activity in China dropped to a low level during the pandemic. The impact of the COVID-19 pandemic on the economy is observed from the supply side by measuring electricity consumption levels during the pandemic.

The results of all regression models in this paper are calculated by STATA16 SE software. The main results are presented in Table 4. Column (1) estimates the impact of COVID-19 on electricity consumption using the pooled regression model, which did not consider the individual and temporal characteristics of the sample. While the difference in electricity consumption before and after the Wuhan lockdown was statistically significant, the standard error was large. Moreover, there were unobservable factors across cities and controls, which may have affected the estimation results. Hence, the year and city fixed effects are unobservable factors across cities and controls, which may have affected the estimations. To solve this problem, this paper further controlled for the daily fixed effects. However, the values of the unobservable factors across cities and controls, which may have affected the estimation results, this study used smoothing by averaging daily data on a weekly basis. The results are shown in columns (4, 5). In column (4), this paper uses the pooled estimation model. In column (5), the daily fixed effect is switched into a weekly fixed effect. The estimated coefficients of the smoothing transform process were essentially the same as those in column (3).

High-frequency data pose serial correlation problems when used. This study drew on a solution from Bertrand et al. (2004), in which a two-period DID model was used to verify the robustness of the estimates. Specifically, we divided the sample into two periods, before and after the COVID-19 pandemic, by using the Wuhan lockdown shock as the boundary, and the data were averaged by period. The results are shown in column (6). Because the sample is collapsed into two periods, and it could not control for the daily fixed effects. However, the values of the units of the electricity consumption are kWh.

| Variable                  | N (before) | Mean (before) | N (after) | Mean (after) | MeanDiff | N (before) | Mean (before) | N (after) | Mean (after) | MeanDiff |
|---------------------------|------------|---------------|-----------|--------------|----------|------------|---------------|-----------|--------------|----------|
| ln(electricity consumption) | 8244        | 5.238          | 19,473    | 5.186        | 0.052*   | 8954       | 5.306         | 21,405    | 5.524        | -0.218*** |
| electricity consumption    | 9982        | 753.749        | 23,506    | 659.115      | 94.634***| 741.448    | 23,506        | 795.743   | 353.294***   |
| Panel A 2020 sample         | N (before) | Mean (before) | N (after) | Mean (after) | MeanDiff | N (before) | Mean (before) | N (after) | Mean (after) | MeanDiff |
| id                         | 33,488     | 161.50         | 92,954    | 1            | 161.5    | 322        | 2019          | 0         | 2019.5       | 2020     |
| Year                       | 33,488     | 2019.00        | 0.000     | 0            | 0        | 0          | 2019          | 0         | 2019         | 2019     |
| dd                         | 33,488     | 0.35           | 0.477     | 0            | 0        | 0          | 2019          | 0         | 2019         | 2019     |
| ln(electricity consumption) | 30,359     | 5.46           | 2.114     | -4.60517     | 5.944216 | 9.958189   |
| Electricity consumption    | 33,488     | 779.56         | 1527.800  | 0            | 260.765  | 21,124.5   |
| Panel C 2020 sample         | N (before) | Mean (before) | N (after) | Mean (after) | MeanDiff | N (before) | Mean (before) | N (after) | Mean (after) | MeanDiff |
| id                         | 33,488     | 161.50         | 92,954    | 1            | 161.5    | 322        | 2019          | 0         | 2019.5       | 2020     |
| Year                       | 33,488     | 2020.00        | 0.000     | 0            | 0        | 0          | 2020          | 0         | 2020         | 2020     |
| dd                         | 33,488     | 0.70           | 0.457     | 0            | 1        | 1          | 2020          | 0         | 2020         | 2020     |
| ln(electricity consumption) | 27,717     | 5.20           | 2.294     | -4.60517     | 5.874594 | 9.958189   |
| Electricity consumption    | 33,488     | 687.32         | 1705.488  | 0            | 202.725  | 21,124.5   |

