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The discrepancies in the impacts of COVID-19 lockdowns on electricity consumption in China: Is the short-term pain worth it?

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\textbf{A B S T R A C T}

The COVID-19 pandemic caused severe economic contraction and paralyzed industrial activity. Despite a growing body of literature on the impacts of COVID-19 mitigation measures, scant evidence currently exists on the impacts of lockdowns on the economic and industrial activities of developing countries. Our study provides an empirical assessment of lockdown measures using 298,354 data points on daily electricity consumption in 396 sub-industries. To infer causal relationships, we employ difference-in-differences models that compare cities with and without lockdown policies and provide quantitative evidence on whether the long-term gain of lockdowns outweighs the short-term loss. The results show that lockdown policies led to a significant short-term drop in electricity consumption of 15.2\% relative to the control group. However, the electricity loss under the no-lockdown scenario is 2.6 times larger than that under the strict lockdown scenario within 4 months of the outbreak. Discrepancies in the impacts among industries are identified, and even within the same industry, lockdowns have heterogeneous effects. The impact of lockdowns on small and medium-sized enterprises in developing countries is seriously underestimated, raising concerns about the distributional impact of subsidy measures. This study serves as a crucial reference for the government when facing public health emergencies and shocks to support better policies.

\textbf{1. Introduction}

The COVID-19 pandemic, which broke out in December 2019, has spread rapidly across many countries, becoming a global health crisis (World Health Organization, 2021). People have different attitudes regarding whether lockdown policies are an effective way to control the pandemic and ultimately lead to economic growth or economic losses, and governments have taken different preventive measures (Lai et al., 2020; Edomah and Ndulue, 2020). The Chinese government enforced strict lockdown measures when a city was experiencing the COVID-19 pandemic. In locked down cities, residents were required to stay at home; schools and workplaces were closed; and all forms of travel were largely banned (Lai et al., 2020; Yang et al., 2020; He et al., 2020). These measures contained the spread of the pandemic within 3 months and reduced the number of infections by >700,000 people (Cole et al., 2020; Chinazzi et al., 2020). Many countries adopted a “weak control model”, under which non-essential businesses, such as restaurants and bars, were closed but schools and factories remained open to avoid excessive economic losses in the early stage of the outbreak of the pandemic (Sebastiani et al., 2020; Perez-Bermejo and Murillo-Llorente, 2020; Persico and Johnson, 2021).

Whether lockdown measures bring pain or gain has sparked debates among researchers around the world (Kissler et al., 2020; Lewnard and Lo, 2020). Lai et al. (2020) found that while earlier diagnosis prevented more infections, the combination with nonpharmacological interventions produced the strongest and most rapid effects. Tian et al. (2020) also indicated that adopting a lockdown policy as early as possible is the most effective measure for curbing the development of the pandemic. Mckibbin and Fernando (2020) demonstrated that lockdown measures such as quarantining affected people and reducing large-scale social interactions is an effective response for the recovery of the global economy. However, a few researchers have questioned the effectiveness of lockdown policies in containing the pandemic. Kupferschmidt and Cohen (2020) worried that due to differences in cultures and social...
systems, lockdown policies may not be effective in all regions. After a lockdown is lifted, the pandemic is likely to break out again. Fernandes (2020) estimated that the global GDP growth in 2020 was $-2.5\%$ on average under a 1.5-month lockdown scenario.

The impacts of COVID-19 mitigation measures on industrial economic activities in Western countries have been widely explored (Michie, 2020; Fernandes, 2020; Ozili and Arun, 2020; Warwick and Roshen, 2020). Santiago et al. (2021) analysed how confinement measures changed electricity consumption in Spain, one of the countries most affected by this pandemic. Ruan et al. (2020) tracked and quantified the short-term impact of COVID-19 on the US electricity sector using a cross-domain, data-driven approach. Previous research has also focused on the short-term inhibiting effect of COVID-19 mitigation measures on economic development (Barthik et al., 2020; Fairlie, 2020) rather than the overall impact of these measures from a medium-term perspective. For these issues, research gaps remain regarding the effects of strict lockdown policies on industrial activities in developing countries, which is extremely important for the design and evaluation of economic recovery and subsidy policies.

