Technological and Economic Development of Economy
ISSN: 2029-4913 / eISSN: 2029-4921
2022 Volume 28 Issue 5: 1221–1241
https://doi.org/10.3846/tede.2022.17027

ESTIMATING THE REAL SHOCK TO THE ECONOMY FROM COVID-19: THE EXAMPLE OF ELECTRICITY USE IN CHINA

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Received 04 November 2021; accepted 21 March 2022; first published online 09 June 2022

Abstract. Quantifying the shock to the economy from the COVID-19 pandemic is difficult. Although this shock is easily linked to financial markets as a sort of monetary shock, few studies have been done on its effect on the real economy. This study takes a particular economic perspective, focusing on electricity uses in various sectors of the economy. We propose a novel method for comparing electricity use in 2019Q1 and 2020Q1, based on which we derive the degree of the real shock to some important economic sectors from COVID-19. In our theoretical framework, demand for energy and its influencing factors are related to the total scale of the economy, i.e., the gross domestic product. Using suitable empirical methods, we obtain certain marginal effects and then calculate the corresponding ratio as the real shock from COVID-19. The ratio between these marginal effects reveals the need for a balance between stocks and the corresponding differences in the economy. In our cases, the electricity use in various economic sectors plays a role in both stocks and the differences. We find that, although manufacturing and consumption are affected, the services are more vulnerable to the shock from the COVID-19 pandemic. Our findings offer implications for policymakers.

Keywords: electricity use, COVID-19, economic impact, shock to the real economy, Chinese cities.

JEL Classification: H12, I15, I18, Q41, Q43, Q54.

Introduction

In late December 2019 and early 2020, widespread cases of an unidentified variety of pneumonia occurred in China due to the novel coronavirus (COVID-19) (Huang et al., 2020; Zhou et al., 2020). The infections quickly spread across China because COVID-19 is characterized by rapid and pervasive person-to-person transmission, and it broke out just as the Spring Festival travel season began (Xu et al., 2020). On January 23, 2020, the Wuhan local government put the city on lockdown to avoid the spread of infection caused by people's gathering and travel. Subsequently, other cities in Hubei Province made a similar decision.

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To further effectively control the spread of the disease and protect public health, the central and local provincial governments strictly restricted travel, requiring compliance with quarantining at home (Muhammad et al., 2020).

Although in China COVID-19 was contained quickly, the global pandemic is still evolving. In response, governments worldwide have taken policy actions such as closing off the country to foreign travelers and restricting people's movements and travel (Tosepu et al., 2020; Vos, 2020). However, because of the lockdowns, the pandemic caused by COVID-19 is not merely a public health problem but an economic crisis worldwide. The concern is focused not only on the health effects on COVID-19 but the tremendous social impact of this economic disruption (Agdas & Barooah, 2020; Qureshi, 2021; Zhang et al., 2021). Economic activity has been reduced, with a dramatic impact on both production and consumption (Wang & Su, 2020; Fernandes, 2020; Zhang et al., 2021). According to the latest World Economic Outlook published by International Monetary Fund, the global economy was expected to contract 3%, the largest contraction since the Great Depression in 1929. In addition, the cumulative loss of global gross domestic product (GDP) could be about US$9 trillion, more than that of Japan and Germany combined (International Monetary Fund, 2020).

Because of the COVID-19 crisis, macroeconomic conditions, together with microeconomic conditions and political circumstances, have greatly changed (Rugani & Caro, 2020; Laing, 2020; Zambrano-Monserrate et al., 2020), with the potential to destroy individual livelihoods, businesses, industries, and entire economies in both the short and long run. Estimating the impact of the COVID-19 pandemic on economic development and environmental performance is a critical task in academic research and is particularly salient for policymakers as they design policies in the future.

Consequently, tracking changes in the consumption of electricity is helpful for policymakers who need to understand the relative impact of the COVID-19 pandemic on human activities and determine suitable future trajectories (Quéré et al., 2020). However, performing an accurate calculation of economic loss in a crisis is difficult, because it relies on having enough data and a complex empirical methodology. Although this kind of shock is easily linked to financial markets as a sort of monetary shock, few studies on such shocks have been performed regarding the real economy.

The COVID-19 pandemic is undoubtedly a human disaster from both the medical and economic perspectives, as well as many other social aspects. How we fight against and cope with the COVID-19 pandemic is an urgent application of disaster management (Sodhi, 2016). However, the details of this disaster management vary substantially among different areas in our daily life. In this study, we focus on energy use and consumption (Morrice et al., 2016) as well as the macroeconomy. We derive a novel method for linking electricity use and the aggregate economy, from which we can quantify the real shock to the economy from the COVID-19 pandemic.

As we have seen, COVID-19 has several negative effects on social and economic processes. This study aims to provide useful insights concerning these negative effects. We, therefore, consider a particular perspective on the economy, which focuses on electricity uses in various economic sectors. The study has two motivations. First, understanding the real shock to the economy from COVID-19 is challenging because the disease is new and the impacts have an unprecedented scale. Second, the pandemic is still ongoing, and the situation is far from stable, so our available information is very limited. Thus, we look at China, where the COVID-19 pandemic was largely contained soon after the local outbreak, which offers valuable estimates with "stable" information. We primarily look at urban electricity use, which plays an important role in modern daily life. Electricity use in an urban setting has many applications (Bompard et al., 2020; Zhang et al., 2020). Observation of changes in electricity use after the outbreak of COVID-19 is not new in related studies. However, it is difficult to draw valid conclusions based on this observation in isolation as it lacks a basis for comparison. Here, we propose a novel method for comparing electricity use in China in 2020Q1 and 2019Q1, from which we can derive the degree of the real shock to some important economic sectors from COVID-19.

