Journal of Environmental Management 248 (2019) 109252

Contents lists available at ScienceDirect

Journal of Environmental Management

journal homepage: www.elsevier.com/locate/jenvman

Research article

Using electricity prices to curb industrial pollution

Jie-Sheng Tan-Soo[a], Xiao-Bing Zhang[b,*], Ping Qin[b], Lunyu Xie[b]

[a] Lee Kuan Yew School of Public Policy, National University of Singapore, Singapore
[b] School of Applied Economics, Renmin University of China, Beijing, China

ARTICLE INFO

Keywords:
Electricity price
Industrial pollution emissions
China
Difference-in-differences
Air pollution

ABSTRACT

In this study, we show that changes in electricity prices in China have significant environmental consequences through its effect on industrial pollution emissions concentrations. To investigate this relationship, we pair a novel dataset of hourly smokestack-level pollutant emissions of industrial plants in Anhui, China with changes in hourly electricity prices. Using a difference-in-differences (DID) regression model, we find that pollution emissions from these plants have an inverse relationship with electricity prices. This relationship is most prominent for firms in the highly competitive and energy-intensive sectors of metals and cement production. On average, we find that a 1% decrease in electricity price leads to around 1%–5.8% increase in sulfur dioxide and particulate matters emissions concentrations. Similarly, we also found impacts on the number of hours in which emissions were observed. These results suggest that electricity prices could be an effective policy tool for managing air pollution – a challenge currently faced by many low- and middle-income countries. More generally, policymakers need to be cognizant that electricity sector-related policies could generate unintended consequences for the environment.

1. Introduction

It is a tenet among multilateral agencies and development experts that access to cheap and reliable electricity will greatly contribute towards economic development (Akinlo, 2009; Besant-Jones, 2006; Lipscomb et al., 2013; Shiu and Lam, 2004; Tang, 2008; Wolde-Rufael, 2006; J. Yuan et al., 2007; Zhang and Cheng, 2009). As a result, increasing access to electricity, regulation of electricity prices, and development of electricity markets are often regarded as top-priority policy decisions in developing economies (Lam, 2004; Ma, 2011; Murry and Nan, 1994). Similarly, due to its important economic and societal role, electricity sector has also undergone extensive reforms to improve service efficiency and lower prices in developed economies (Jamasb and Pollitt, 2005; Joskow, 1997; D. Sharma, 2003). However, even though cheap and reliable electricity can accelerate economic growth, it could also result in environmental problems (Cole et al., 2008; Jalil and Feridun, 2011; Zhang and Cheng, 2009). The mechanism comes not only from power stations using highly-polluting fuels such as coal in their production of electricity, but also from the type of energy-intensive industries that 'cheap' electricity tends to induce (Elliott et al., 2019). For instance, China has been heavily subsidizing electricity rates (Lam, 2004; Ma, 2011; Wang and Lin, 2017), and in turn her spectacular economic growth in the past few decades was spurred on mainly by the steel, iron ore, aluminum, cement, and other similarly energy-intensive and high-polluting industries (Tao et al., 2008; Zhang and Cheng, 2009). By similar logic, it may be possible for policymakers to control pollution by using electricity tariffs. However, to consider using electricity tariffs as a policy tool, we need to fill current knowledge gaps on the extent of its effectiveness, and the type of industries it works best on.

Toward this end, we take a first step in understanding how electricity policy could affect environmental outcomes by conducting an empirical investigation of the relationship between electricity prices and industrial pollution emissions. One challenge of investigating such relationships is that changes in electricity price are often infrequent. Moreover, even if changes in electricity prices are observed, they could be accompanied by confounding changes in related-policies, and economy-wide and seasonal factors. In response, we conduct this empirical investigation by combining a novel dataset of hourly pollution emissions with a unique scenario of changes in electricity prices (where prices either increased, decreased, or remained the same for different hours of the day) in hourly time-of-use (TOU) electricity prices in Anhui, China. Using a difference-in-differences regression model, we find that, relative to the shoulder period (hours where electricity price remained the same), emissions of sulfur dioxide (SO_2) and particulate matters (PM) mostly increased in peak period (hours where electricity

* Corresponding author. School of Applied Economics, Renmin University of China, Beijing, 100872, China.
E-mail address: xbzhmail@gmail.com (X.-B. Zhang).

https://doi.org/10.1016/j.jenvman.2019.07.023
Received 27 March 2019; Received in revised form 4 July 2019; Accepted 7 July 2019
Available online 17 July 2019
0301-4797/

price decreased). On the other hand, emissions mostly decreased during off-peak period (hours where electricity price increased). These analyses were conducted using two different dependent variables (i.e. emissions concentrations and number of hours in which emissions were observed) and along industrial types, where firms are categorized into pollution- and energy-intensive sectors of metals production, cement, and chemicals (Hasanbeigi et al., 2013; Hasanbeigi et al., 2013; Liu et al., 2012). To rule out competing explanations, we conducted robustness checks on contiguous work-shift hours, alternate standard errors clustering, and falsification tests. In all, we find that elasticity of electricity prices with respect to pollution emissions concentrations ranges from -1 to -5.8, with the largest effects observed in the energy-intensive and highly-competitive industries.

1.1. Background on time-on-use electricity prices

Time-of-use (TOU) or tiered electricity price had been implemented in many Chinese provinces since the mid-2000s. Typically, TOU pricing in China is divided into three distinct price tiers – peak, shoulder, and off-peak. As the name implies, peak tier is scheduled during hours where electricity demand is highest (such as morning and evening rush hours), and consumers have to pay the highest rate to use electricity during these hours. Similarly, the shoulder tier and off-peak tier respectively occur during hours of intermediate and lowest demand for electricity. This study is implemented using hourly emissions data from the province of Anhui in China – a highly-industrialized province that is home to a large number of industries, including cement and steel production plants. Across China, electricity prices are controlled by the central government (Lam, 2004), and with effect from 1st January 2016, there was a unique change in Anhui's electricity price for industrial customers where prices were reduced for peak hours, remained unchanged for shoulder hours, and increased for off-peak hours. While there were also changes in electricity prices during this time period in other provinces such as Gansu and Zhejiang, changes in these places were either in uniform direction or did not affect industrial users. Evidence from earlier studies also showed that the centrally-set electricity prices in China are mostly motivated by macroeconomic factors such as exchange rates, development goals, and cost of electricity production (Lam, 2004; Zhang, 2012). Hence, it is unlikely that the end-users prompted these price changes. While sub-provincial governments had been documented to offer lower-than-stipulated electricity prices in the 1990s and early-2000s, such practices were weeded out by the central government since 2010 (Chen, 2011). Because of this exogenous and non-uniform change in TOU price in Anhui, we can implement a difference-in-differences model to isolate the impact of price changes on industrial pollutant emissions.

1.2. Literature review

There is a rich literature documenting the contribution of industrial polluters towards air pollution in China. Using various policy scenarios, Streets and Waldhoff (2000) projected that Chinese industries' (including power sector) share of sulfur dioxide (SO_2) emissions in the year 2020 will be around 50–70% of total emissions. Another study by Lei et al. (2011) examined specifically the Chinese cement industry, and concluded that they contributed around 5.1% and 25% of SO_2 and particulate matters (PM) emissions over the entire country in 2005. Similarly, it was estimated that the steel and iron industries contributed around 20% and 27% of total SO_2 and dust pollution respective in 2013 (Wang et al., 2016). A recent study by Cai et al. (2018) found that coal usage by industrial plants is currently the largest contributor to nitrous oxide, SO_2, and PM emissions, and likely to remain the case in the projected future. Aside from manufacturing plants, coal-fueled electricity plants are also major contributors to air pollution in China. It has been estimated from various studies that China's power sector account for around 31–59% of SO_2, 21–44% of nitrous oxides, and 9% of PM emissions (see Zhao et al., 2010 for a list of studies documenting contribution of power plants to air pollution). From these studies, it is obvious that industrial emissions play a major role in China's environmental pollution.