With the promotion of electrification, the social economy is increasingly dependent upon electricity (Yuan et al., 2007; Squalli, 2007; Hirsh and Koomey, 2015). Changes in electricity consumption can be an early indicator of the economic impacts of COVID-19 that are not yet reflected in traditional economic indicators such as the GDP growth rate (Ferguson et al., 2000; Ruan et al., 2020). As a “barometer” reflecting economic development (Prol and Sungmin, 2020), electricity consumption provides an alternative perspective for analysing the impact of lockdown policies on industrial activities. Fine-grained power data can not only help us explore the effects of lockdowns on economic activities over time but also quantitatively reflect the effects on specific industries. Therefore, we propose three hypotheses.

First, lockdown policies restrict economic activity overall, although certain industries have a special role in a pandemic. While the government closed down small medical institutions to contain the virus, the pandemic increased the energy demand of large health institutions (Santiago et al., 2021). Confining people in their home may lead to a surge in electricity demand from the public management and service sector (Widen and Waecelgard, 2010; Santiago et al., 2014). In addition, working from home requires internet and communication technology support, making the information industry important during a lockdown period (Edomah and Ndulue, 2020; Santiago et al., 2021). We thus hypothesize that lockdown policies have no statistically significant reduction effects on these sectors. Existing studies focus on investigating the negative impacts of COVID-19 mitigation measures on business operations (Ruan et al., 2020; Santiago et al., 2021). However, these studies fall short in evaluating the effects of lockdowns on certain industries that play a special role during or after the outbreak of COVID-19, which might lead to biases in the evaluation of the economic impact of lockdowns. Our study fills this gap in the literature by analysing daily electricity consumption data from 396 sub-industries.

Second, small and medium-sized enterprises (SMEs) may face more pressure due to their single business model and weak ability to overcome shocks and leaving them on the verge of bankruptcy (Zhu et al., 2020; Wu and Xu, 2021). Worse, large-scale enterprises have natural advantages in borrowing financing (Flussain et al., 2006; Hernández-Cánovas and Martínez-Solano, 2010). Therefore, we propose that lockdown measures have a greater impact on the electricity consumption of SMEs than on that of large-scale enterprises. Existing studies focus on the impact of counter-COVID-19 measures on SMEs in developed countries (Barthik et al., 2020; Fairlie, 2020). Few studies have explored the effects of lockdowns on SMEs in developing countries. Compared with developed countries, the business environment of SMEs is more adverse in developing countries (Wang, 2016). These findings of early-stage losses to SME activities have important implications for policy-making, income losses, and future economic inequality in developing countries.

Finally, strict lockdown policies might seriously affect the routine operations of many sectors in the short run. However, if these measures effectively contain the spread of a pandemic, then economic activity may recover more quickly in the long run (Fernandes, 2020). While lockdown policies significantly reduced overall electricity consumption in the early stage, electricity consumption may exceed the scenario without lockdown policies once economic recovery begins in the long run. Therefore, we hypothesize that the benefits of lockdown policies will surpass the losses in the long term.

In April 2020, Wuhan lifted its lockdown, and the first wave of the pandemic in China was brought under control. However, separate outbreaks subsequently occurred in different cities, such as Beijing, Dalian and Urumqi. Governments also imposed strict lockdown measures on these cities. Taking cities that have been subjected to lockdowns during the second wave of the pandemic as a quasi-natural experiment subject, this paper employs the difference-in-difference (DID) model to explore the impacts of lockdowns on the economic activities of industries, and electricity consumption is used as a proxy variable for economic activities. The DID model allows us to control for various confounding factors that potentially affect electricity consumption and to identify the plausible causal impact of lockdown policies. Whether the effects of lockdowns vary across different types of industries and sizes has been investigated. Moreover, the electricity consumption scenarios in the absence of COVID-19 and with COVID-19 but no lockdown have been investigated through neural network algorithms. The electricity loss in the lockdown scenario and no-lockdown scenario are compared in the short and medium terms, shedding light on the trade-off between the short-term losses and long-term gains of lockdown policies. This study serves as a crucial reference for the government when facing public health emergencies to support better policies. In addition, using electricity consumption data, this paper identifies in a timely manner the industries or enterprises that have suffered serious losses due to lockdowns, which can enable the government to issue more targeted subsidies and avoid the large-scale collapse of firms. Moreover, identifying industries with potential for development after lockdowns can provide a scientific reference for use by practitioners in the post-pandemic era.

2. Data and methodology

Taking cities that faced a secondary lockdown as a quasi-natural experimental subject, we employ a DID model to explore the impacts of the lockdown on the economic activities of industries using electricity consumption as a proxy variable.