This table reports the mean differences of the samples. Panel A. compares the mean values before and after the shock in the control group and treatment group. Panel B. keep the samples in 2019. Panel C. describes the sample of the treatment group, which is in the year of 2020. The units of the electricity consumption are kWh.
4.2. Empirical analyses

4.2.1. Parallel trend test

The rationality of the DID model is based on several assumptions. The first and foremost is the parallel trend assumption, i.e., the treatment and control groups were trending the same before treatment. Otherwise, the DID model would not be applicable. This study borrowed the event study method to test the parallel trend assumption (Nunn and Qian, 2011; Ai et al., 2021; Gu et al., 2021; Huang and Zhang, 2021).

The model is as follow:

$$Y_{i,c,j} = \alpha + \delta_j c + \gamma_j j + \lambda_{i,c} + \pi_{i,c,j} + \sum_{j=22}^{N} \beta_j * dd_{i,c,j} + \epsilon_{i,c,j}$$ (3)

The parallel trend between the treatment group and the control group can be observed in the variation in the core coefficients $\beta_j$. First, if $\beta_j$ was statistically insignificant before the event shock, then the trend of the treatment group and the control group was not different before treatment. Second, if $\beta_j$ was significantly different from zero after the event shock, a significant treatment effect was observed. More importantly, the parallel trend assumption was confirmed when the two situations existed simultaneously.

Notes: This figure reports on the results of the parallel trend test. The red reference line represents the date of the Wuhan lockdown. The green reference line represents the date that the end of Wuhan's lockdown. In the horizontal direction, pre_x refers to the x day before the Wuhan lockdown. The “current” mark represents the day of the Wuhan lockdown. Post_x refers to the x day after the Wuhan lockdown. The vertical direction represents the coefficient and confident intervals of the COVID-19 impact.

Therefore, this paper supposed that the electricity consumption of the control and treatment groups before the Wuhan lockdown was indifferent. However, after lockdown, the difference between the two groups began to increase. This paper collected the coefficients from Eq. (3) and constructed Fig. 2. Then, this paper found that before the Wuhan lockdown, the values of coefficients $\beta_j$ fluctuated around 0 and were statistically insignificant. Furthermore, the results indicated that before the Wuhan lockdown, the electricity consumption level in 2020 was similar to the same lunar calendar date in 2019. Therefore, if there was no COVID-19 pandemic, the electricity consumption level in 2020 should have been similar to the same lunar calendar date in 2019. Within a month of the Wuhan lockdown, the value of the coefficients $\beta_j$ dropped rapidly to negative ones, and these were statistically significant. This means that after the Wuhan lockdown, the electricity consumption level significantly decreased. A month after the Wuhan lockdown, the estimated coefficient values gradually began to rise. Meanwhile, in Hunan Province, the COVID-19 pandemic was under
control (Fig. 3), and the government announced an orderly resumption of production.\(^3\) Hence, after a month of lockdown, the impact of the COVID-19 pandemic started to fade, and the Hunan provincial government began to focus on economic recovery.

This paper also carried out the parallel test by using the smoothed weekly data, and the result is presented in Fig. 4. The result is similar to Fig. 2. On the left side of the red reference line, the coefficient is positive and insignificant. On the right side of the red reference line, the coefficient turns into negative and significant. About four weeks after the Wuhan lockdown, the coefficient starts to rise. The results show no significant difference between the treatment group and control group before the Wuhan lockdown. After the COVID-19 break, the negative impact appears.

4.2.2. Exogenous assumption

The second assumption is that event shocks should be exogenous. When inferring causality with the help of the DID model, it is important to research an exogenous shock. The endogenous issue usually comes from the correlation between an event shock and the dependent variable. In this study, the COVID-19 pandemic outbreak is utilized as a quasi-experiment. COVID-19 is exogenous and unpredictable Therefore, the identification strategy in this study met the exogenous assumption.