Due to the large amount of pollution attributed to industrial emissions, the Chinese government has introduced an array of policies designed to curb industrial pollution in the last few decades. He et al. (2012) and Zhang and Wen (2008) provided detailed summaries and timeline of Chinese environmental policies where they described the evolution of these policies in three time periods. The first wave (around 1970s to early 1990s) of government action mostly consists of command-and-control policies where the focus is on end-of-pipe treatment of point-source polluters such as power plants and industrial manufacturing plants. For example, the Chinese Ministry of Environmental Protection tightened emissions limits of coal-fired power plants in 1991 (X. Yuan et al., 2013). The second wave of policies (1990s to late 2000s) moved up the pollution chain, and instead targeted source industrial polluters by shutting down heavy polluters where thousands of small-scale and highly-polluting factories, mines, and power plants were closed down by authorities (Zhang and Wen, 2008). From 2010s onward, the Chinese government is relying more on legislative tools and stricter enforcement by the Ministry of Environmental Protection (MEP) to further rein in industrial pollution (Zhang et al., 2017). For instance, the MEP inspected 1.77 million enterprises in 2015, and handed enforcement actions to more 300,000 of these enterprises (Zhang et al., 2017). Also, instead of just relying on command-and-control policies, the Chinese government has used price instruments (such as emissions trading) or economic incentives (such as tax breaks and subsidies) to encourage lower industrial pollution (Zhang et al., 2016; Zhang and Wen, 2008). One such example of using economic incentives to lower industrial pollution is by allowing power plants with desulfurization facilities to retain a larger share of tariff revenues (Yuan et al., 2013).

A third strand of literature related to our study looked at factors influencing manufacturing plants' pollution emissions. While there are no existing studies that examined the relationship between electricity prices and industrial emissions, there is some evidence that Chinese industries are highly sensitive to energy (in particular, electricity) prices. Hang and Tu (2007) computed the price elasticities of three major energy sources for Chinese manufacturing industries – coal, oil, and electricity - and found that after the year 1995, electricity demand has a positive price elasticity among Chinese industries (i.e. consumption increases with price). While this relationship is not causal, the positive relationship between electricity price and electricity consumption attests to the growing demand and importance of electricity as a production input. To underscore how sensitive is the Chinese economy to electricity prices, a computational general equilibrium model by He et al. (2010) predicted that increase in electricity prices will have significantly adverse impacts on the Chinese economy through drop in production output and accelerated inflation. Similarly, evidence from Chen et al. (2018) showed that policies to reduce SO_2 emissions (mostly achieved through closing of power plants) negatively affected GDP growth of cities to a large extent. Lastly, using data from 2005 to 2007, Elliott et al. (2019) showed that Chinese firms switched from higher to lower energy-intensive industries after electricity price has increased.

Toward this end, it is clear from these studies that industrial polluters are one of the major sources of pollution in China, and the Chinese government have used an array of policies over the past decades to control their emissions. On this backdrop, this study makes two contributions to the literature on environmental and energy policy. Foremost, this is one of the first studies to investigate the impacts of electricity prices on manufacturing plants' pollution emissions. Second, we utilize micro-level data (daily hourly emissions collected from sensors at individual smokestack) to conduct an empirical investigation. Such high-frequency and detailed 'big-data' is becoming more prevalent, and this study demonstrates an application of using such data to answer policy-relevant questions.

2. Methods and data

2.1. Theoretical framework

We present a simple model to illustrate how changes in electricity price could lead to a change in pollution emissions.

First, consider a representative firm making production decision:

$$q = f(E) \Rightarrow E = g(q) \tag{1}$$

$$\text{where } g(q) = 0,\ g'(q) > 0,\ g''(q) > 0 \tag{2}$$

Equation (1) states that production output q is a function of electricity input E and, we can restate usage of electricity input as a function of production in Equation (2). Without loss of generality, other inputs have been suppressed for exposition reasons. We assume in Equation (2) that electricity usage has a positive relationship with output, and this relationship increases at an increasing rate (i.e. decreasing marginal returns).

Second, in line with the research question of this study, we assume the firm faces TOU electricity price where there are three tiers over the course of a day. The daily profit maximization problem can be written as:

$$\underset{0\le q_t\le q}{\text{Max}}\ p\sum_{t=1}^{T} q_t - \underline{\pi}\sum_{t=1}^{\tau} g(q_t) - \pi\sum_{t=\tau+1}^{\tau+h} g(q_t) - \bar{\pi}\sum_{t=\tau+h+1}^{T} g(q_t) - F \tag{3}$$

where p and π are the output price and electricity price respectively. The firm is assumed to be a price-taker as the industries we examined (e.g. steel, cement, aluminum) are producers of global commodities. Furthermore, the empirical analysis is conducted at the smokestack level and it is unlikely any single smokestack have substantial market power to affect world's prices. The first term in Equation (3) refers to the daily revenue as q_t is the production output for hour t. The second to fourth term in Equation (3) respectively represents to the total cost of electricity usage for each price tier from the lowest unit price to the highest (prices in increasing order of $\underline{\pi}$, π, $\bar{\pi}$). However, note that price of the output remained the same regardless of which electricity price tier in which the output was produced.

Third, we can solve for the optimal level of production q_t^* at each price tier by taking first-order condition in Equation (3) to obtain:

$$G(q, \pi) = p - \pi g'(q_t^*) = 0 \tag{4}$$

Using implicit function theorem, we can see how q_t^* changes with electricity price:

$$\frac{\partial q_t^*}{\partial \pi} = -\left(\frac{\partial G}{\partial \pi}\right)\Big/\left(\frac{\partial G}{\partial q_t}\right) = \frac{g'}{\pi g''} < 0 \tag{5}$$

According to Equation (5), the optimal level of production will drop as electricity price increases and *vice versa* (It is also possible for optimal level of production to remain unchanged if the change in electricity price is not large enough or if the firm is already producing at maximum capacity). Fourth, we now see how change in production level may affect the firm's pollutant emissions by assuming emissions of sulfur dioxide and particulate matters are linked to production via:

$$e_{SO_2} = \phi(q) \text{ and } e_{PM} = \varphi(q) \tag{6}$$

$$\text{where } \phi'(q) > 0 \text{ and } \varphi'(q) > 0 \tag{7}$$

Put together, Equations (6) and (7) essentially state that firms emit pollutant only when they produce, and emissions increase together with production. Next, we can see using implicit function theorem that emissions also have a negative relationship with electricity price:

$$\frac{\partial e_{SO_2}}{\partial \pi} = \phi'(q)\frac{\partial q_t^*}{\partial \pi} < 0 \tag{8a}$$

$$\frac{\partial e_{PM}}{\partial \pi} = \varphi'(q)\frac{\partial q_t^*}{\partial \pi} < 0 \tag{8b}$$

It should be noted that $\frac{\partial e_{SO_2}}{\partial \pi}$ and $\frac{\partial e_{PM}}{\partial \pi}$ are generally not expected to be similar in magnitude unless their respective output-emissions relationships, i.e. $\phi(q)$ and $\varphi(q)$ are identical. In all, this simple theoretical model predicts that price changes in electricity would affect pollutants emissions through the production channel.

2.2. Empirical strategy

Our empirical strategy involves using a difference-in-differences (DID) model to recover the effects of electricity price change on industrial pollution emissions. On 1st January 2016, electricity prices in Anhui province were changed in the following manner: decreased for peak hours, increased for off-peak hours, and remained the same for shoulder hours. As such, shoulder hours are classified as the non-treatment group, while peak and off-peak hours are classified as treatment groups.

The estimating equation is as follows:

$$ln(y_{ijpt_1t_2t_3}) = \beta_0 + \beta_1 Treat_{ijp} + \beta_2 Post_{ijpt_1t_2} + \beta_3 Treat_{ijp} * Post_{ijpt_1t_2} + \gamma_{t_2} + \delta_{ijt_3} + \varepsilon_{ijt_1t_2t_3} \tag{9}$$

$ln(y_{ijpt_1t_2t_3})$ is log-transformed emissions concentrations for smokestack i of firm j at electricity price tier p for year t_1, month t_2, and day-of-week t_3.[1] Observations during peak or off-peak hours are assigned a value of 1 in the *Treat* variable while observations during shoulder hours are assigned a value of 0. The variable *Post* is also a binary variable where observations on and after 1st January 2016 (the day when the price change took effect) are coded as 1 and observations before this date are coded as 0. Several fixed effects are included in the estimating equation to control for time- and space-invariant factors. First, γ_{t_2} are a vector of month fixed effects to account for any monthly factors that affects all smokestacks similarly, e.g. costs of other inputs, climatic conditions, and others. Second, δ_{ijt_3} is a composite fixed effect at the firm, smokestack, and day-of-week level. This fixed effect control for all characteristics unique to the smokestack of a firm at a particular day of the week. For instance, it is possible that a firm may choose to rotate operations across their emissions points across a week. Lastly, $\varepsilon_{ijt_1t_2t_3}$ is the idiosyncratic standard error and is clustered at the smokestack-by-day of week level.