2.1. Data

We integrated multi-source data for the empirical analysis. To analyse the overall and heterogeneous effects of lockdowns on various industries, we used the daily electricity consumption data of 396 sub-industries and 402,700 firms in 14 cities in China for a sample period extending from 16 days before to 13 days after a lockdown. Due to data confidentiality, we are unable to specify the names of the cities and the specific lockdown dates. We aggregated the 396 sub-industries into 11 first-level industries based on the classification standards of the National Bureau of Statistics (NBS). The electricity consumption data come from the national state grid of China. All analysis results are analysed in the data management platform of the state grid and are used for academic research only after desanitization. We also collected the COVID-19 cases and weather data during the period from the official government website and the China Meteorological Data Sharing Service system, which contains the daily mean temperature, daily maximum temperature, daily minimum temperature, wind speed and average relative humidity.
For the forecast of electricity consumption in the absence of COVID-19, we used historical daily electricity consumption data (seven months before the COVID-19 outbreak), weather data and monthly electricity consumption data from 2016 to 2019. For the forecast of electricity consumption with the COVID-19 outbreak but without lockdowns, we collected daily electricity consumption data, weather data and COVID-19 cases in Boston and Houston from January 1, 2020, to November 11, 2020. All data are from the COVID-EMDA+ data hub. We predicted the daily electricity consumption of all industries approximately four months after the COVID-19 outbreak.

2.2. Variables

Consistent with the dependent variables studied by Yuan et al. (2007), Squalli (2007), and Hirsh and Koomey (2015), we selected industry daily electricity consumption to measure economic activities. For the core independent variables, lockdown and post are policy group dummy and time dummy variables, respectively. lockdwnc is a dummy variable equal to 1 if the city is locked down and 0 otherwise. post equals 0 if date t is before the lockdown and 1 otherwise. In addition to the impacts of lockdown measures on economic activities, there are many other factors that can have an effect. Thus, the interference of these exogenous factors also needs to be controlled for. Ruan et al.’s (2020) study found a significant reduction in electricity consumption that is strongly correlated with the number of COVID-19 cases. Blázquez et al. (2013) indicated that weather conditions have a significant impact on electricity use. Lou et al. (2021) insisted that in addition to temperature, the day of the week is a significant driver of electricity consumption. Therefore, we chose daily temperature, weekend dummy variables and the number of new confirmed cases as control variables.

2.3. Models

We used DID models to identify the impacts of lockdowns on electricity consumption. The DID model is a measurement model used to estimate causal effects. The basic idea of the DID model is to regard a policy as a natural experiment (Nunn and Qian, 2011). For the evaluation of policy effects, some empirical studies use the single-difference method to evaluate policy effects by comparing the differences in outcomes before and after policy measures are implemented. Clearly, before and after the implementation of a policy, the variation in the dependent variable includes two parts, the “time effect” and the “policy effect”. The disadvantage of this simple comparison method is that it fails to find a suitable control group for locked-down cities to identify the net effect of lockdowns under the premise that the parallel trend assumption is satisfied. Compared with the ordinary single-difference method, the DID model can eliminate the interference of other joint determinants and obtain the net effect of lockdown policies on the electricity consumption of industries (Wang et al., 2021). There are >300 cities in China, and when the pandemic broke out in a certain city, lockdown measures were implemented. This process is full of uncertainties. Therefore, the randomness of the treatment (lockdown policy) and the selection of the industry of a certain city as the treatment group are ensured. The implementation of a lockdown can be regarded as a policy experiment in which the industries in a locked-down city are the treatment group and the remaining 13 nonlocked-down cities are the control. The cities in the control and treatment groups are from the same province to ensure that the cities in the two groups are as similar as possible in all aspects except for the lockdown measures. We also added industry fixed effects and time fixed effects to the model to control for industry heterogeneity, which is difficult to measure, and accidental external shocks at different time points to reduce the impact of omitted factors. In addition, we took the important factors affecting industry electricity consumption into consideration as control variables, such as daily temperature, weekend dummy variables and the number of new confirmed cases. Although this procedure does not completely solve the endogeneity problem, we demonstrate the causal effect by means of a parallel trend test and placebo test. We estimated the relative change in electricity consumption between the treatment and control groups using the following model:

$$\ln(\text{elec}_t) = \beta_0 + \beta_1 \text{lock}_t + \beta_2 \text{control}_t + \eta_t + \gamma_t + \epsilon_t$$  (1)