We organize the rest of the paper as follows. After the literature review in Section 1, Section 2 derives a theoretical framework that shows the real shock to the economy from COVID-19. The data source, as well as data management, are shown in Section 3. The estimates and discussions of the results are presented in Sections 4 and 5. The last Section offers our conclusions based on the theoretical model and empirical evidence.

1. Literature review

1.1. The relationship between electricity consumption and the real economy

Some existing studies have linked electricity use and the economy (Brounen et al., 2012; Baranzini et al., 2013; Arora & Lieskovsky, 2016) before the pandemic. As for the relationship between electricity consumption and the real economy, scholars reach different conclusions using different data sets and empirical methods. Some scholars find that they are positively correlated. Narayan and Singh (2007) analyze the relationship between energy consumption and the gross domestic product (GDP) in Fiji using a multivariate framework, which implies that electricity consumption is positively correlated with economic growth and development. Using data on 157 countries from 1960 to 2014, Shahbaz et al. (2017) confirm that developing countries rely heavily on electricity consumption for economic growth. Studying data on the sub-Saharan African economies, Lawal et al. (2020) employ system-GMM and find that the relationship between electricity consumption and economic growth is significantly positive. In addition, Cui et al. (2021) explore the spatially heterogeneous nature of the relationship between industrial electricity consumption and industrial GDP. Over the period 1999–2014, the relationship varies over space and time and becomes increasingly related.

Some scholars believe that electricity consumption and economic performance have no causal relationship. Massa and Rosellon (2020) employ two linear and one nonlinear tests with data on Mexico from 1965 to 2018 and find no evidence of Granger causality between electricity production and GDP. Singh and Vashishtha (2020) re-examine the relationship between per capita electricity consumption and per capita GDP, and their study finds no evidence of a long-term equilibrium relationship between them. In addition, real economic costs are also linked with electricity consumption (Ai et al., 2022).

Other scholars see their relationship as more complicated. Ouédraogo (2010) finds that in Burkina Faso over the period 1968–2003, electricity consumption and real GDP have a long-term bidirectional causal relationship. Srivastava (2016) uses cross-state panel data in

India and finds a similar bidirectional cause. Furthermore, their analysis implies that income growth is Granger caused by electricity consumption by consumers and in heavy industry, but not other industries. Baranzini et al. (2013) find a possible decoupling between GDP growth and energy consumption in Switzerland. Hu and Lin (2013) construct long-term equilibrium models and ECMs to investigate the relationship between electricity consumption in primary, secondary, and tertiary industries and GDP growth in Hainan from 1988 to 2009. They argue that the electricity consumption in primary and tertiary industry Granger causes GDP, but not secondary industry. Hasan and Mozumder (2017) investigate the relationship between energy use and income at the household level in Bangladesh, finding that it is U-shaped. Bouznit et al. (2018) analyze the relationship between residential electricity consumption and GDP per capita in Algeria over the period 1970–2013. They argue that the relationship between electricity use and GDP takes an inverted *N*-shape, and Algeria has reached the second turning point. Wu et al. (2019) identify the contingency of causality between electricity consumption and real GDP by employing a bootstrap autoregressive-distributed lag test over the period 1971–2014. Tiwari et al. (2021) employed panel cointegration tests with a structural break, a heterogeneous panel causality test, and a panel VAR-based impulse-response model at the state and sectoral levels in India. The results confirm that electricity consumption Granger causes economic growth in agriculture, but the relationship is reversed in industry.

1.2. The economic consequences of the COVID-19 pandemic

Many studies have been conducted about the economic consequences of the COVID-19 pandemic. In a country-level analysis, Helm (2020) analyzes the impact of COVID-19 on environmental performance in both the short and long run. He argues that the pandemic has led to reductions in carbon emissions, benefiting air quality, but the environmental improvement might be temporary, reversing after the economy returns to normal. Saadat et al. (2020) claim that lockdowns due to COVID-19 not only improved air quality but reduced water pollution. Studying China, Qian and Fan (2020) explore the impact of COVID-19 on income based on data collected through an online survey. They report that the people in China who owe the long-standing status markers can reduce the negative effects of COVID-19 on any income losses.

In an industry-level analysis, Sigala (2020) discusses the influence of the pandemic on tourism by dividing it into three stages: response, recovery, and reset. He argues that traditional leadership, recruitment, management, and motivational incentives will not play a crucial role in attracting employees. Based on a one-way analysis of variance, Mongaji (2020) investigates the effect of COVID-19 on the transportation sector in Lagos, Nigeria. He shows that the imposition of lockdowns and restrictions on movement are not effective in a state with high population density and poor transportation infrastructure. Laing (2020) claims that the COVID-19 crisis will have terrible consequences in the mining industry in the short, medium, and long run. More recent studies examine other economic impacts (Tang et al., 2021), such as vacation rentals (Liang et al., 2021).

More recent studies of this strand can be seen in the macroeconomy (Zinecker et al., 2021; Guo et al., 2022), financial market (Wang & Liu, 2022), among others.

1.3. The electricity use and the COVID-19 pandemic

Since the outbreak of COVID-19, more related studies have appeared (Cicala, 2020; Gu et al., 2020; Janzen & Radulescu, 2020; Agdas & Barooah, 2020; Maas, 2020; Abulibdeh, 2021; Wang et al., 2021). Electricity consumption is a vital input of economic activity, so its evolution and reduction are quite informative in various respects. First, changes in electricity consumption can be regarded as a quantitative indicator of the density of economic activity. Ferguson et al. (2000) find that, based on data for over one hundred countries, electricity use and economic development have a strong correlation. Their results show that the electricity ratio could replace the energy ratio as a development indicator. Ouédraogo (2010) reaches a similar conclusion. In China, county-level electricity consumption data can be more sensitive, objective, and effective in reflecting economic performance (Shi et al., 2020). Second, unlike in previous economic crises, electricity use will immediately recover its normal patterns after the pandemic is under control (Quéré et al., 2020).