4.2.3. Stable unit treatment value assumption

The third assumption is that exogenous event shocks only affect the treatment group. In this study, the treatment group was the individual electric consumption of 2020 in Hunan Province. The control group was the individual electric consumption of 2019 in Hunan Province. The event shock in 2020 did not affect this situation in 2019. Therefore, the COVID-19 pandemic only affected electricity consumption in 2020.

4.2.4. Chinese New Year (CNY) effect

Nevertheless, our empirical model may encounter other challenges. One of the most challenging ones is related to the disturbance of the CNY. The CNY is a traditional festival in China. The importance of the CNY in China is similar to Christmas in Western countries. Most Chinese people believe that the CNY is a symbol of the beginning of the new year. Although the date of the CNY is the first day of the first month of the lunar calendar, the activities of CNY are not limited to a particular day. The symbol of the beginning of the CNY is the Spring Festival Transport. The Spring Festival Transport is a large-scale phenomenon of high transportation pressure in China around the CNY. Many people who worked and went to school outside returned to their hometowns to celebrate the CNY. The Spring Festival Transport starts approximately from the 15th day of the lunar month to the 25th day of the first month of the following year in the lunar calendar, about 40 days. Holiday break postpones most economic activities of firms. Therefore, there is a decrease in the electricity consumption of firms during the CNY period. The start of the COVID-19 virus spreading in China in 2020 coincides with the CNY. Two days before the CNY, the Wuhan lockdown is the sign of the Chinese government’s declaration of war on the COVID-19. The decrease in electricity consumption caused by the CNY confuses estimates of the economic costs of the COVID-19 pandemic.

Fig. 4. Parallel trend test results and smoothed week data.
The red reference line represents the date of the Wuhan lockdown. In the horizontal direction, pre-x means the x weeks before the Wuhan lockdown. The current represents the day of the Wuhan lockdown. post-x refers to the x weeks after the Wuhan lockdown.

\(^3\) The official documents can be found on the Hunan Provincial People’s Government website. [http://www.hunan.gov.cn/hnmxw/szfl/zfhyjj/zfcwhj/cwhyy20200217/t/202002/t20200217_11184225.html](http://www.hunan.gov.cn/hnmxw/szfl/zfhyjj/zfcwhj/cwhyy20200217/t/202002/t20200217_11184225.html)
To address this issue, this paper converted the method of date counting into the Chinese lunar calendar, and then the data is matched for the treatment and control groups. There are two advantages to this conversion. Firstly, both groups experienced CNY and CNY underwent a similar process each year. By identifying the sample of the exact date of the lunar calendar and controlling for daily fixed effects was able to subtract the same effect for the same period. Secondly, the CNY disturbance offsets the difference between the treatment and control groups and isolates the direct effect of the COVID-19. Most firms are under the holiday break during the CNY period and maintain the lowest electricity consumption level. The electricity consumption in 2019 and 2020 is similar because of the turnoff of the extra production. It enhances the fitness of the model setting to parallel trend assumption of DID strategy.

4.2.5. Anticipatory effect

The average treatment effects may have come from other contingency shocks. COVID-19 was first reported by the Wuhan Municipal Health Commission in Wuhan, China, on December 30, 2019 (Xu et al., 2020). Because the 2019 novel coronavirus is a novel virus, it did not attract much attention initially. However, on January 20, the National Health Commission of the People’s Republic of China (NHC) held a press conference. They announced the first human-to-human transmission evidence of the 2019 novel coronavirus (NHC, 2020). After this, people became more concerned about this virus. This study relied on the timing of the Wuhan lockdown (January 23, 2020) as the starting point for the impact of the COVID-19 pandemic. However, some of the pioneers may already have put strategies in place after the NHC announcement. Therefore, to exclude the anticipated effects of the COVID-19 pandemic, this study follows the methodology of Topalova (2010), including an interaction term in the baseline model for the shock dummy variable with an advanced variable for the actual shock time Treat$_{t-i}$ * pre$_{t}$, as shown in Eq. (4).