where $\ln(\text{elec}_t)$ is the natural log of the daily electricity consumption of industry $i$ in city $c$ on day $t$. We used the natural log of electricity consumption so that we could interpret the treatment effects approximately in percentage terms. The treatment effects in exact percentage terms can be obtained by exp($\beta_1$)-1. lock is a dummy variable equal to 1 if the city is locked down and 0 otherwise. control is a dummy variable equal to 1 if the day is weekend and 0 otherwise. post equals 0 if date $t$ is before the lockdown and 1 otherwise. control is a vector of control variables, including the daily temperature, weekend dummy variables and the number of new confirmed cases. We used the daily average temperature for the baseline regression and the daily maximum temperature and HDD and CDD for robustness tests. The variable $\eta_t$ is the industry fixed effect, which is used to control for the time-invariant attributes of an industry, such as the capital and business scope as well as the energy consumption structure. The time fixed effect $\gamma_t$ controls for time-varying factors across days, such as economic development and the international pandemic situation. We clustered standard errors at the industry level to adjust for serial correlation.

We analysed how the impacts of lockdowns differ across industries. Based on the NBS classification standards, we divided the 396 sub-industries into 11 first-level sectors and three major sectors. In addition, we explored the impacts of lockdowns on large enterprises and SMEs in each sector. Existing studies have reported that SMEs in China account for 90% of the total number of enterprises. Therefore, if a firm’s average electricity consumption in a week ranks in the top 10% of all firms, then it falls into the large-scale enterprise group, and a firm’s average electricity consumption in a week ranks in the bottom 90% of all firms, it falls into the SME group.

The underlying assumption of the DID strategy is that the treatment and control cities have parallel trends in electricity consumption in the absence of lockdowns. For the analysis, we adopted the event study approach and fitted the following equation:

$$\ln(\text{elec}_t) = a_0 + \beta_1 \sum_{t=1}^{12} \text{lock}_{t-12} \text{date} + \phi \text{control}_t + \eta_t + \gamma_t + \epsilon_t$$  (2)

where date is a set of dummy variables indicating the treatment status at different dates. date equals 1 when $k = b$ and 0 otherwise. We omit the dummy for $k = -1$ in Eq. (2) to ensure that the post-lockdown effects are relative to the period immediately before the launch of the policy. The coefficient $\beta_k$ measures the difference in electricity consumption between industries in the treatment and control groups on day $k$ relative to the difference 1 day before the lockdown. If the coefficient $\beta_k$ is statistically significant when $k \leq -2$, then the evidence suggests that the parallel trend hypothesis is rejected.

To compare the electricity loss under a lockdown and otherwise, we used two sets of multi-layer neural network models to forecast daily electricity consumption. We first forecast the daily electricity consumption without a COVID-19 outbreak. We aggregated the potential external shocks at different time points to reduce the impact of omitted factors. In addition, we took the important factors affecting industry electricity consumption into consideration as control variables, such as daily temperature, weekend dummy variables and the number of new confirmed cases. Although this procedure does not completely solve the endogeneity problem, we demonstrate the causal effect by means of a parallel trend test and placebo test. We estimated the relative change in electricity consumption between the treatment and control groups using the following model:

$$E_{\text{elec pred}} = \frac{1}{n} \sum_{i=1}^{n} f_i(\text{Temp}_{m}, \text{Hum}_{m}, \text{Wind}_{m}, \text{Elec}_{i, m}, \text{Calen}_{i, m})$$  (3)

where $E_{\text{elec pred}}$ is the estimated daily average electricity consumption in the absence of COVID-19 for month $m$ and day $t$. Temp, Hum, Wind are temperature (daily mean temperature, daily maximum temperature
and daily minimum temperature), average relative humidity and wind speed. $\text{Elec}_{\text{mt}}$ represents the historical daily electricity consumption data (seven months before the COVID-19 outbreak) and monthly electricity consumption data from 2016 to 2019. $\text{Calen}_{\text{mt}}$ represents the calendar information (month, day, weekday and holiday). $n$ is the number of models. We randomly selected 20% of the electricity consumption data before the COVID-19 outbreak as the test set and used the rest as the training set. Our multi-layer perceptron (MLP) is a 4-layer neural network, including 1 input layer, 2 hidden layers and 1 output layer. We randomly generated 100 hidden layer structure parameters to form 100 models, and each model was iterated 500 times for the estimation. The loss function (evaluation index) is the mean square error (MSE).