Under this setup, the coefficient of interest (also known as the DID estimator) is β_3 in Equation (9), and its statistical identification is reliant on variation at the smokestack-by-day of week level. β_3 is interpreted as the change in emissions in the treated period relative to the no-treatment period. This change could occur in two ways. First, we can think of each period as being independent of each other. That is, as with the theoretical model introduced in Section 3, optimal production decisions are made based on the conditions for that period alone. In this regard, β_3 only captures the direct effect of price change on emissions for the tier. Second, it is also possible that the firm has a fixed daily production target to meet. As such, the firm manager would allocate production across the three tiers to minimize production costs where an increase (decrease) of production in one period would lead to a corresponding decrease (increase) in the other periods. Consider the comparison between shoulder and off-peak periods: production in off-peak period would decrease due to the hike in electricity price, and the reduced production would be distributed to the peak and/or shoulder tiers. In this regard, β_3 capture both the direct and indirect effects of this

[1] The dependent variable is not log-transformed i.e., $y_{ijpt_1t_2t_3}$, when number of hours in which emissions are observed is used.

price change on emissions. In either of these cases, β_3 is most accurately interpreted as the relative change in emissions between the treated period and the no-treatment period.

This study setting and empirical strategy confer several advantages in identifying the effects of electricity price on pollution emissions. First, the non-uniform changes in TOU prices allow us to control all factors that affect every hour of the day equally, such as costs of other inputs or price of output. Second, participation in the TOU pricing scheme is mandatory for Chinese industrial customers. In contrast, many TOU pricing programs in other countries operate on an opt-in basis. As a result, users with the most to gain will likely self-select into the TOU scheme and thus bias the results (Baladi et al., 1998). Third, electricity price in China are exogenously determined by the central government and it is unlikely the price change was manipulated by customers or the provincial governments (Lam, 2004).

According to the theoretical model of firm's optimal level of production, we expect the firm's production to have either no changes or positive treatment effects when comparing between peak and shoulder tiers, i.e. we expect $\beta_3 \geq 0$. On the other hand, when comparing between off-peak and shoulder tiers, we expect to see either no changes or negative treatment effects, i.e. we expect $\beta_3 \leq 0$.

We focus on two outcome variables to account for different parameters of the output production decision: Emissions concentrations (measured in mg/m^3) and hours of operation. First, emissions concentrations represents the intensive margin of production. The rationale is that as the marginal cost of production increases, firms may decide to alter the intensity of production, e.g. producing x-1 units per hour instead of x units. Consequently, altering the production intensity would likely lead to changes in emissions concentrations. It should also be noted that emissions concentrations is a widely used indicator of industrial pollution (e.g. environmental authorities around the world typically define industrial emissions standards in terms of maximum allowable emissions concentrations) (Karplus et al., 2018; Yuan et al., 2013). Additionally, emissions concentrations were used to predict effects of air quality management policies (e.g. rollback method) in earlier decades when more sophisticated modeling techniques were not available (Atkinson and Lewis, 1974; Sharma et al., 2013).[2]

Second, the extensive margin of production is represented by the number of hours with non-zero emissions. The rationale behind this metric is that firms may decide to alter their hours of production independently of the intensity of production, e.g. produce for y-1 hours instead of y hours. In other words, production intensity is kept at the same rate, but overall production decreases because of reduced operating hours.

The pollutants measured are sulfur dioxide (SO_2) and particulate matters (PM) – both of which are tracked in the Chinese government air quality index (Wang et al., 2014). SO_2 is a key air pollutant and a known precursor to $PM_{2.5}$ (Huang et al., 2014). Particulate matters essentially consist of different types of pollutants ranging from total suspended particulates to PM_{10} and $PM_{2.5}$. Put together, there are four dependent variables (two for each type of pollutants).

2.3. Elasticity

Using the treatment effects recovered from the DID estimations, we can compute an empirical price elasticity measure to provide a more general interpretation of our results. Elasticity is defined as:

$$\varepsilon = \frac{ReE\,|post = 1 - ReE|\,post = 0}{ReE \mid post = 0} \bigg/ \frac{ReP\,|post = 1 - ReP|\,post = 0}{ReP \mid post = 0} \tag{10}$$

where $ReE = \dfrac{emissions_{treat}}{emissions_{control}}$ and $ReP = eprice_{treat} - eprice_{control}$

The numerator of Equation (10) is the percentage change in relative proportion of emissions concentrations and the denominator is percentage change in price. This measure of elasticity represents the percentage change in emissions concentrations for the treatment unit relative to control unit for a 1 percentage change in electricity price. This definition is convenient for our purpose as we can directly retrieve the numerator from the empirical estimation of Equation (9). To see this, note that from the numerator in Equation (10) can be expressed as:

$$ReE_{|post=1} = \frac{e^{\beta_0+\beta_1+\beta_2+\beta_3}}{e^{\beta_0+\beta_2}} \tag{11}$$

$$ReE_{|post=0} = \frac{e^{\beta_0+\beta_1}}{e^{\beta_0}}$$

The terms in Equation (11) are directly obtained from the empirical estimation of Equation (9). Lastly, the denominator in Equation (10) is the percentage change in price is directly calculated off the actual change in electricity prices.

2.4. Selection of industrial sectors

We analyze firms from three different sectors – metals production (e.g., steel, iron, and aluminum), cement, and chemicals (e.g. fertilizers, petroleum-related products) – for several reasons. First, these firms are heavy users of electricity as this input accounts for a sizeable portion of the cost-of-production: around 20–30% of per-unit production costs in cement manufacturing, and around 15–50% of per-unit production costs for metals production (see SI for additional sources). Second and related, the metals production and cement industries have been plagued by issues of over-expansion and overcapacity. As such, the profit margin has been driven to extremely low levels of around 1%–10%, and even negative in some cases (Xu and Liu, 2018). Third and related, due to over-expansion, competition in these industries are extremely high. For example, the Herfindahl-Hirschman Index (HHI) for China's steel industry is at around 0.03 (considered as a highly-competitive industry according to the US Department of Justice benchmark) (Hurst, 2017). In comparison, the HHI index for Japan, South Korea, and United States' steel industries ranged from 0.3 to 0.5 (Hurst, 2017). Competition in China's cement industry is also very keen as the HHI index is at 0.002 (Hubbard, 2016). Fourth, firms in these sectors are not only energy-intensive, but also pollution-intensive (Vallero, 2014; S. Zhang, Worrell and Crijns-Graus, 2015). On top of electricity, most of these firms also use other types of pollutant-emitting energy sources, such as coal and natural gas, in their production process (Liu et al., 2012). As such, through the mechanism of altering production output, a change in electricity price would prompt a change in the usage of these other energy sources. Moreover, firms in these sectors could also generate emissions directly through their manufacturing process. For example, cement plants use the process of 'calcination' to break large pieces of granite into fine powder, and this process generates large amounts of particulate matters (Lei et al., 2011; Schuhmacher et al., 2004). For all these reasons, it is possible that even a seemingly inconsequential change in electricity price could drastically affect firms' profitability, and have an outsized-role in affecting production levels especially in the metals production and cement industries where profit margins are low and electricity accounts for a large share of production costs.

[2] An alternate measure of intensive margin is total pollutant emissions mass (which can be computed by multiplying emissions concentrations with gas flow). We are, however, unable to use this measurement in this study due to lack of information on volumetric gas flow.