\[Y_{i,t} = \alpha + \delta_i + \gamma_j + \lambda_k + \pi + \beta^*dd_{i,t} + \sum_{j=1}^{N} \theta \text{Treat}_{t-i}^* \text{pre}_{t} + \epsilon_{i,t} \quad (4)\]

Because the NHC announcement came three days prior to the Wuhan lockdown, in columns (1) to (4) of Table 5, this paper used daily data and added interactions from one day ahead to four days ahead in that order. In column (5), this paper used the smoothed weekly data and added the interaction term one week ahead. The coefficient from Eq. (3) was close to the baseline results. The coefficients of the interaction term Treat$_{t}$ * pre were close to zero and not significant. Therefore, this paper concluded that there was no evidence to support the anticipated effect before the Wuhan lockdown.

4.3. Robustness

4.3.1. Falsification test

To check the robustness of our estimations, this paper set up a series of tests, for example, a falsification test and a placebo test.

In the falsification, this paper follows Li et al. (2021) to test the robustness of DID estimation by changing the implementation date of the external shock. A fake interaction item is created by manipulating the date of the COVID-19 outbreak. In detail, this paper dropped off the sample after the COVID-19 outbreak and manipulated the date of treatment to 1, 2, or 3 weeks before the real outbreak date (January 23, 2020), and then, the model was estimated as follows:

\[Y_{i,t} = \alpha + \delta_i + \gamma_j + \lambda_k + \pi + \beta^*fakedd_{i,t} + \epsilon_{i,t} \quad (5)\]

A statistically insignificant coefficient of fakedd$_{t-i,j}$ meant that no contingency shocks before COVID-19 affected the treatment and control groups. Columns (1) to (3) in Table 6 show the estimates of manipulating the advancement of the COVID-19 outbreak to 1, 2, and 3 weeks. The results showed that manipulating the time of the COVID-19 outbreak did not affect the estimations. Simultaneously, the data partly excluded the possibility of a compound from the external environment before the COVID-19 outbreak. Next, the external compound is excluded through the placebo test.

4.3.2. Placebo test

In the placebo test, treatment groups and control groups are randomly set repeatedly (Murphy et al., 1989; Chetty et al., 2009). The logic of this test is that the deviation of the real estimation from the random setting estimation coefficient distribution indicates the insignificance of the unobservable factors. The coefficient of fakedd$_{t-i,j}$ is expressed as follows:

\[\hat{\beta} = \beta + \rho \cdot \frac{\text{cov}(dd_{t-i,j}, \epsilon_{t-i,j}|\text{control})}{\text{var}(dd_{t-i,j}|\text{control})} \quad (6)\]

where control denotes the fixed effects and $\rho$ denotes the effect of unobservable factors on the independent variables. If $\rho = 0$ and the unobservable factors have no impact on the estimated results, then $\hat{\beta}$ is an unbiased estimate. However, it is hard to verify whether $\rho$ is equal to zero directly. Next, this paper randomly generated a fake variable that

Table 5
Anticipatory effect.

|                  | (1)   | (2)   | (3)   | (4)   | (5)   |
|------------------|-------|-------|-------|-------|-------|
|                  | model 1 | model 2 | model 3 | model 4 | model 5 |
| $dd_{t-i,j}$     | -0.329*** | -0.329*** | -0.331*** | -0.334*** | -0.307*** |
| (6.62)           | (6.60) | (6.61) | (6.65) | (5.31) |       |
| $pre_1$          | 0.049  | 0.050  | 0.048  | 0.044  | -0.010 |
| (0.85)           | (0.84) | (0.79) | (0.72) | (0.19) |       |
| $pre_2$          | 0.012  | 0.010  | 0.006  |       |       |
| (0.22)           | (0.17) | (0.11) |       |       |       |
| $pre_3$          | -0.060 | -0.063 | -0.060 |       |       |
| (0.91)           | (0.94) |       |       |       |       |
| $pre_4$          | -0.094 |       |       |       |       |
| (1.52)           |       |       |       |       |       |
| $cons$           | 5.446*** | 5.446*** | 5.447*** | 5.449*** | 5.249*** |
| (326.59)         | (325.83) | (322.88) | (320.49) | 255.91 |       |
| Year FE          | Yes    | Yes    | Yes    | Yes    | Yes    |
| City FE          | Yes    | Yes    | Yes    | Yes    | Yes    |
| Industry FE      | Yes    | Yes    | Yes    | Yes    | Yes    |
| Week FE          | No     | No     | No     | No     | Yes    |
| Day FE           | Yes    | Yes    | Yes    | Yes    | No     |
| Firm FE          | Yes    | Yes    | Yes    | Yes    | Yes    |
| Cluster          | Yes    | Yes    | Yes    | Yes    | Yes    |
| $r^2$ adj        | 0.77   | 0.77   | 0.77   | 0.77   | 0.78   |