We next estimated the electricity consumption if no lockdown measures were taken after the COVID-19 outbreak. We added the data for Boston and Houston to the model to extract the electricity consumption features without lockdown measures after the outbreak, including weather variables, epidemic situation variable and date of year. If a city experiences an outbreak, the Chinese government took strict lockdown measures to prevent an escalation of the epidemic. Therefore, we adopted the idea of migration learning to use the data of two cities in the United States to help forecast the electricity consumption of cities in China in the no-lockdown scenario.

$$E_{\text{No lock mt}} = \frac{1}{n} \sum_{i=1}^{n} \left( \text{Temp}_{\text{mt}}, \text{Humi}_{\text{mt}}, \text{Wind}_{\text{mt}}, \text{Confirm}_{\text{mt}}, \text{Calen}_{\text{mt}} \right)$$

where $E_{\text{No lock mt}}$ is the estimated daily average electricity consumption without lockdowns for month $m$ and day $t$. $\text{Confirm}_{\text{mt}}$ represents new confirmed cases. The detailed procedure adopted here for estimation is identical to that above, except that we added the data of Boston and Houston to the MLP model as an auxiliary training set.

3. Results

Based on the industrial-level and firm-level electricity consumption data before and after the lockdown in China, this paper makes a systematic quantitative analysis on the heterogeneity effects of lockdown policies through difference-in-difference (DID) model (see Methods). We set the industries of the locked down city as the treatment group, and the industries of the rest 13 unlocked down cities as the control group. In addition, we predict the electricity consumption in the absence of COVID-19 and in the absence of the lockdown policies in the short and medium-term through machine learning algorithms.

Fig. 1 illustrates the change rate in electricity consumption among different industries before and after lockdowns. Lockdowns did not affect the electricity consumption of agriculture significantly. Industrial electricity consumption decreased two days before the lockdown, while that of the tertiary industry showed a significant drop immediately after the lockdown, especially for the retail sector. However, we find no sharp drop in the electricity consumption of information transmission and public service industries after the lockdown. A preliminary before-after comparison can be problematic because it lacks a proper counterfactual; although COVID-19 affected all countries, electricity demand was already showing a declining trend, especially in China (Zhong et al., 2020). However, the simple difference in eccentricity consumption before and after a lockdown does not account for important factors that affect electricity consumption such as temperature and weekends. Hence, we next discern the net effect of lockdown policies on industrial electricity consumption through a difference-in-difference DID estimation strategy using cities without lockdown policies as the counterfactual.

3.1. DID model estimation results

We estimate the changes in electricity consumption before and after the implementation of lockdowns between the treatment group
(industries of locked-down cities and the control group (industries of non-locked-down cities) through a DID model (Table 1 and Eq. (1)). There is a significant negative causal relationship between the implementation of lockdown measures and overall industrial electricity consumption. Compared to cities without lockdowns, industrial electricity consumption declined by 15.2% overall (Column 1 in Table 1). This result indicates that the lockdown measures paralyzed industrial economic activities and caused a temporary economic depression. The stay-at-home measures restricted employees’ return to work, making it difficult for enterprises to engage in production activities. In addition, lockdowns did not significantly affect the electricity consumption of the primary industry (Column 3 in Table 1). This result may be because the population in rural areas is relatively scattered, the lockdown measures are not as strict as those in urban areas, and the electricity consumption of the primary industry in a city is extremely low, accounting for only 0.6% of the electricity consumption of all industries. However, lockdowns led to a 10.6% and 23.1% decrease, respectively, in the electricity consumption of the secondary and tertiary industries (Columns 5 and 7 in Table 1). This result suggests that tertiary sectors suffered the most from lockdown policies. The lockdown policies forced a large number of businesses to close and people to be confined to their homes, leading to a significant reduction in economic activities in the secondary and tertiary industries (He et al., 2020). The estimates are remarkably robust when we control for time-invariant individual characteristics (individual fixed effects) and individual-invariant differences in the sample periods (time fixed effects) (Columns 2, 4, 6 and 8 in Table 1).

As the DID method assumes that there is no significant difference in electricity consumption before lockdowns, re-estimating the DID model in the same way in the time period before lockdowns should result in nonsignificant coefficients. If the results are contrary to our expectations, then our findings may be driven by some unobserved differences between the treatment and control groups. We assume that the dates for a lockdown are 5 days, 7 days, and 10 days before the actual date of the lockdown and conduct a placebo test. The resulting coefficient of the interaction term is statistically nonsignificant, which gives us additional confidence that we estimated the true causal effect of lockdowns on the reduction in industrial electricity consumption (Table 2).