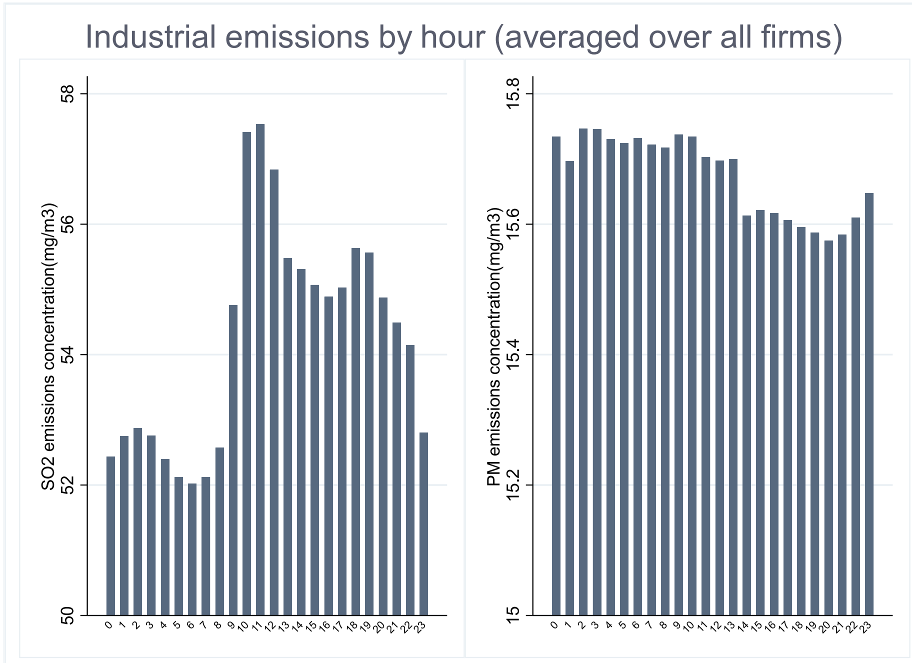


Fig. 1. Hourly emissions concentrations of pollutants averaged over all firms-type.

2.5. Data

Since 2010, the Chinese Ministry of Environmental Protection has publicly identified major air, water, and soil pollution sources in each province across the entire country (Ministry of Environmental Protection, 2009). These sources (mostly industrial factories, wastewater treatment plants, heating plants, and power stations), once identified as major pollution sources, need to install continuous emissions monitoring devices at each emissions output point (or 'smokestack'). A snapshot record of the emissions concentrations for major pollutants is taken at each hour and these emissions data are then automatically uploaded to a public server. For air pollution sources, the main pollutants measured are sulfur dioxide and particulate matters. From the list of pollution sources in Anhui, there are a total of 28 cement factories, seven metals production factories, and 21 chemical plants. The pollution emissions dataset spans from 1st June 2015 to 1st June 2016, where a price change took place during this period on 1st January 2016.

Over the course of a day, The TOU hours in Anhui are designated as follows: Peak hours are from 9am to 11am inclusive, and 5pm–9pm inclusive; Shoulder hours are 8am, 12pm–4pm inclusive, and 10pm; Off-peak hours are from 11pm to 7am inclusive. Before 1st January 2016, electricity was priced at 0.9081 CNY/kwH for peak hours, 0.6074 CNY/kwH for shoulder hours, and 0.3833 CNY/kwH for off-peak hours. Following the change on 1st January 2016, peak electricity decreased by around 0.24% to 0.9059 CNY/kwH, shoulder electricity price remained unchanged, and off-peak electricity increased by around 0.42% to 0.3849 CNY/kwH. While emissions data are available at the hourly level for each smokestack in each firm, this empirical application is better served by aggregating hourly emissions to the level of each price tier. Hence, over the course of a day, there are three pollution emissions readings corresponding to each price tier for each smokestack. Other than the unique price change scenario, Anhui was chosen as the location for this empirical application for several reasons. First, Anhui is a mid-sized industrialized province where her total CO_2 emissions (a proxy for air pollution emissions and energy consumption) ranks around 12th (out of the 30 provinces) in the country (Shan et al., 2016). Similarly, Anhui's GDP and GDP per capita also rank around the midpoint at around 13th and 16th places respectively. Second, about 44% of Anhui's GDP in 2017 is contributed by the manufacturing sectors, which is comparable to the national's average of 41% (China Statistical Bureau, 2018). Hence, even though we are only using data from firms in one province, national statistics have shown that Anhui's income and industrialization level are near the country's average and it is likely that their reactions towards electricity price changes is fairly representative of firms throughout the country. Moreover, the types of firms under examination in this study – cement, metals production, chemicals – are highly competitive and ubiquitous across the Chinese manufacturing landscape. As such, it is unlikely that firms in Anhui would react differently towards changes in input costs compared to firms from other provinces.

The descriptive statistics are collected in Fig. 1 and Table 1. First, Fig. 1 shows the average hourly emissions for SO_2 and PM across the three types of firms. We can see that SO_2 has very distinctive emissions patterns with respect to different hours of the day whereas PM emissions has less variation.[3] When summarized to the TOU tiers (Table 1), we can see that emissions concentrations for both SO_2 and PM are generally lower during off-peak hours even though electricity prices are lowest during this period. This is most likely because other factors of production (e.g. labor) are more expensive during off-peak hours. Hence, we may arrive at a counter-intuitive outcome of positive relationship between electricity prices and industrial emissions concentrations if our empirical approach is simply a cross-sectional analysis of electricity prices and industrial emissions concentrations. Second, we also see that SO_2 emissions concentrations are generally

[3] We also show normalized average hourly emissions by firms type in Figure A1. The emissions concentrations follow different patterns for each industry, hence necessitating separate analyses for each sector.

Table 1
Descriptive statistics.

	N (number of obs)	Mean	Std. Dev.	Min	Max
Number of Metals and iron factories	7				
Number of cement factories	21				
Number of chemical factories	28				
log SO_2 emissions during peak tier (mg/m^3)	25,082	3.28	1.37	−4.49	6.21
log SO_2 emissions during shoulder tier (mg/m^3)	34,412	3.29	1.36	−4.47	6.26
log SO_2 emissions during off-peak tier (mg/m^3)	34,954	3.17	1.43	−4.5	6.3
log PM emissions during peak tier (mg/m^3)	34,982	2.69	0.51	−4.05	4
log PM emissions during shoulder tier (mg/m^3)	47,975	2.71	0.52	−4.35	4.05
log PM emissions during off-peak tier (mg/m^3)	48,756	2.68	0.55	−4.4	4.02
Number of hours where nonzero SO_2 emissions were observed during peak tier	25,082	7.48	1.19	1	8
Number of hours where nonzero SO_2 emissions were observed during shoulder tier	34,412	6.53	1.13	1	7
Number of hours where nonzero SO_2 emissions were observed during off-peak tier	34,954	8.31	1.74	1	9
Number of hours where nonzero PM emissions were observed during peak tier	34,982	7.94	0.47	1	8
Number of hours where nonzero PM emissions were observed during shoulder tier	47,975	6.91	0.62	1	7
Number of hours where nonzero PM emissions were observed during off-peak tier	48,756	8.76	1.17	1	9

larger than PM emissions concentrations. One possible explanation that these industries are heavy users of coal in their production processes. However, compared to SO_2 emissions, the number of hours in which PM emissions are observed is higher. This is likely because the latter is a more general category of pollutants that are emitted through a larger variety of processes. Lastly, it should be noted that the number of hours in which pollutant emissions are observed should be viewed in perspective to the total number of hours in their respective tiers. From the TOU pricing scheme, the total number of hours in peak, shoulder, and off-peak tiers are eight, seven, and 9 h respectively. Hence, this explains why there are large differences in their averages.

3. Results

3.1. Baseline results

We first investigate impacts on the extensive margin as measured by the number of hours where SO_2 emissions are observed for each smokestack. The results in Table 2 show the DID estimators for each industrial sector of metals production, cement, and chemical. For metals production plants, there are no statistically significant changes in the extensive margin between peak and shoulder tiers. On the other hand, the number of hours in which SO_2 emissions are observed decreases by around 0.31 h for off-peak relative to shoulder tiers (Table 2, Columns 1 and 2). Cement plants tell a similar story as there is no difference between peak and shoulder tiers while the number of hours where SO_2 emissions are observed decreased by 0.28 h in off-peak relative to shoulder tier. Lastly, for chemical firms, we observe a slightly different result as both peak and off-peak hours decreased relative to shoulder tiers by around 0.09 and 0.33 h respectively (Table 2, Columns 9 and 10).