More recent studies of this strand can also be seen in its impact on energy (Jia et al., 2021; Wang & Han, 2021; Armeanu et al., 2022), electricity demand (Norouzi et al., 2020), electricity demand in the United States (Agdas & Barooah, 2020; Burleyson et al., 2021; Ruan et al., 2021), in Europe (Werth et al., 2021), and Spain (Bompard et al., 2020). In addition, some more studies have emerged in the residential electricity consumption (Krarti & Aldubyan, 2021; Khalil & Fatmi, 2022; Ku et al., 2022), energy consumption at a disaggregated level (García et al., 2021), and provincial-level electricity consumption in China (Ai et al., 2022). At last, although we are not focusing on the electricity supply in this study, the electricity power production in the COVID-19 pandemic is also noted (Ahmad et al., 2022).

1.4. Research gap

To our knowledge, although an increasing number of studies show the influence of COVID-19 on various aspects of the economy, most of them lack a sufficient discussion of the in-depth mechanism through which this influence occurs. In particular, few studies have linked electricity use and the shock to the economy from the COVID-19 pandemic. We, therefore, hope the new method proposed in this study contributes to related studies.

2. The theoretical framework

The idea to set up the theoretical framework for the analytical purpose of our research problem is inspired by what we commonly see in the field of Economics. But we jump out of the traditional Economics in the sense that we contribute a smart way to link the energy demand and the total scale of the economy, and hence find a way to introduce the shock of the COVID-19 pandemic to the real side of the economy.

In the following, we divide the economy into the manufacturing sector and non-manufacturing sectors including the residential sector and others first. Then, we model the energy demand in different sectors in the economy and sum them together with appropriate prices to simulate the total scale of the economy (i.e., GDP). Third, we model the shock of the COVID-19 pandemic to the real side of the economy, by which the change in GDP can be expressed. At last, we derive the empirical implication and the solution to the direct shocks.

2.1. Energy demand and its influencing factors

We denote E_T as the total quantity of electricity use in a city at a given time. E_M is the quantity of electricity use in manufacturing. E_R is the quantity of electricity use by consumers. E_O is the quantity of electricity use by other sectors. Although we do not specify what these other sectors are, they are important to include to make the model complete.

These three categories of electricity use are then assumed to be linked linearly to the corresponding stock of human activities, as follows:

$$E_M = \theta_M M; \tag{1}$$

$$E_R = \theta_R R; \tag{2}$$

$$E_O = \theta_O O, \tag{3}$$

where M is the total quantity of manufacturing, R is the aggregate number of urban residents, and O is the total amount of other users of electricity in the city. The corresponding parameters of θ_M, θ_R, and θ_O represent the complex transformation of human activities into electricity use. They are all assumed to be in proportion to human activity. This assumption is simple, but it is an efficient way to quantify electricity use. In particular, this method offers a direct comparison of electricity use between manufacturing and consumers.

2.2. GDP and energy demand

Because the purpose of this study is to examine the shock to the economy from COVID-19, we introduce the scale of the economy, which is commonly proxied by GDP. By doing so, we reveal the hidden mechanism in electricity use and the economy. We, therefore, construct the total scale of the local economy as follows:

$$GDP = P_M M + P_C C + P_O O, \tag{4}$$

where C is residential consumption, and P is the corresponding price. In addition, we assume the following relationship between C and R.

$$C = \varsigma_C R, \tag{5}$$

where the coefficient ζ_C stands for a quantitative transition from the residential population to aggregate consumption.

2.3. Impact of COVID-19 on energy demand and the economy

With the foregoing assumptions, we can discuss the impact of COVID-19 on energy demand in terms of urban electricity use. Essentially, the COVID-19 pandemic causes shock to human activities, so it affects urban electricity use. For example, production activity is minimized because of the complete or partial lockdowns due to the pandemic, leading to a large decline in the use of electricity in manufacturing. At the same time, most people are remaining at home, raising residential electricity use or at least not affecting it very much.

Using the same notations as earlier, we construct equations for the economic shock from COVID-19 in various sectors as follows.

$$\Delta M = \frac{\Delta E_M}{\theta_M}; \tag{6}$$

$$\Delta R = \frac{\Delta E_R}{\theta_R}; \tag{7}$$

$$\Delta O = \frac{\Delta E_O}{\theta_O}. \tag{8}$$

Recalling Eq. (5), we have:

$$\Delta C = \varsigma_C \Delta R, \tag{9}$$

which can be revised as:

$$\Delta C = \varsigma_C \frac{\Delta E_R}{\theta_R}. \tag{10}$$

We consider the equation for GDP implicitly as shown in Eq. (4). Thus, the impact of COVID-19 on the economy can be derived as:

$$\Delta GDP = \frac{P_M}{\theta_M}\Delta E_M + \frac{P_C \varsigma_C}{\theta_R}\Delta E_R + \frac{P_O}{\theta_O}\Delta E_O. \tag{11}$$

2.4. The empirical implication and the solution to the direct shocks

Now we introduce the direct shock to three economic sectors from COVID-19:

$$\Delta M = \gamma_{COVID\_M} M; \tag{12}$$

$$\Delta C = \gamma_{COVID\_C} C; \tag{13}$$

$$\Delta O = \gamma_{COVID\_O} O, \tag{14}$$

where the coefficients of γ_{COVID} s are the direct shocks to the various economic sectors from the pandemic.