This table reports the results of eq. (3). The standard errors are clustered at the firm level. ***, **, and * indicate the 1%, 5%, and 10% significance levels, respectively.

Table 6
Falsification test.

|                  | (1)   | (2)   | (3)   |
|------------------|-------|-------|-------|
|                  | 1 Week advance | 2 Weeks advance | 3 Weeks advance |
| fakedd$_{t-i,j}$ | -0.017 | 0.002 | 0.025 |
| (0.21)           | (0.04) | (0.43) |      |
| $cons$           | 5.448*** | 5.445*** | 5.435*** |
| (435.94)         | (291.65) | (211.10) |      |
| Year FE          | Yes    | Yes    | Yes    |
| City FE          | Yes    | Yes    | Yes    |
| Industry FE      | Yes    | Yes    | Yes    |
| Day FE           | Yes    | Yes    | Yes    |
| Firm FE          | Yes    | Yes    | Yes    |
| Cluster          | Yes    | Yes    | Yes    |
| $r^2$ adj        | 0.89   | 0.89   | 0.89   |

This table reports the results of eq. (4). The standard errors are clustered at the firm level. ***, **, and * indicate the 1%, 5%, and 10% significance levels, respectively.
1%, 5%, and 10% significance levels, respectively. Because the fake variable was randomly generated, \( \beta = 0 \). Under this condition, if the estimated result \( \hat{\beta} \) was still equal to 0, then \( \rho = 0 \) could be reversed. Further, the treatment effect was not a "chance finding" and was statistically unrelated to the unobservable. Then, the estimation coefficient distribution between the real estimation coefficient and random setting estimation is compared. In practice, this paper set up the simulation process to 1000 times and then obtained the random setting estimation coefficient distribution. The result shows that the value of the real estimation deviated significantly from the random setting estimation coefficient distribution (Fig. 5). Therefore, compounds from external sources are excluded.

### 4.3.3. Change the estimation bandwidth

In this study, the sample time interval of the DID model ranged from 23 days before the lockdown to 81 days after the Wuhan lockdown. The DID estimate represents the average treatment effect of the treatment and control groups before and after treatment. Hence, the robustness of the estimation may be affected by the selection of the sample time interval. To test robustness, this paper shifted the bandwidth of the estimation coefficient distribution (Fig. 5). Therefore, compounds from external sources are excluded.

### Table 7

|          | 2 Week | 3 Weeks | 4 Weeks |
|----------|--------|---------|---------|
| \( \text{dd}, \ i, j \) | -0.641*** | -0.670*** | -0.650*** |
| \( \text{cons} \) | (-8.66) | (-9.16) | (-9.04) |
| \( \text{Year FE} \) | 5.123*** | 5.240*** | 5.273*** |
| \( \text{City FE} \) | (811.32) | (523.35) | (416.21) |
| \( \text{Day FE} \) | Yes | Yes | Yes |
| \( \text{Industry FE} \) | Yes | Yes | Yes |
| \( \text{Firm FE} \) | Yes | Yes | Yes |
| \( \text{Cluster} \) | Yes | Yes | Yes |
| \( N \) | 14,744 | 22,539 | 27,577 |
| \( R^2 \) | 0.87 | 0.86 | 0.85 |

This table reports the results of the test of transferring the estimation bandwidth. The standard errors are clustered at the firm level. *** *, and * indicate the 1%, 5%, and 10% significance levels, respectively.