We now look at impacts on the intensive margin where the dependent variable is the natural log of average emissions concentrations for SO_2 (Table 2). Metals production firms showed no changes in SO_2 emissions concentrations between peak and shoulder hours. However, there is a 4% decrease in SO_2 emissions concentrations in the off-peak period compared to shoulder. Combined with earlier results, this suggests that, relative to the shoulder hours, metals production factories are not only decreasing the number of hours of operations, but also reducing the production intensity in off-peak period. SO_2 emissions concentrations of cement firms increased by 2.1% during peak period relative to shoulder period, and decreased by 2.7% during off-peak period relative to shoulder period. Lastly, SO_2 emissions concentrations for chemical factories did not change in either price tiers relative to shoulder period.

So far, the 12 sets of results we have looked at are largely consistent with the hypothesis that electricity price decrease (increase) prompted either an increase (decrease) in emissions concentrations of SO_2 and/or the number of hours in which SO_2 emissions were observed.

Next, the above analyses are repeated for PM emissions (Table 3). The signs of the coefficients and statistical significance are consistent with those of SO_2. On average, PM emissions are observed around 0.05 h more at peak period compared to shoulder period for both metals production and cement plants. On the other hand, PM emissions are observed around 0.15 h lesser for the off-peak relative to shoulder period for all the three sectors. Results for intensive margin of production also tell a similar story as PM emissions concentrations at metals production firms increased by 1.3% for peak hours relative to shoulder hours and decreased by 2.4% for off-peak relative to shoulder. For cement factories, the change in emissions concentrations at peak relative to shoulder is 0.7% and −3% at off-peak relative to shoulder. Lastly, results are not statistically significant for the chemical firms for emissions concentration.

3.2. Elasticity measurements

Price elasticities of emissions concentrations are computed using the formula in Equations (10) and (11) and the results from the empirical estimation of Equation (9). This elasticity measure is interpreted as the percentage change in relative emissions concentrations for a one percent increase in electricity price. Towards this end, elasticities are computed only for intensive margin (i.e. emissions concentrations) rather than hours where emissions are observed. The reason is that hours are recorded in discrete format and this makes the elasticity measures lumpier and less precise. Table 4 shows the elasticity measurements for emissions concentrations.

First, we can see that the elasticities for peak relative to shoulder period are generally smaller in magnitude than the elasticities for off-

Table 2
Main results from difference-in-differences estimator of how SO_2 pollution emissions change with electricity price.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
VARIABLES	Extensive-SO2-Peak-Shoulder-Metals	Extensive-SO2-Offpeak-Shoulder-Metals	Intensive-SO2-Peak-Shoulder-Metals	Intensive-SO2-Offpeak-Shoulder-Metals	Extensive-SO2-Peak-Shoulder-Cement	Extensive-SO2-Offpeak-Shoulder-Cement	Intensive-SO2-Peak-Shoulder-Cement	Intensive-SO2-Offpeak-Shoulder-Cement	Extensive-SO2-Peak-Shoulder-Chem	Extensive-SO2-Offpeak-Shoulder-Chem	Intensive-SO2-Peak-Shoulder-Chem	Intensive-SO2-OffPeak-Shoulder-Chem
treat (1 = Shoulder or peak; 0 = off-peal)	1.031***	1.948***	0.031***	0.015	0.940***	1.918***	0.014**	−0.130***	1.047***	1.970***	0.045***	−0.043**
	(0.026)	(0.030)	(0.011)	(0.011)	(0.016)	(0.018)	(0.007)	(0.009)	(0.027)	(0.047)	(0.012)	(0.018)
post (1 = On or after 1st January 2016)	−0.257***	−0.149***	−0.286***	−0.211***	−0.234***	−0.207***	−0.059*	−0.098***	−0.163**	−0.081	−0.176***	−0.148**
	(0.058)	(0.053)	(0.072)	(0.062)	(0.040)	(0.040)	(0.035)	(0.025)	(0.066)	(0.086)	(0.059)	(0.069)
treatXpost (DID estimator)	−0.022	−0.265***	−0.011	−0.040**	0.009	−0.249***	0.021**	−0.027**	−0.091***	−0.383***	−0.010	−0.037
	(0.029)	(0.046)	(0.014)	(0.018)	(0.019)	(0.031)	(0.010)	(0.011)	(0.031)	(0.067)	(0.014)	(0.027)
Holiday fixed-effects	0.194***	−0.064	−0.078	−0.083*	0.102***	−0.060	0.015	−0.042*	0.246***	−0.168	0.145***	0.003
	(0.056)	(0.076)	(0.062)	(0.045)	(0.056)	(0.049)	(0.030)	(0.025)	(0.043)	(0.105)	(0.048)	(0.060)
Constant	6.599***	6.615***	3.681***	3.634***	6.534***	6.575***	2.956***	3.073***	6.297***	6.309***	3.688***	3.333***
	(0.038)	(0.032)	(0.048)	(0.043)	(0.023)	(0.025)	(0.026)	(0.019)	(0.043)	(0.043)	(0.044)	(0.052)
Observations	13,136	15,168	13,136	15,168	32,053	37,627	32,053	37,627	14,305	16,571	14,305	16,571
R-squared	0.191	0.316	0.009	0.009	0.175	0.299	0.004	0.017	0.173	0.298	0.030	0.034
Number of groups	266	266	266	266	497	497	497	497	266	266	266	266

Clustered standard errors at the smokestack-day-of-week level in parentheses. All models estimated with months fixed-effects, and smokestack-day-of-week composite fixed effects.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 3
Main results from difference-in-difference estimator of how PM emissions change with electricity price.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
VARIABLES	Extensive-PM-Peak-Shoulder-Metals	Extensive- PM -Offpeak-Shoulder-Metals	Intensive- PM -Peak-Shoulder-Metals	Intensive- PM -Offpeak-Shoulder-Metals	Extensive- PM -Peak-Shoulder-Cement	Extensive- PM -Offpeak-Shoulder-Cement	Intensive- PM -Peak-Shoulder-Cement	Intensive- PM -Offpeak-Shoulder-Cement	Extensive- PM -Peak-Shoulder-Chem	Extensive- PM -Offpeak-Shoulder-Chem	Intensive- PM -Peak-Shoulder-Chem	Intensive- PM -OffPeak-Shoulder-Chem
treat (1 = Shoulder or peak; 0 = off-peal)	1.030***	1.955***	0.013***	0.011**	1.025***	1.937***	0.010***	−0.011***	1.015***	1.930***	0.004	−0.046***
	(0.017)	(0.018)	(0.005)	(0.005)	(0.009)	(0.009)	(0.003)	(0.002)	(0.022)	(0.021)	(0.006)	(0.012)
post (1 = On or after 1st January 2016)	−0.030	−0.061	0.022	0.012	−0.090***	−0.167***	−0.063***	−0.080***	−0.083***	−0.147***	−0.008	−0.035
	(0.024)	(0.037)	(0.029)	(0.030)	(0.015)	(0.023)	(0.010)	(0.010)	(0.029)	(0.040)	(0.019)	(0.022)
treatXpost (DID estimator)	0.049**	−0.161***	0.013**	−0.024**	0.035***	−0.167***	0.007**	−0.030***	0.034	−0.154***	0.006	0.001
	(0.021)	(0.033)	(0.007)	(0.009)	(0.011)	(0.018)	(0.003)	(0.004)	(0.025)	(0.040)	(0.007)	(0.014)
Holiday fixed-effects	0.071***	−0.151***	0.007	−0.043*	0.063***	−0.101***	0.016*	−0.024**	0.103***	−0.113*	−0.023	−0.067**
	(0.018)	(0.052)	(0.022)	(0.025)	(0.014)	(0.026)	(0.008)	(0.010)	(0.017)	(0.061)	(0.026)	(0.027)
Constant	6.922***	6.912***	2.507***	2.508***	6.931***	6.938***	2.794***	2.794***	6.954***	6.969***	2.709***	2.734***
	(0.016)	(0.023)	(0.024)	(0.024)	(0.009)	(0.011)	(0.005)	(0.006)	(0.016)	(0.023)	(0.020)	(0.026)
Observations	15,847	17,921	15,847	17,921	56,289	66,334	56,289	66,334	10,821	12,476	10,821	12,476
R-squared	0.514	0.522	0.025	0.027	0.441	0.500	0.011	0.020	0.502	0.518	0.011	0.015
Number of groups	322	322	322	322	854	854	854	854	196	195	196	195

Clustered standard errors at the smokestack-day-of-week level in parentheses. All models estimated with months fixed-effects, and smokestack-day-of-week composite fixed effects.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 4
Price elasticity of relative emissions.