If we combine Eqs (6), (8), and (10) with Eqs (12), (13), and (14), respectively, we have:

$$\Delta M = \frac{\Delta E_M}{\theta_M} = \gamma_{COVID\_M} M; \tag{15}$$

$$\Delta C = \varsigma_C \frac{\Delta E_R}{\theta_R} = \gamma_{COVID\_C} C; \tag{16}$$

$$\Delta O = \frac{\Delta E_O}{\theta_O} = \gamma_{COVID\_O} O. \tag{17}$$

By multiplying these equations by the corresponding prices on both sides, we obtain:

$$\Delta E_M \frac{P_M}{\theta_M} = \gamma_{COVID\_M} P_M M; \tag{18}$$

$$\Delta E_R \frac{\varsigma_C P_C}{\theta_R} = \gamma_{COVID\_C} P_C C; \tag{19}$$

$$\Delta E_O \frac{P_O}{\theta_O} = \gamma_{COVID\_O} P_O O. \tag{20}$$

Then, we can also obtain the following equation from Eq. (11):

$$\Delta GDP = P_M \gamma_{COVID\_M} M + P_C \gamma_{COVID\_C} C + P_O \gamma_{COVID\_O} O. \quad (21)$$

Recalling Eq. (5), we have:

$$\Delta GDP = \gamma_{COVID\_M} P_M M + \gamma_{COVID\_C} \varsigma_C P_C R + \gamma_{COVID\_O} P_O O. \quad (22)$$

Now, let us discuss the empirical implications of Eq. (11) in the following way.

$$\Delta GDP = \frac{P_M}{\theta_M} \Delta E_M + \frac{P_C \varsigma_C}{\theta_R} \Delta E_R + \frac{P_O}{\theta_O} \Delta E_O + \beta_X X + \varepsilon, \quad (23)$$

where X stands for the control variables. Let us define the following:

$$\widehat{\beta}_{E_M} = \frac{P_M}{\theta_M}; \quad (24)$$

$$\widehat{\beta}_{E_R} = \frac{P_C \varsigma_C}{\theta_R}; \quad (25)$$

$$\widehat{\beta}_{E_O} = \frac{P_O}{\theta_O}. \quad (26)$$

The empirical implications of these definitions are obvious, in the sense that they are in fact the estimation parameters in the regression. Therefore, we have:

$$P_M = \widehat{\beta}_{E_M} \theta_M; \quad (27)$$

$$\varsigma_C P_C = \widehat{\beta}_{E_R} \theta_R; \quad (28)$$

$$P_O = \widehat{\beta}_{E_O} \theta_O. \quad (29)$$

Substituting the above equations to Eq. (22), we have:

$$\Delta GDP = \gamma_{COVID\_M} \widehat{\beta}_{E_M} \theta_M M + \gamma_{COVID\_C} \widehat{\beta}_{E_R} \theta_R R + \gamma_{COVID\_O} \widehat{\beta}_{E_O} \theta_O O. \quad (30)$$

Now, we recall Eqs (1) to (3), and the equation can be transformed as follows:

$$\Delta GDP = \gamma_{COVID\_M} \widehat{\beta}_{E_M} E_M + \gamma_{COVID\_C} \widehat{\beta}_{E_R} E_R + \gamma_{COVID\_O} \widehat{\beta}_{E_O} E_O. \quad (31)$$

Eq. (31) has close empirical implications, which can be demonstrated as follows.

$$\Delta GDP = \gamma_{COVID\_M} \widehat{\beta}_{E_M} E_M + \gamma_{COVID\_C} \widehat{\beta}_{E_R} E_R + \gamma_{COVID\_O} \widehat{\beta}_{E_O} E_O + \beta_X X + \varepsilon. \quad (32)$$

Now, we can define the following terms from the equation, which are again the estimation parameters in the regression shown in Eq. (32).

$$\widehat{\beta}_{\gamma\_E_M} = \gamma_{COVID\_M} \widehat{\beta}_{E_M}; \quad (33)$$

$$\widehat{\beta}_{\gamma\_E_R} = \gamma_{COVID\_C} \widehat{\beta}_{E_R}; \quad (34)$$

$$\widehat{\beta}_{\gamma\_E_O} = \gamma_{COVID\_O} \widehat{\beta}_{E_O}. \quad (35)$$

By comparing the estimation parameters on both sides of Eqs (33)–(35), we can obtain the direct shock to the economy from COVID-19 via the following calculation.

$$\gamma_{COVID\_M} = \frac{\widehat{\beta}_{\gamma\_E_M}}{\widehat{\beta}_{E_M}}; \tag{36}$$

$$\gamma_{COVID\_C} = \frac{\widehat{\beta}_{\gamma\_E_R}}{\widehat{\beta}_{E_R}}; \tag{37}$$

$$\gamma_{COVID\_O} = \frac{\widehat{\beta}_{\gamma\_E_O}}{\widehat{\beta}_{E_O}}. \tag{38}$$

It is noteworthy that prices are absent from these equations, so they represent the economic impact of COVID-19 in terms of real quantities, not monetary values. To our knowledge, the theoretical framework presented here is our novel design, which might contribute to the methodology used in future analyses.

3. Data management

Given our research purpose, we primarily compare the economic scale and the corresponding electricity use in the first quarters of 2019 (i.e., 2019Q1) and 2020 (i.e., 2020Q1). This comparison is meaningful because the COVID-19 outbreak largely affected China in the first quarter of 2020, and in the second quarter of 2020, the local economy gradually recovered as work resumed. Therefore, from the perspective of energy use, the comparison of the first quarter in these two years is the most accurate way to quantify the economic impact of COVID-19. Although introducing later data would be useful, it also complicates our analysis because the pandemic is still ongoing around the world and affects sociospatial processes and energy use. Many other factors might also influence electricity use. For example, changes in population and economic activity could be taken into account if the period of study is longer. Therefore, comparing the first quarters of these two years would be appropriate for our research.