We conducted additional analyses to validate the robustness of our results. Previous studies indicated that temperature greatly affects electricity consumption (Bessec and Fouquau, 2008; Jovanović et al., 2015). Therefore, for the regression, we selected the highest daily temperature as an alternative to the average temperature. To avoid the influence of the nonlinear relationship between temperature and electricity consumption on the results, we use 18 degrees Celsius as the equilibrium temperature to construct the index of a heating degree day (HDD) or a cooling degree day (CDD) (Midlarska, 2010). We find that the results are all similar even if we adopt different temperature indices (Table 3). The checks suggest that our baseline results are robust.

### 3.3. Heterogeneity across industries and sizes

Heterogeneity across industries and sizes. We next verify the hypothesis that lockdowns do not affect the operations of industries that play a special role during a pandemic period. We separately investigate the impact of lockdowns on the electricity consumption of the information industry, the public management and service industry, and the medical industry. The coefficient of the interaction term is statistically nonsignificant (Table 4); thus, the hypothesis that lockdowns have no effect on these sectors cannot be rejected. This result indicates that during the lockdown period, these industries still maintain normal operations to ensure people’s basic needs, such as telecommuting, daily life and medical treatment (Santiago et al., 2021).

We then examine the heterogeneous effects of lockdowns on enterprises of different sizes in each industry, which is crucial for the government to formulate a scientific and equitable subsidy distribution policy in the post-pandemic period. The ability to withstand risk and cash flow pressure is likely to make it difficult for SMEs to maintain and resume operations after a city lifts its lockdown. We divide the sample

| Table 1 Effects of lockdowns on electricity consumption. |
|-----------------|-----------------|-----------------|-----------------|-----------------|
|                 | Overall          | Primary industry | Secondary industry | Tertiary industry |
| lock_dum        | –0.152**         | 0.0230           | 0.0230            | 0.0230           |
| Temp            | –6.146-06        | –0.0000287       | –0.0000272***     | –0.0000272***    |
| Confirmed       | –0.00210***      | –0.0000967*      | –0.0000278        | –0.0000278       |
| Weekend         | –0.00135         | 0.0000356        | 0.0147***         | 0.0442           |
| Cons            | 12.632***        | 11.117***        | 11.165***         | 14.406***        |
| Time fixed effects | Y               | Y               | Y                | Y               |
| Individual fixed effects | Y               | Y               | Y                | Y               |
| Obs             | 4466             | 2436             | 2436             | 2814             |

Notes: This table shows the estimation results for eq. (1). The dependent variable is the log of industry-level daily electricity consumption. lock_dum is the core independent variable, lock_dum is lock_dum × post. lock_dum is a dummy variable equal to 1 if the city is locked down and 0 otherwise. post equals 0 if the date t is before the lockdown and 1 otherwise. The control variables include temperature (Temp), a weekend dummy variable (Weekend), and the number of new confirmed cases (confirmed). *P < 0.1, **P < 0.05, ***P < 0.01. Obs denotes the sample size. Standard errors are clustered at the industry level and reported below the coefficients.
into large enterprises and SMEs based on the ranking of average electricity consumption to conduct separate regression analyses for each industry. The results clearly show differing impacts of lockdowns on enterprises (Fig. 3). The electricity consumption of SMEs in almost all sectors experienced a more substantial reduction except for the leasing and transportation industries. Specifically, SMEs in the retail industry were the most affected, with electricity consumption falling by an average of 72.9%. The electricity consumption of large enterprises in the real estate industry dropped by 13.0%, while that of SMEs dropped by 38.8%, which is approximately three times the reduction experienced by large enterprises. The reduction in the electricity consumption of large enterprises and SMEs is roughly the same, 18.7% and 17.7%, respectively, in the accommodation and catering industry and 9.4% and 9.3%, respectively, in the financial industry. These findings validate our hypothesis that SMEs suffer more losses than large enterprises, which is made worse by SMEs’ general disadvantage with regard to financing. Without government subsidies, they are likely to face the risk of bankruptcy. Notably, the electricity consumption of the public management and service industry and the information industry was hardly affected by lockdowns. In particular, the electricity consumption of SMEs in the information industry showed a statistically significant increase after a lockdown, with electricity consumption increasing by 5%. Such heterogeneity analysis is crucial to uncovering the distributional impact of the pandemic and provides important implications for more equitable rescue and subsidy policies in the face of strict lockdown measures.