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	Intensive-SO2-Peak-Shoulder-Metals	Intensive-SO2-Offpeak-Shoulder-Metals	Intensive-SO2-Peak-Shoulder-Cement	Intensive-SO2-Offpeak-Shoulder-Cement	Intensive-SO2-Peak-Shoulder-Chem	Intensive-SO2-OffPeak-Shoulder-Chem	Intensive- PM -Peak-Shoulder-Metals	Intensive- PM -Offpeak-Shoulder-Metals	Intensive- PM -Peak-Shoulder-Cement	Intensive- PM -Offpeak-Shoulder-Cement	Intensive- PM -Peak-Shoulder-Chem	Intensive- PM -OffPeak-Shoulder-Chem
treatXpost (DID estimator)	−0.011	−0.040**	0.021**	−0.027**	−0.010	−0.037	0.013**	−0.024**	0.007**	−0.030***	0.006	0.001
Marginal effect of DID estimator (%)	Not significant	−4.1	2.1	−2.7	Not significant	Not significant	1.3	−2.4	0.7	−3	Not significant	
Percentage change in relative price		0.71	−0.73	0.71			−0.73	0.71	−0.73	0.71		
Elasticity		**−5.8**	**−2.9**	**−3.8**			**−1.8**	**−3.4**	**−0.96**	**−4.2**		

Note: The percentage changes in relative price are calculated by assessing the price difference between peak (and off-peak) and Shoulder tiers before and after the price change.

peak relative to shoulder period. One plausible explanation is that firms were already producing at maximum or close to maximum capacity during the peak period, and thus there is little room to increase production even when the cost of input falls (especially in this case where we are examining the immediate impacts following a price change). Conversely, the elasticities for off-peak relative to shoulder period is larger, ranging from 3.4 to 5.8. Along the lines of the previous explanation, this is likely because firms find it easier to reduce their production level in the off-peak period (as opposed to increase production).

Second, when comparing across industries, it is clear that the largest effects are observed at metals production and cement industries. This is not surprising as compared to chemicals companies, these two industries have lower profit margins, face keener market competition, and have a larger proportion of their cost-of-production attributable to electricity. As such, their production decisions are more likely to be affected by changes in electricity prices.

3.3. Falsification tests

While the fixed-effects DID strategy provided rigorous statistical identification of the treatment effects, results could still be biased if there exist confounding factors which i) are correlated with the timing of the electricity price changes, and ii) affect pollution emissions in the same direction. To verify that the results are not driven by these confounding factors, we conduct a placebo test by using emissions data (from October 2014 to May 2015) prior to the TOU price change on 1st January 2016. In conducting this falsification test, we assume that there is a similar price change on 1st January 2015, when there is in fact none. Hence, endogeneity issues would be a cause for concern if similar patterns are observed in the 'placebo' DID estimators. As can be seen from the results in Table 5, Panel B, there are no discernible patterns in the DID estimators for either SO_2 or PM pollution in any of the three sectors for both intensive and extensive margins.

A second falsification test is conducted using data from the adjacent province of Shandong for the same time period of 1st June 2015 to 1st June 2016. Just as Anhui, Shandong is a highly-industrialized province and is home to many of the same manufacturing sectors. However, because there are no corresponding TOU electricity schemes in Shandong, we should not expect to see the same emissions patterns for firms in Shandong. The results in Table 5, Panel C again show no discernible patterns in the DID estimators for SO_2 pollution (PM emissions are not monitored in Shandong).

3.4. Work hours

As the hours for peak and shoulder periods under Anhui's TOU scheme are distributed throughout the day, it is less likely for the price changes to coincide with other policy measures. However, it is also possible that plant managers make production decisions in terms of continuous hours. Here, we attempt to mimic a typical work-day in a plant by assuming that each day is separated into three distinct work-shifts from 6am to 2pm, 2pm–10pm, and 10pm to 6am. From these assumed work-shifts, the hours of the first shift are evenly spread out among the three TOU electricity rate periods, the second shift has more hours in the peak TOU rate period, and the third shift has more hours in the off-peak TOU rate period. Using the same logic as before, the first, second, and third work-shifts correspond (imperfectly) to shoulder, peak, and off-peak TOU tiers respectively. Hence, the hypothesis here is that even though these work-shifts hours do not match the TOU tiers perfectly, we should still see similar treatment effects of electricity

Table 5
Summary of results. Panel A: Main results summarized from Tables 1 and 2.

Industry	Metals production				Cement				Chemical			
	SO_2		PM		SO_2		PM		SO_2		PM	
	Peak-Shoulder	Offpeak-Shoulder	Peak-Shoulder	Offpeak-Shoulder	Peak-Shoulder	Offpeak-Shoulder	Peak-Shoulder	Offpeak-Shoulder	Peak-Shoulder	Offpeak-Shoulder	Peak-Shoulder	Offpeak-Shoulder
DID estimator for hours of emissions observed (hours)	Not significant	−0.265***	0.049**	−0.161***	Not significant	−0.249***	0.035***	−0.167***	−0.091***	−0.383***	Not significant	−0.154***
DID estimator for emissions concentrations (%tage change)	Not significant	−0.040**	0.013**	−0.024**	0.021**	−0.027**	0.007**	−0.030***	Not significant	Not significant	Not significant	Not significant

Industry	Metals production				Cement				Chemical			
	SO_2		PM		SO_2		PM		SO_2		PM	
	Peak-Shoulder	Offpeak-Shoulder	Peak-Shoulder	Offpeak-Shoulder	Peak-Shoulder	Offpeak-Shoulder	Peak-Shoulder	Offpeak-Shoulder	Peak-Shoulder	Offpeak-Shoulder	Peak-Shoulder	Offpeak-Shoulder
DID estimator for hours of emissions observed (hours)	Not significant	Not significant	Not significant	Not significant	Not significant	Not significant	Not significant	Not significant	Not significant	Not significant	Not significant	Not significant
DID estimator for emissions concentrations (%tage change)	−0.107**	Not significant	−0.106***	Not significant	−0.055**	Not significant	−0.064***	Not significant	Not significant	Not significant	−0.117***	Not significant

Industry	Metals production		Cement		Chemical	
	SO_2		SO_2		SO_2	
	Peak-Shoulder	Offpeak-Shoulder	Peak-Shoulder	Offpeak-Shoulder	Peak-Shoulder	Offpeak-Shoulder
DID estimator for hours of emissions observed (hours)	Not significant	Not significant	Not significant	Not significant	Not significant	0.087***
DID estimator for emissions concentrations (%tage change)	−0.019*	Not significant	Not significant	Not significant	Not significant	Not significant

°Coefficients highlighted in red are statistically significant, but not of the expected sign.
°°Not significant means not significant at the 95% confidence level.

prices on emissions as it is more likely that plant managers manage operations in contiguous hours. The results shown in Table A1 display similar patterns and coefficients' magnitudes as the baseline results.

3.5. Clustered standard errors

Standard errors need to be clustered when that the main covariate of interest affects all observations of a particular unit uniformly (Moulton, 1986). In this case, the standard errors were clustered at the smokestack-by-day of week level. However, the level of clustering could affect the size of the standard errors, especially if the clusters are defined too finely (Cameron and Trivedi, 2005). Hence, we redefine the clusters to the largest possible at the smokestack level. We find the statistical significance of the baseline results are mostly unchanged and all previously significant coefficients are still at least statistically significant at the 10% level (Table A2).

4. Discussions

Access to cheap and reliable electricity is seen as a conduit to economic growth. However, such economic growth is also often accompanied by polluting industries. Hence, we explore in this study if changes to electricity tariffs would have environmental consequences via the impacts on industrial emissions. This mode of investigation is especially relevant for countries that are maturing into higher-income economies where they face growing social and political pressure to balance between economic growth and environmental performance. For instance, China for all its polluting industries, has been intensively combating air pollution in recent years using an array of policies. Hence, we made use of a non-uniform change in time-of-use (TOU) electricity price in Anhui, China to examine how industrial pollution emissions react to electricity prices. In total, 60 difference-in-differences regression models were estimated independently, and the results are consistent throughout. On average, pollutant emissions concentrations of sulfur dioxide and particulate matters increased by around 1.3% in peak hours relative to shoulder hours following the electricity price change and decreased by around 3% in off-peak hours relative to shoulder hours. Hours in which pollutant emissions are observed increased by an average of 0.04 h in peak period relative to shoulder and decrease by around 0.22 h in the off-peak period. Additionally, we uncover heterogenous findings along the lines of i) sectors; ii) time periods; and iii) pollutant types. First, compared to the chemicals sector, the relationship between prices and emissions are more apparent in the metals production and cement sectors where electricity accounts for a large proportion of cost-of-production and are highly price-competitive. Second, decrease in electricity price in the peak tier has a comparatively lower impact on pollution emissions than the price increase in off-peak tier possibly due to limits on production capacity. Third, we see that while the directions of change are as predicted, magnitude of impacts for PM and SO_2 emissions are different, suggesting that the impact of electricity price on industrial emissions are not uniform across different pollutants. Put together, our results demonstrate that production decisions of industrial firms in key sectors in China are sensitive towards electricity prices and in turn, this has impacts on their pollution emissions.