This study uses a combined data set from various sources, which essentially covers 284 cities in China with reported COVID-19 cases. We obtain data on GDP in the first quarters of 2019 and 2020 from the National Bureau of Statistics in China (n.d.). It is more complicated to obtain data on electricity use, however. Because we do not have data on city-level electricity uses in 2019Q1 and 2020Q1, we take two steps to obtain it. First, we obtain data on electricity use at the provincial level where available at Polaris Power Grid (n.d.). Second, we obtain city-level electricity use data from the China Entrepreneur Investment Club (CEIC) for 2016. Then, we transform the data to obtain details for 2020Q1, as follows. First, we make a simple but meaningful assumption that the proportion of urban electricity uses in a province has remained stable since 2017. In fact, this assumption is generally valid because the share of electricity uses in Chinese provinces does not change too much over a time horizon of only three years (i.e., from 2017 to 2019). Therefore, after we calculate the city-level ratio of electricity use in a province, we can multiply the ratio by the provincial level of electricity use, and then we can obtain data on city-level electricity use in 2020Q1. We can use the same method to determine city-level electricity use data for 2019Q1.

In order to match GDP as well as electricity use, we obtain data on the pandemic by using the number of confirmed COVID-19 cases in the corresponding cities from DingxiangYuan (2020). For most cities, we obtain COVID-19 data on the morning of April 1, 2020, to match the first quarter of 2020. However, for cities in Hubei Province, especially Wuhan, we obtain the data on the evening of June 27, 2020. Liu (2020) explains the lag in reporting data on COVID-19 cases in Wuhan and other cities in Hubei. The spread of COVID-19 in cities of Hubei (including Wuhan) stabilized by late June, so the data on confirmed COVID-19 cases in these cities is much more reliable than that from April 1.

Then, we introduce two important control variables, the urban area, and the urban population, from the *China City Statistical Yearbook 2018* (China National Bureau of Statistics, 2019). These two variables are expected to take care of the heterogeneity as the scale effect of the cities. Notably, the role of urban characteristics on the transmission of COVID-19 is discussed by Liu (2020), among others. All the variables mentioned are summarized in Table 1.

Table 1. The descriptive statistics (N = 284)

Variables	Explanation	Unit	Mean	Std. Dev.	Min	Max
GDP_2019	City-level GDP in 2019Q1.	10 million yuan	722.583	1050.259	41.600	8308.280
GDP_2020	City-level GDP in 2020Q1.	10 million yuan	687.499	986.499	43.470	7856.620
E_M_2019	City-level electricity use in the manufacturing sector in 2019Q1.	10,000 kWh	349909.096	390024.557	6600.000	3083028.690
E_M_2020	City-level electricity use in the manufacturing sector in 2020Q1.	10,000 kWh	304817.738	338664.701	6500.000	2676068.910
E_R_2019	City-level electricity use in the residential sector in 2019Q1.	10,000 kWh	45609.372	63922.107	3539.430	577989.750
E_R_2020	City-level electricity use in the residential sector in 2020Q1.	10,000 kWh	40798.897	58100.388	2205.930	513670.550
NUM_CONFIRMED	City-level confirmed cases of COVID-19.	person	286.169	2999.618	1.000	50340.000
URBAN_AREA	City-level urban area.	Square Kilometer	538.495	1202.678	21.870	16410.000
URBAN_POPULATION	City-level population.	10,000 persons	117.688	222.797	6.890	2418.330

4. Results

4.1. Results with the empirical model of Eq. (23)

Using the basic estimation model shown in Eq. (23), we obtain several groups of estimation results, shown in Table 2. Here, all the differences in the variables are defined by subtracting the corresponding values in 2020Q1 from those in 2019Q1. In addition, all the results represent a subsample totaling 247 cities, in which some observations with extreme values are deleted from the full sample of 284 cities.

In addition to using traditional ordinary least squares (OLS) estimation, we employ several other statistical methods. First, we use robust least squares (RLS) to overcome the possible "outlier" effect when our cross-sectional sample size is not large enough. In general, RLS with S estimation has more significant results than other options, such as M estimation as well as MM estimation. Second, to deal with possible endogeneity problems in the empirical regression, we also use two-stage least squares (2SLS), in which the instrumental variable (IV) is chosen as the city-level annual GDP in 2019, which provides a perfect proxy for the

Table 2. Empirical estimation results with dependent variable ΔGDP according to Eq. (24) (N = 247)

	Model (2-1) OLS	Model (2-2) RLS (S-estimation)	Model (2-3) 2SLS (Endogenous variable: ΔE_M, IV: GDP_2019)	Model (2-4) 2SLS (Endogenous variable: ΔE_R, IV: GDP_2019)	Model (2-5) LIML (Endogenous variable: ΔE_R, IV: GDP_2019)	Model (2-6) Bootstrapping with resampling residuals (10,000 repetitions)
ΔE_M	0.000 (1.065)	0.000* (1.787)	0.002* (1.690)	−0.001 (−1.432)	−0.001 (−1.432)	0.000 (1.058)
ΔE_R	−0.000 (−0.253)	0.000 (0.348)	−0.011 (−1.584)	0.023* (1.786)	0.023* (1.786)	−0.000 (−0.266)
ΔE_O	0.000*** (5.498)	0.000 (0.092)	0.000*** (3.197)	0.000** (2.517)	0.000** (2.517)	0.000*** (5.556)
NUM_CONFIRMED	−0.024*** (−6.093)	−0.033*** (−34.740)	−0.029*** (−3.797)	−0.008 (−0.712)	−0.008 (−0.712)	−0.024*** (−6.135)
URBAN_AREA	−0.683*** (−5.200)	0.507*** (−15.669)	−0.982*** (−3.307)	−0.162 (−0.460)	−0.162 (−0.460)	−0.684*** (−5.197)
URBAN_ POPULATION	0.202 (0.783)	1.189*** (18.673)	0.619 (1.178)	0.411 (0.973)	0.411 (0.973)	0.203 (0.781)
Adjusted R^2	0.296	0.188	−1.218	−0.748	−0.748	0.296
Endogeneity Test (Difference in J-stats)			8.342***	8.342***		
Weak Instrument Diagnostics (Cragg-Donald F-stat)			3.878	5.620		