### 5. Heterogeneity and economic significance

#### 5.1. Heterogeneity

Different departments have different production processes. Therefore, the impacts of COVID-19 on different departments were expected to be heterogeneous. This study followed the GB/T 4754–2017 standard designed by the NBS. It separates the sample into primary, secondary, and tertiary industry departments. Then, a regression was carried out based on Eq. (1), and the results are shown in Fig. 6. The results show that the impacts of COVID-19 on primary industry departments were small and statistically insignificant. However, the pandemic had significant negative impacts on the secondary and tertiary industry departments.

To propose targeted policies for economic recovery, it is reasonable to acquire a comprehensive understanding of the COVID-19 impacts. Driving by this aim, the secondary and tertiary industry department is subdivided into several categories based on the production nature and operation of the samples. Specifically, the secondary industry department is subdivided into mining, manufacturing, resource supply, and construction categories. The tertiary industry department was subdivided into transportation and public service categories. The results found that the manufacturing and transportation categories were the most negatively impacted among all categories (Fig. 7). The mining, electricity, gas, and water supply, construction, and public services sectors were less affected by the COVID-19 pandemic.

#### 5.2. Economic significance

Economic activity is closely related to electricity consumption. Specifically, each production and operation process requires an elec-

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4 The GB/T 4754–2017 standard designed by the National Bureau of Statistics of the People’s Republic of China. The more detail can be found on the following website. http://www.stats.gov.cn/tjsj/tjbz/hyflbz/201710/t20171012_1541679.html
Moreover, electricity consumption can be used to measure economic output that is not reflected in the official registration form. Although the reduction in electricity consumption can serve as acceptable proof of the economic losses caused by the COVID-19 pandemic, its economic significance is still not straightforward. Therefore, it is feasible to estimate the direct economic cost of the COVID-19 pandemic by further calculating the GDP loss per kilowatt-hour of electricity consumption. Specifically, the annual GDP of Hunan Province in 2019 was 3975.212 billion yuan. Its total electricity consumption was 186.4 billion kWh. Hence, the calculations indicated that electricity consumption per kilowatt-hour can bring about 21.34 yuan in terms of the electricity input. Moreover, electricity consumption can be used to measure economic losses caused by the COVID-19 pandemic in this paper to further calculating the GDP loss per kilowatt-hour of electricity consumption. Specifically, the annual GDP of Hunan Province in 2019 was 3975.212 billion yuan. Its total electricity consumption was 186.4 billion kWh. Hence, the calculations indicated that electricity consumption per kilowatt-hour can bring about 21.34 yuan in terms of the GDP. According to the estimated results, COVID-19 will lead to approximately 56.948 billion kilowatt-hours of electricity consumption loss in Hunan Province. Hence, the total economic loss caused by the COVID-19 pandemic in Hunan Province was estimated at approximately 1.214487 trillion yuan.

Meanwhile, in 2019, the electricity consumption of the primary, secondary, and tertiary industry department in Hunan Province was 1.66 billion, 98.76 billion, and 35.07 billion kilowatt-hours, respectively. According to our estimates, the COVID-19 pandemic reduced the electricity consumption of the primary, secondary, and tertiary industries by 9.6%, 29.8%, and 30%, respectively. Therefore, the economic losses caused by the COVID-19 pandemic to these three major industries amounted to approximately 37.61 billion, 8946.5 billion, and 3220.74 billion yuan, respectively.