3.4. Electricity consumption forecast in two scenarios

To compare the impact of COVID-19 on economic activities under different policy scenarios, we use machine learning methods to forecast electricity consumption in the absence of COVID-19 and the no-lockdown scenario. The Chinese government implemented drastic

![Graph showing electricity consumption decrease rate% over time](image)

**Table 2**

|       | Pre-5 Day | Pre-7 Day | Pre-10 Day |
|-------|-----------|-----------|------------|
| Lock Drupal | -0.0803   | -0.0697   | -0.0534    |
| Temp   | 0.0146*** | 0.0148*** | 0.0149***  |
| Confirmed | -0.00259*** | -0.00260*** | -0.00261*** |
| Weekend | -0.0219   | -0.0231   | -0.0242    |
| Cons   | 12.438*** | 12.434*** | 12.432***  |
| Time fixed effects | Y        | Y         | Y          |
| Individual fixed effects | Y         | Y         | Y          |
| Obs    | 4466      | 4466      | 4466       |

Notes: *P < 0.1, **P < 0.05, ***P < 0.01. Obs denotes the sample size. Standard errors are clustered at the industry level and reported below the coefficients.

**Table 3**

|       | (1) | (2) | (3) |
|-------|-----|-----|-----|
| Lock Drupal | -0.152** | -0.168** | -0.152** |
| Temp | -0.0000287 |       |       |
| HDD   |       | -0.0522** |       |
| CDD   |       | -0.00149 |       |
| Max Temp |       | 0.0109* |       |
| Confirmed | -0.00216*** | -0.00241*** | -0.00210*** |
| Weekend | 0.0373*** | -0.000144 | 0.0442** |
| Cons   | 12.752*** | 12.397*** | 12.754*** |
| Time fixed effects | Y         | Y         | Y          |
| Individual fixed effects | Y         | Y         | Y          |
| Obs    | 4466  | 4466  | 4466  |

Notes: *P < 0.1, **P < 0.05, ***P < 0.01. Obs denotes the sample size. Standard errors are clustered at the industry level and reported below the coefficients.
measures for almost all areas with a COVID-19 outbreak. There are no cities in China where there is a pandemic and no control measures are taken. It is difficult for us to find an appropriate city in China to predict electricity usage trends without lockdowns. Therefore, we used the neural network model to learn the electricity consumption trends of Boston and Houston in the United States after the outbreak and before a lockdown and thus predicted the electricity consumption of cities in China if lockdowns were not implemented after an outbreak. In addition, previous studies have shown that the development of the pandemic has a significant impact on electricity consumption. The speed of the spread of the pandemic in cities without aggressive lockdown measures should be similar to that in Boston and Houston. Fig. 4 plots our estimations. The strong match among the curves indicates that the estimations of these two scenarios reliably verify the nonsignificant change in electricity consumption before the COVID-19 outbreak and the much larger change afterwards. As shown in Fig. 4, in the short run, daily electricity consumption declined significantly after the implementation of lockdown measures (blue line), with such consumption being lower than that without a lockdown after the COVID-19 outbreak (grey line). However, electricity consumption is significantly higher than that of the no-lockdown scenario for approximately two months. The total electricity consumption from the date of the lockdown to the next four months is 18.372 TWh. In comparison, the estimations show that the total electricity consumption in the absence of COVID-19 is 18.922 TWh and 17.496 TWh without lockdown measures. The result suggests that the electricity loss of the no-lockdown scenario is 2.6 times that of the strict lockdown scenario within 4 months of the outbreak. Therefore, in the long run, the costs of lockdowns are less than those of not taking this aggressive countermeasure. Although the enforcement of lockdowns severely affected economic activity in the short term (Ruan et al., 2020), these measures could prevent the escalation of COVID-19 transmission and help return the economy to a normal state thereafter.

### 4. Concluding remarks

This study explored the impact of lockdowns on industrial electricity consumption and evaluated the overall electricity losses avoided compared with the scenario without lockdowns. Our results show that tertiary industry is not only the most affected by the lockdown, but also the fastest response to the lockdown. However, information, public management and service and medical sectors remain unaffected, some even evidence an increase during lockdown. Identifying industries with development potential after the lockdown has important implications for solving the massive unemployment problem caused by the COVID-19 epidemic. Our heterogeneity analysis shows that SMEs have a greater reduction in electricity consumption than large enterprises, especially in the retail and real estate sectors. The impact of the lockdown on SMEs in developing economies have been seriously underestimated. Lou et al. (2021) found that the mandates of school closures and limiting business operations significantly reduced the electricity consumption of SMEs in retail sector by 8% compared to 4% in large businesses in the United States. By contrast, we observed a 70% reduction in retail sector of electricity consumption of SMEs in China. Such heterogeneity analysis is crucial to uncovering the distributional impact of the pandemic and provides important implications for more equitable rescue and subsidy policies when faced with strict lockdown measures. While previous