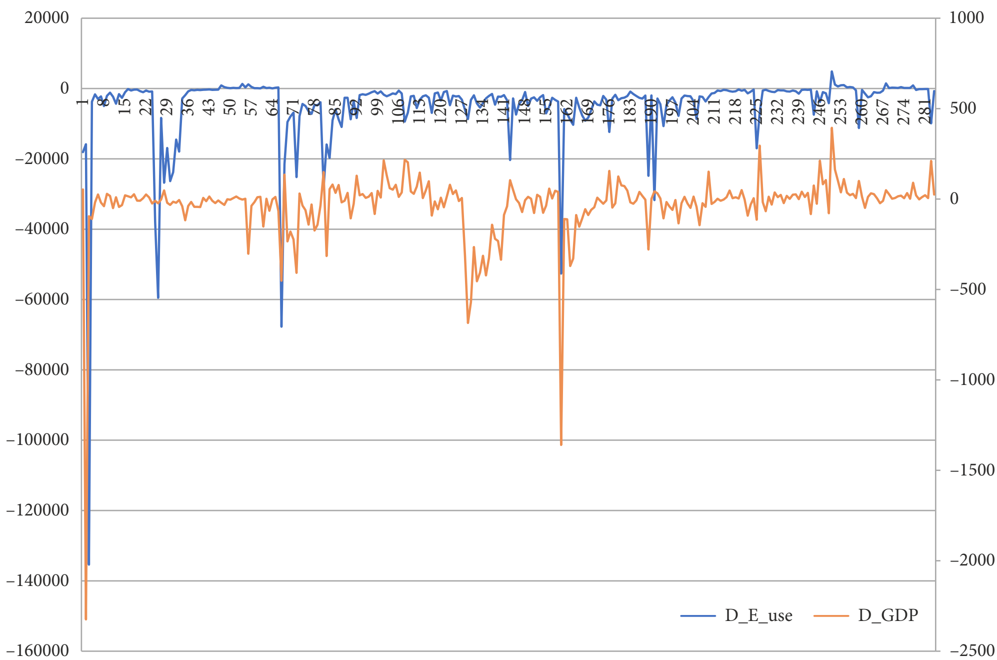
Note: The values of the constant terms are not reported. t statistics are presented in parentheses; *** $p \leq 0.01$, ** $0.01 < p < 0.05$, *$0.05 < p < 0.1$.

local economic scale without the disturbance of COVID-19. We try ΔE_M and ΔE_R as the endogenous variable separately, and the results are in Models (2-3) or (2-4).

In Table 2, the significant results of the endogeneity test confirm the need to consider endogeneity issues in our study. ΔE_R is a better choice as the endogenous variable because the F value is slightly larger in the weak instrument diagnostics. However, the result of the weak instrument diagnostics is still not good enough (i.e., $F<10$). We, therefore, use limited information maximum likelihood (LIML) estimation instead of the 2SLS estimation, because it has better results when the weak instrument diagnostics are not satisfactory.

Moreover, to enlarge the sample size and to check the robustness of the estimation, we then introduce the simulation-based method, in which we are particularly interested in the bootstrapping with resampling technique. In Model (2-6), bootstrapping with resampling residuals of 10,000 repetitions shows robust estimation parameters compared with the OLS results.

In general, the results of this group of models are not as good as anticipated. Because the key variables of most concern are ΔE_M and ΔE_R, we expect both of their estimation coefficients to be statistically significant. In Model (2-5), the coefficient of ΔE_R is barely significant (i.e., $p = 0.075$), and its positive sign indicates that consumer use of electricity has an increasing marginal impact on the local economy. This is the difference-in-difference relationship, in the sense that ΔE_R has a positive marginal effect on ΔGDP. Because we define the differences by subtracting 2020Q1 from 2019Q1, which generally has a negative value (see Figure 1), this finding confirms that a smaller drop in consumer electricity use (i.e., higher value of ΔE_R) reduces the drop in GDP (i.e., higher value of ΔGDP).



Note: The primary vertical axis on the left-hand side stands for the ΔE (i.e., D_E_use), and the secondary vertical axis on the right-hand side stands for the ΔGDP (i.e., D_GDP). Both of the two differences are calculated by the subtraction of 2020Q1 by 2019Q1.

Figure 1. Comparison of ΔE and ΔGDP

For the control variables, the number of confirmed COVID-19 cases is found to have a negative impact on the difference in local GDP, which means that when the pandemic is worse, the difficulties for the local economy are greater. In urban areas, the coefficient is generally negative, which suggests that small economies (i.e., small cities) are more vulnerable to the shock from COVID-19. In addition, although the variable for the urban population has a positive sign, its coefficient is generally not statistically significant. We therefore cannot reach a clear conclusion about it yet.

4.2. Results with the empirical model of Eq. (32)

Instead of using the difference in electricity use between 2020Q1 and 2019Q1 in the empirical model shown in Eq. (23), here we use the original values of electricity uses in either 2020Q1 or 2019Q1, as suggested by the functional form in Eq. (32). Eq. (32) does not specify the year for which we should use the data. Therefore, we try both years, but not at the same time.