Our findings yield several policy implications that are especially relevant for developing economies that are dependent on energy- and pollution-intensive industries as sources of economic growth.

First, many cities in developing economies (such as China and India) are currently experiencing unprecedented levels of air pollution (WHO, 2018), and their governments are facing an uphill challenge to improve environmental conditions (Mun and Nielsen, 2017). Our results contribute to this cause by showing that electricity tariffs could be an effective price instrument for curbing industrial air pollution. On top of that, the heterogenous findings found here provide additional guidance for policymakers: that one would also need to carefully consider the nature of the firms and sectors, and production capacity when using electricity prices as a pollution management tool. Second, there has been a strong drive towards reforming electricity sector predominantly in developing countries, and countries around the world are in various stages of this development (Besant-Jones, 2006; Lee and Usman, 2018; Phadke & Rajan, 2003; Urpelainen et al., 2018). As one of the textbook prediction of revamping electricity market is lower electricity rates through efficiency gains (Jamasb et al., 2005; Lee and Usman, 2018; Pollitt, 2004; Urpelainen et al., 2018; Williams and Ghanadan, 2006; Zhang et al., 2008), policymakers thus need to be cognizant that an unintended consequence of reforming the electricity market is that it may interfere with existing policies to curb air pollution. For example, China's 'Blue Skies' policy which was launched in June 2018 to enact a comprehensive list of measures to improve air quality across the country co-exists with another nationwide effort to reform its electricity market (China State Council, 2018; Pollitt et al., 2017). Similarly India, in its ongoing electricity market reforms, recently started on 1st April 2019 an electricity wholesale market to connect generators and customers, for the explicit goal of reducing tariffs (CERC, 2018). These reforms are taking alongside a National Clean Air Program started in early-2019 to improve the fast-deteriorating air quality across multiple Indian cities.[4]

Third, these results revealed that it may be possible to use TOU electricity prices to shift pollution across different hours of the day. For instance, just as traffic congestion charges which are used to de-congest traffic flow during peak hours (Mahendra, 2008), city planners can shift more industrial pollution to night-time – when there are fewer sources of pollution and most people are at home – by increasing and decreasing day-time and night-time industrial electricity prices respectively.

Finally, findings from this study are limited in the following ways. First, we are only providing a point estimate of a single price change. Given sufficient variation in electricity prices, future studies in this area could expand to estimate a full schedule of the relationship between electricity prices and pollution. Such parameters will be conducive to the formulation of more intricate pollution control policies. Second and related, we are only using data from the province of Anhui in this study. While province-level statistics indicate that Anhui has average income and industrialization levels, our results could be skewed to the extent that firms in Anhui respond differently to electricity price changes compared to firms in other parts of the country. Third, we are only examining the short-term impact on pollution. It is possible that, in the longer term, firms expand production capacity in response to lower prices and/or deploy more energy-efficient production techniques in response to higher prices. In such cases, the impacts of electricity price changes on industrial pollution may differ from what is estimated in this study.

Acknowledgements

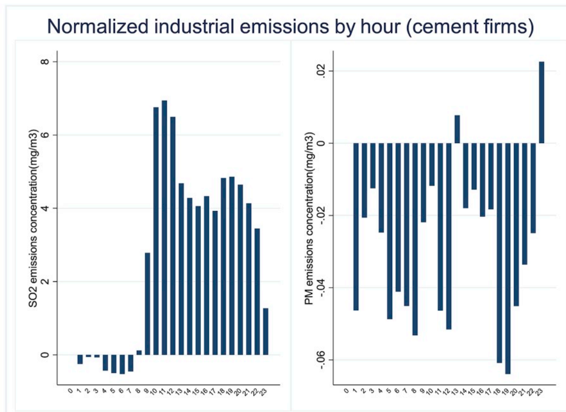
The authors gratefully thank two anonymous referees for their helpful comments and suggestions on the preliminary draft of this paper, according to which the content was improved. All errors and

[4] < i > http://pib.nic.in/newsite/PrintRelease.aspx?relid=187400Government launches National Clean Air Programme(NCAP)" < / i > Last accessed: June 11, 2019.

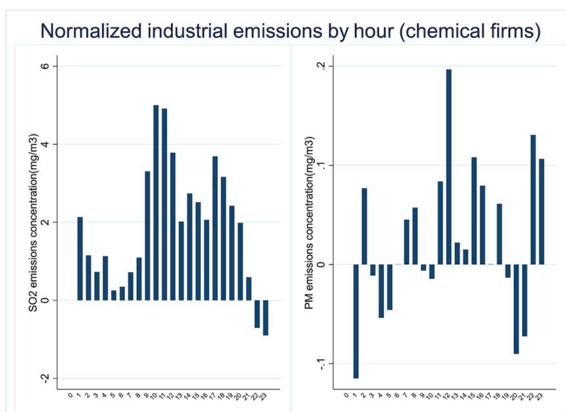
omissions remain the sole responsibility of the authors. Generous financial support was given by the Singapore Ministry of Education (start-up grant: R603000237133 to Jie-Sheng Tan-Soo). Xiao-Bing Zhang is grateful to financial support from the National Natural Science Foundation of China (No. 71603267). The authors declare that there is no conflict of interests and no other financial support.

Appendix A. Supplementary data

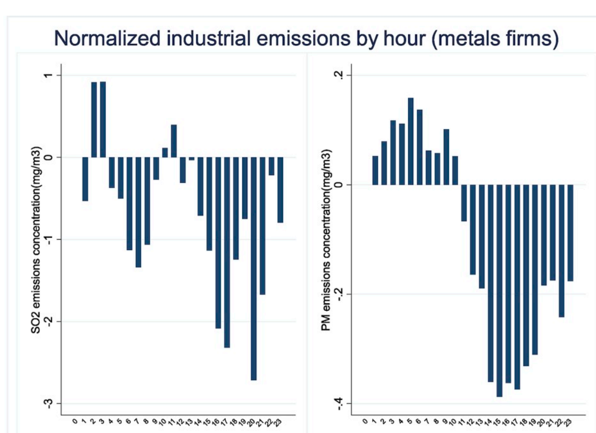
Supplementary data to this article can be found online at https://doi.org/10.1016/j.jenvman.2019.07.023.



Note: Hourly emissions concentrations are normalized by taking the differencing against average emissions concentration at 0000 hr.



Note: Hourly emissions concentrations are normalized by taking the differencing against average emissions concentration at 0000 hr.



Note: Hourly emissions concentrations are normalized by taking the differencing against average emissions concentration at 0000 hr.

Fig. A1. Normalized hourly emissions concentrations of pollutants averaged over firms in each sector.

Table A1
Robustness check by using alternate work-shift hours

Industry	Metals Production				Cement				Chemical			
	SO_2		PM		SO_2		PM		SO_2		PM	
	2nd shift-1st shift	3rd shift-1st shift	2nd shift-1st shift	3rd shift-1st shift	2nd shift-1st shift	3rd shift-1st shift	2nd shift-1st shift	3rd shift-1st shift	2nd shift-1st shift	3rd shift-1st shift	2nd shift-1st shift	3rd shift-1st shift
DID estimator for hours of emissions observed (hours)	0.129***	−0.204***	0.078***	−0.103***	0.059***	−0.159***	0.064***	−0.080***	−0.008	−0.184***	0.088***	−0.059**
DID estimator for emissions concentrations (%tage change)	0.019	−0.059***	0.013*	−0.011	0.030**	−0.024**	0.018***	−0.005*	0.014	−0.042**	0.022***	0.020

Note: First shift is defined as from 6am to 2pm, second shift is from 2pm to 10pm, third is from 10pm to 6am. When compared to the time-of-use electricity rate periods, the first shift corresponds to the Shoulder rate period, second shift corresponds to the peak period, and third shift corresponds to the off-peak period.