### Table 4

| Indic | Information industry | Public management and service industry | Medical industry |
|-------|----------------------|----------------------------------------|-----------------|
| lock dum | -0.0275 (0.057) | -0.0159 (0.045) | 0.0627 (0.108) |
| Temp | 3.12e-07 (0.000015) | -0.000011 (0.00023) | 9.48e-06 (0.000060) |
| Confirmed | -0.00082* (0.00048) | -0.00011*** (0.00022) | -0.000161** (0.00093) |
| Weekend | 0.0243 (0.022) | 0.018* (0.010) | 0.069 (0.052) |
| Cons | 10.30*** (0.012) | 11.32*** (0.0094) | 8.47*** (0.032) |
| Time fixed effects | Y | Y | Y |
| Individual fixed effects | Y | Y | Y |
| Obs | 1218 | 2436 | 1595 |

Notes: *P < 0.1, **P < 0.05, ***P < 0.01. Obs denotes the sample size. Standard errors are clustered at the industry level and reported below the coefficients.
studies predominately focus on the economic losses caused by lock-
downs in the short run, we find that the electricity loss of the no-
lockdown scenario is 2.6 times that of the lockdown scenario within 4
months since the outbreak. In the short run, the daily economic activities
decreased significantly after the implementation of the lockdown mea-
sures. However, the daily electricity consumption is significantly higher
than that of the no-lockdown scenario in two months and the electricity
loss is made up in two and a half months, shedding light on the tradeoff
between short-term loss and long-term gain of lockdown policies. These
results indicate that the COVID-19 lockdown leads to faster economic
activity recovery than its counterfactual result in China.

This study has several key implications for policy makers. First,
governments of cities facing the threat of an epidemic should take a
long-term perspective and comprehensively evaluate the economic ac-
tivities of the counterfactual baseline ‘business as usual’ with COVID-19
and actual lockdowns. Protecting the economy blindly without lock-
down policies is unadvisable; doing so may not only lead to more serious
economic losses, but also risk a higher COVID caseload. Second,
although lockdowns cause a decline in electricity consumption overall,
it also promotes the development of certain industries such as the in-
formation sector and public management and service sector. Digital
services made considerable progress during the lockdowns, creating the
opportunity for greater financial investment in these digital and auto-
mation industries to create more jobs and promote economic recovery.
Third, subsidies should vary by industry and focus on SMEs with a larger
reduction in electricity consumption. Monitoring the changes in elec-
tricity consumption might be a powerful tool for policy makers to
quickly provide subsidies to specific industries and to avoid a high
bankruptcy rate among firms due to cash flow pressure.

Our results can provide valuable implications for countries with
dense populations and similar medical conditions experiencing the
COVID-19 epidemic. The lockdown effects may differ due to cultural
differences, so our results should be interpreted with this caution. In
addition, our dataset lacks information on firm characteristics besides
electricity consumption (e.g. assets, revenue and production). Thus, we
cannot accurately identify the lockdown effects on electricity con-
sumption based on such characteristics. In future research, we aim to
obtain this information through surveys for further details on the
mechanisms that we discuss.

Our study has some limitations. First, although there are 396 sub-
industries and 11 first-level sectors, it contains one city in the treat-
ment group. The empirical results would be more convincing if there
were more cities in the treatment group. Second, due to data limitations,
we obtained industrial electricity consumption data only four months
after the COVID-19 outbreak to study the long-term effect of lockdown
policies. If the time span of the data is longer, future research can better
reflect the long-term impact of lockdowns on economic activities. While
more research is certainly needed, we hope that this paper has provided
a solid foundation for this new and exciting area of research.

CRediT authorship contribution statement

Nana Deng: Writing – original draft. Bo Wang: Writing – review &
editing. Yueming Qiu: Writing – review & editing. Jie Liu: Visualiza-
tion, Investigation. Han Shi: Data curation, Software. Bin Zhang:
Conceptualization, Writing – review & editing. Zhaohua Wang: Writing –
review & editing.

Acknowledgments

This study is supported by National Natural Science Foundation of
China (Reference No. 72074026, 72141302), Social Science Foundation
of Beijing (Reference No. 21GLC057), Natural Science Foundation of
Beijing Municipality (Reference No. 9212016), Science and Technology
Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.eneco.2022.106318.

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