Table 3 shows the use of data for 2020Q1, and the results are generally much better than those in Table 2. Model (3-2) shows promising results because all the explanatory variables are statistically significant. The positive and significant coefficient of the urban population

Table 3. Empirical estimation results with dependent variable ΔGDP according to Eq. (33) using data of 2020Q1 (N = 256)

	Model (3-1) OLS	Model (3-2) RLS (S-estimation)	Model (3-3) 2SLS (Endogenous variable: ΔE_M, IV: GDP_2019)	Model (3-4) 2SLS (Endogenous variable: ΔE_R, IV: GDP_2019)	Model (3-5) Bootstrapping with resampling residuals (10,000 repetitions)
E_M_2020Q1	−0.000*** (−3.451)	−0.000*** (−4.029)	−0.000 (−1.545)	−0.000*** (−3.284)	−0.000*** (−3.514)
E_R_2020Q1	0.001* (1.739)	0.001*** (3.678)	0.001* (1.768)	0.001 (0.401)	0.001* (1.761)
E_O_2020Q1	−0.000 (−0.585)	0.000*** (4.114)	−0.000 (−0.185)	−0.000 (−0.270)	−0.000 (−0.564)
NUM_CONFIRMED	−0.025*** (−6.487)	−0.038*** (−41.915)	−0.025*** (−6.446)	−0.025*** (−6.371)	−0.025*** (−6.449)
URBAN_AREA	−0.592** (−2.571)	−0.557*** (−10.253)	−0.604** (−2.590)	0.478 (−1.216)	−0.593*** (−2.642)
URBAN_POPULATION	0.317 (1.159)	0.621*** (9.641)	0.305 (1.107)	0.355 (1.207)	0.315 (1.148)
Adjusted R^2	0.252	0.182	0.249	0.250	0.252
Endogeneity Test (Difference in J-stats)			0.128	0.127	
Weak Instrument Diagnostics (Cragg-Donald F-stat)			34.018	50.980	

Note: The values of the constant terms are not reported. *t* statistics are presented in parentheses; *** $p \leq 0.01$, ** $0.01 < p < 0.05$, *$0.05 < p < 0.1$.

makes sense because more populated cities have a higher "baseline level" of consumption, which makes the cities less vulnerable to the shock from COVID-19. Concerning the endogeneity issue in Models (3-3) and (3-4), the results of the endogeneity test are not significant. Therefore, we consider Model (3-2) our best shot in this group of models.

Table 4 uses data for 2019Q1. Overall, the results using 2019Q1 and 2020Q1 are not very different, but those in Table 3 are slightly better. We, therefore, prefer to use data for 2020Q1, rather than 2019Q1.

In this study, for all the core empirical results (i.e., Tables 2, 3, 4), we have compared several estimation methods such as OLS, RLS, 2LSL (with different settings in the endogenous variable and instrumental variable). Especially, we have also used Bootstrapping with resampling residuals (10,000 repetitions) to check if our results change substantially in the simulation-based models. Therefore, our results in this study are robust.

Table 4. Empirical estimation results with dependent variable ΔGDP according to Eq. (33) using data of 2019Q1 (N = 256)

	Model (4-1) OLS	Model (4-2) RLS (S-estimation)	Model (4-3) 2SLS (Endogenous variable: ΔE_M, IV: GDP_2019)	Model (4-4) 2SLS (Endogenous variable: ΔE_R, IV: GDP_2019)	Model (4-5) Bootstrapping with resampling residuals (10,000 repetitions)
E_M_2019Q1	−0.000*** (−3.100)	−0.000*** (−4.727)	−0.000 (−1.027)	−0.000*** (−2.989)	−0.000*** (−3.183)
E_R_2019Q1	0.001* (1.733)	0.001*** (3.126)	0.001* (1.698)	0.001 (0.482)	0.001* (1.735)
E_O_2019Q1	−0.000 (−1.052)	0.000*** (3.526)	−0.000 (−0.635)	−0.000 (−0.585)	−0.000 (−1.060)
NUM_CONFIRMED	−0.026*** (−6.514)	−0.040*** (−42.291)	−0.026*** (−6.384)	−0.025*** (5.850)	−0.026*** (−6.677)
URBAN_AREA	−0.564*** (−2.598)	−0.517*** (−9.846)	−0.570** (−2.516)	−0.529 (−1.257)	−0.564*** (−2.655)
URBAN_POPULATION	0.382 (1.390)	0.631*** (9.495)	0.379 (1.371)	0.393 (1.331)	0.381 (1.414)
Adjusted R^2	0.249	0.172	0.248	0.248	0.249
Endogeneity Test (Difference in J-stats)			0.010	0.010	
Weak Instrument Diagnostics (Cragg-Donald F-stat)			24.095	29.707	

Note: The values of the constant terms are not reported. *t* statistics are presented in parentheses; *** $p \leq 0.01$, ** $0.01 < p < 0.05$, *$0.05 < p < 0.1$.

5. Discussion of results

Now that we have obtained all the necessary empirical results via appropriate statistical estimation, we perform our final calculation as shown in Eqs (36) to (38).

As shown in Model (2-5), the specific values are ΔE_M = –0.000546, ΔE_R = 0.023340, and ΔE_O = 0.000276. In addition, as demonstrated in Model (3-2), the specific values are E_M_2020Q1 = –4.40E-05, E_R_2020Q1 = 0.000666, and E_O_2020Q1 = 0.000215. Therefore, we can calculate the solutions to Eqs (36) to (38) as $\gamma_{COVID\_M} = 8.059\%$, $\gamma_{COVID\_C} = 2.854\%$, and $\gamma_{COVID\_O} = 77.899\%$.