6. Conclusion

COVID-19 is having severe and profound impacts on human beings. Countries worldwide have spent a substantial amount of money to fight the COVID-19 pandemic. This study innovatively used electricity consumption data to measure the economic losses related to COVID-19. Specifically, The DID model is employed to analyze the decreasing electricity consumption caused by the COVID-19 pandemic in this paper and draw the following conclusions. First, the COVID-19 pandemic has had a tremendous negative impact on the economy. This conclusion remained unchanged after a variety of robustness tests. After the outbreak of COVID-19, government restrictions on population movement and economic blockades directly led to a sharp decrease in electricity consumption, which was indicative of economic contraction. DID model estimates indicate that electricity consumption in Hunan Province decreased by 27.8%, which reflects an economic loss of about 121.187 billion yuan during the COVID-19 pandemic. Second, economic activity began to recover when the spread of COVID-19 was brought under control. The result indicates that one month after the lockdown in Wuhan, the economic impact of COVID-19 began to shrink, and the economy recovered slowly. Third, the impact of the COVID-19 pandemic on the economy was mainly concentrated in the secondary and tertiary industries. More specifically, among these industries, the manufacturing (secondary) and transportation (tertiary) industries were the most seriously affected. The results showed that the electricity consumption levels of the secondary and tertiary industries decreased by 29.8% and 30%, respectively, during the COVID-19 period, and that the economic losses were approximately 8946.5 billion yuan and 3220.74 billion yuan, respectively.

Therefore, the following suggestions were proposed based on the above conclusions. First, the COVID-19 pandemic generated a great impact on the economy and society. The government should assess the situation and make appropriate decisions. Economic growth should not be ignored while preventing the spread of the COVID-19 pandemic. Specifically, most cities in China have imposed a strict lockdown policy during the COVID-19 pandemic. It raises difficulties to the operation of enterprises, especially in firms with short production cycles and strong cash liquidity. Many companies delayed production during the COVID-19 pandemic, leading to broken capital chains and even bankruptcy. The government should introduce targeted measures, such as tax and rent reductions and low-interest loans issued by banks, to help enterprises get through the difficulties.

Second, the government should prepare for economic recovery. Once the COVID-19 pandemic is under control, the economy will recover. During the COVID-19 pandemic, digital economy industries have received an enormous boost, creating digital transformation opportunities for traditional industries. The new economies are booming, such as digital entertainment, online medical care, online educations, live sales, telecommuting, intelligent production, and remote services. It puts forward higher requirements for ubiquitous connectivity, efficient transmission, intelligent processing, security, and digital infrastructure reliability, which leads to explosive growth in the demand for new digital infrastructure construction. Hence, the Hunan Provincial Government should strengthen the new digital infrastructure construction investment support to grasp the new economic growth direction.

Finally, the impact of the COVID-19 pandemic on various departments and industries varies greatly. Government departments should develop targeted control and incentive measures to protect key industries. As far as the secondary industry department is concerned, the production of firms in this department entails the cooperation of upstream and downstream firms. Therefore, the secondary industry department, especially manufacturing, is affected in a more complex way. During the resumption, the government needs to promote the resumption according to the overall of the industrial chain. The tertiary industry department in Hunan province has also been seriously affected. The government should support the resumption from the supply side, implement stimulating policies from the demand side, and at the same time implement strict epidemic prevention. From the supply side, the government should emphasize the digital transformation and upgrading of the service industry. The COVID-19 pandemic has boosted the digital economy industry. Digital service innovation, including service mode, service scope, service delivery, and service experience, has broad application scenarios and becoming a new driving force for restorative economic growth in the post-COVID-19 period. On the demand side, transportation is most seriously affected by COVID-19 in the tertiary industry department in Hunan province due to restrictions policy. After
the epidemic is under control, the government needs to relax traffic restrictions and strengthen inspections to ensure the regular operation of economic activities. At the same time, implement stimulating consumption policy, such as issuing consumption vouchers to consumers, promoting ticket discounts at famous scenic spots, and carrying out cultural tourism promotion activities. In terms of epidemic prevention and control, Hunan province should prepare for the long-term presence of the COVID-19 virus. Therefore, it is necessary to strengthen prevention and control management, especially in areas with large human flows such as subways and stations, to normalize the wearing of masks, vaccinating to herd immunity.

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