According to the definitions in Eqs (12) to (14), the real shocks to the three sectors in the economy from COVID-19 are defined in proportion to their original stocks. Given our research context, these shocks can be considered to be the decrease in the corresponding stocks. As shown above, COVID-19 caused a shock of an 8.059% decrease in the manufacturing sector, but it decreases consumption by 2.854%. Our conclusion indicates that the COVID-19 crisis significantly decreased the electricity consumption of the manufacturing sector, which is also supported by Gu et al. (2020). They show that the electricity consumed by the firms of the manufacturing industry dropped sharply after the crisis of COVID-19 through a difference-in-difference method and a large panel of micro-firm data. Since the price of electricity is heavily charged by the governments, a large percentage of households in China will not react strongly to the expenditure of electricity after the crisis. As the estimates have shown, for the residential consumption of electricity, our finding confirms that the lockdown policy due to COVID-19 did not affect the residential consumption very much. This empirical evidence is partly supported by Aruga et al. (2020), who reports that regions with higher incomes in India are likely to recover energy consumption. However, it has a very big drop of 77.899% in other sectors. Although we do not specify the other sectors in the economy, it is very straightforward for us to consider the tertiary industry, that is, the service sector. For example, tourism, restaurants, shopping malls, and movie theaters suffered a great deal during lockdowns. Indeed, many of these businesses lost a large proportion of their customers after the outbreak of COVID-19. Therefore, our calculated results are reasonable. To our knowledge, this part of the real shock calculation is our novel contribution.

Now, we introduce some economic considerations. In Eqs (36) to (38), all the real shocks are the ratio between the marginal effects of two corresponding equations, a ratio commonly seen in economics, such as the marginal rate of substitution (MRS), the technical rate of substitution (TRS), and the marginal rate of product transformation (MRPT). All the ratios of marginal effects mentioned have an important economic meaning in different scenarios. Then, what can we contribute to the meaning of this ratio here?

In Eqs (36) to (38), we can see meaningful interpretations. On the one hand, as shown in Eqs (24) to (26), the denominators $\widehat{\beta}_E$s reflect the marginal effects of changes in electricity use, i.e., ΔE_M, ΔE_R, and ΔE_O, on change in the economic scale, i.e., ΔGDP. On the other hand, as shown in Eqs (33) to (35), the numerators $\widehat{\beta}_{\gamma\_E}$ s show the marginal effects of electricity use, i.e., E_M, E_R, and E_O, on ΔGDP. Therefore, the ratio of these marginal effects reveals that the economy needs to achieve a balance between the stocks and the corresponding differences. In our case, electricity uses in various economic sectors plays a role in both the stocks and the differences.

Conclusions

As noted above, quantifying the economic shock of the COVID-19 pandemic is difficult. Given the difficulty in estimating the impact of the pandemic on the economy, this study devises a novel approach to estimate the real shock to China's economic growth from the COVID-19 pandemic in 2020 at the city level. To our knowledge, it may offer an original idea and novel contribution to the existing field of research. Even though this paper is a case study for China, as the framework can be applied in any other region or country and the COVID-19 pandemic is a worldwide crisis, the framework and generalizability of the results would not only be valuable as a contribution to the economic literature but also useful for other countries. Our major findings for policymakers are shown as follows.

First, from the macroeconomic perspective, the overall impact of COVID-19 on the economy is large, but it varies substantially across economic sectors. Although manufacturing and consumption are affected, the service sector is more vulnerable to the shock from the COVID-19 epidemic. Therefore, when financial assistance policies are considered, the service sector should be given greater priority for the assistance to have a sufficient impact.

Second, in terms of management implications, managers of firms need to be fully aware of the massive shock from the COVID-19 pandemic. Both supply chains and inventories (Land et al., 2021) must be adjusted as the market environment changes. In service industries, in particular, innovative measures need to be taken. For example, restaurants should consider online take-out food service as a good substitute for indoor food service.

Third, concerning urban policy, unlike the decline in electricity use in many Chinese cities in the first quarter of 2020, in 2021 many cities have experienced an unexpected shortage of electricity for many reasons, such as a decline in coal imports at the end of 2020. Given the vital importance of electricity in modern society, urban leaders need to maintain a stable supply of electricity, keeping in mind the shock to the local electricity sector on both the demand side and the supply side.

Future research topics

Finally, our study also has several limitations, including the fact that the data apply to different years. Perhaps we should consider updating data on urban energy use for more periods. But, as explained earlier, this is a tradeoff, which makes our analysis more focused on our research purpose. In addition, the time span can be introduced at a greater frequency. For example, data on hourly or daily electricity use could be employed. Aside from the increasing difficulty in acquiring related information, it would be hard to match the GDP data as well. These challenges are left for future studies.

First, the microanalysis of the energy consumed by firms or households should be also conducted, such as exploring the responses of the different households with different income levels.

Second, more influencing factors of energy demand should be incorporated into our analysis. For example, incorporating energy efficiency, which is defined by the ratio of energy consumption to real GDP, into the pandemic influence on energy consumption would be another future research.

Third, for the macro research, our theoretical model is beneficial in assessing the effects of COVID-19 on the macroeconomy of a region or nation, however, the scenario analysis through this framework is also popular in analyzing the pandemic influences of different scenarios in the future.

At last, we can extend the analytical framework shown in this study to other countries and regions. More detailed industries or even firm-level studies can be introduced as well.

Acknowledgements

The authors declare no competing interests. The authors would like to thank the valuable comments and suggestions from the editor and anonymous referees. All the remaining mistakes are our own.

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