Table A2
Standard errors clustered at the smokestack level

	Metals production				Cement				Chemical			
	SO_2		PM		SO_2		PM		SO_2		PM	
	Peak-Shoulder	Offpeak-Shoulder	Peak-Shoulder	Offpeak-Shoulder	Peak-Shoulder	Offpeak-Shoulder	Peak-Shoulder	Offpeak-Shoulder	Peak-Shoulder	Offpeak-Shoulder	Peak-Shoulder	Offpeak-Shoulder
DID estimator for hours of emissions observed (hours)	−0.022	−0.265***	0.049***	−0.161***	0.009	−0.249***	0.035***	−0.167***	−0.091***	−0.383***	0.034**	−0.154***
DID estimator for emissions concentrations (%tage change)	−0.011	−0.040**	0.013*	−0.024**	0.021*	−0.027*	0.007***	−0.030***	−0.010	−0.037	0.006	0.001

References

Akinlo, A.E., 2009. Electricity consumption and economic growth in Nigeria: evidence from cointegration and co-feature analysis. J. Policy Model. 31 (5), 681–693.
Atkinson, S.E., Lewis, D.H., 1974. A cost-effectiveness analysis of alternative air quality control strategies. J. Environ. Econ. Manag. 1 (3), 237–250.
Baladi, S.M., Herriges, J.A., Sweeney, T.J., 1998. Residential response to voluntary time-of-use electricity rates. Resour. Energy Econ. 20 (3), 225–244.
Besant-Jones, J.E., 2006. Reforming Power Markets in Developing Countries: what Have We Learned? World Bank, Washington, DC.
Cai, S., Ma, Q., Wang, S., Zhao, B., Brauer, M., Cohen, A., ... Wang, Y., 2018. Impact of air pollution control policies on future PM2. 5 concentrations and their source contributions in China. J. Environ. Manag. 227, 124–133.
Cameron, A.C., Trivedi, P.K., 2005. Microeconometrics: Methods and Applications. Cambridge university press.
CERC, 2018. Discussion Paper on market based economic Dispatch of electricity: Re-designing of day-ahead market (DAM) in India. Delhi, India Retrieved from. http://www.cercind.gov.in/2018/draft_reg/DP31.pdf.
Chen, J., 2011. China's experiment on the differential electricity pricing policy and the struggle for energy conservation. Energy Policy 39 (9), 5076–5085.
Chen, Y.J., Li, P., Lu, Y., 2018. Career concerns and multitasking local bureaucrats: evidence of a target-based performance evaluation system in China. J. Dev. Econ. 133, 84–101.
China State Council, 2018. Blue Skies battle plan. Beijing, China Retrieved from. http://www.gov.cn/zhengce/content/2018-07/03/content_5303158.htm.
China Statistical Bureau, 2018. 2017 Statistical Yearbooks of Various Chinese Provinces.
Cole, M.A., Elliott, R.J., Wu, S., 2008. Industrial activity and the environment in China: an industry-level analysis. China Econ. Rev. 19 (3), 393–408.
Elliott, R., Sun, P., Zhu, T., 2019. Electricity prices and industry switching: evidence from Chinese manufacturing firms. Energy Econ. 78, 567–588.
Hang, L., Tu, M., 2007. The impacts of energy prices on energy intensity: evidence from China. Energy Policy 35 (5), 2978–2988.
Hasanbeigi, A., Jiang, Z., Price, L., 2013a. Analysis of the past and future trends of energy use in key medium-and large-sized Chinese steel enterprises, 2000-2030. Retrieved from. https://china.lbl.gov/publications/analysis-past-and-future-trends.
Hasanbeigi, A., Morrow, W., Masanet, E., Sathaye, J., Xu, T., 2013b. Energy efficiency improvement and CO2 emission reduction opportunities in the cement industry in China. Energy Policy 57, 287–297.
He, G., Lu, Y., Mol, A.P., Beckers, T., 2012. Changes and challenges: China's environmental management in transition. Environ. Dev. 3, 25–38.
He, Y., Zhang, S., Yang, L., Wang, Y., Wang, J., 2010. Economic analysis of coal price–electricity price adjustment in China based on the CGE model. Energy Policy 38 (11), 6629–6637.
Huang, R.-J., Zhang, Y., Bozzetti, C., Ho, K.-F., Cao, J.-J., Han, Y., ... Canonaco, F., 2014. High secondary aerosol contribution to particulate pollution during haze events in China. Nature 514 (7521), 218–222.
Hubbard, P., 2016. Where have China's state monopolies gone? China Econ. J. 9 (1), 75–99.
Hurst, L.W.L., 2017. China's Iron Ore Boom/Luke Hurst. Routledge, Abingdon, Oxon ; New York, NY.
Jalil, A., Feridun, M., 2011. The impact of growth, energy and financial development on the environment in China: a cointegration analysis. Energy Econ. 33 (2), 284–291.
Jamasb, T., Mota, R., Newbery, D., Pollitt, M., 2005. Electricity Sector Reform in Developing Countries: a Survey of Empirical Evidence on Determinants and Performance. The World Bank.
Jamasb, T., Pollitt, M., 2005. Electricity market reform in the European Union: review of progress toward liberalization & integration. Energy J. 11–41.
Joskow, P.L., 1997. Restructuring, competition and regulatory reform in the US electricity sector. J. Econ. Perspect. 11 (3), 119–138.
Karplus, V.J., Zhang, S., Almond, D., 2018. Quantifying coal power plant responses to tighter SO2 emissions standards in China. Proc. Natl. Acad. Sci. Unit. States Am. 115 (27), 7004–7009.
Lam, P.-L., 2004. Pricing of electricity in China. Energy 29 (2), 287–300.
Lee, A.D., Usman, Z., 2018. Taking Stock of the Political Economy of Power Sector Reforms in Developing Countries: a Literature Review. The World Bank.
Lei, Y., Zhang, Q., Nielsen, C., He, K., 2011. An inventory of primary air pollutants and CO2 emissions from cement production in China, 1990–2020. Atmos. Environ. 45 (1), 147–154.
Lipscomb, M., Mobarak, A.M., Barham, T., 2013. Development effects of electrification: evidence from the topographic placement of hydropower plants in Brazil. Am. Econ. J. Appl. Econ. 5 (2), 200–231.
Liu, Z., Geng, Y., Lindner, S., Zhao, H., Fujita, T., Guan, D., 2012. Embodied energy use in China's industrial sectors. Energy Policy 49, 751–758.
Ma, J., 2011. On-grid electricity tariffs in China: development, reform and prospects. Energy Policy 39 (5), 2633–2645.

Mahendra, A., 2008. Vehicle restrictions in four Latin American cities: is congestion pricing possible? Transport Rev. 28 (1), 105–133.

Ministry of Environmental Protection, 2009. Circular on the list of State Key supervisory and control enterprises in 2010. Retrieved from. http://www.mee.gov.cn/gkml/hbb/bgt/201001/t20100119_184559.htm.

Moulton, B., 1986. Random group effects and the precision of regression estimates. J. Econom. 32 (3), 385–397.

Mun, H., Nielsen, C., 2017. Challenges to Reducing Air Pollution in China amid Economic Slowdown. (Resources).

Murry, D.A., Nan, G.D., 1994. A definition of the gross domestic product-electrification interrelationship. J. Energy Dev. 19 (2), 275–283.

Phadke, A., Rajan, S.C., 2003. Electricity reforms in India: not too late to go back to the drawing board. Econ. Pol. Wkly. 3061–3072.

Pollitt, M., 2004. Electricity reform in Chile. Lessons for developing countries. J. Netw. Ind. (3–4), 221–262.

Pollitt, M., Yang, C.-H., Chen, H., 2017. Reforming the Chinese electricity supply sector: lessons from international experience. Retrieved from. https://EconPapers.repec.org/RePEc:cam:camdae:1713.

Schuhmacher, M., Domingo, J.L., Garreta, J., 2004. Pollutants emitted by a cement plant: health risks for the population living in the neighborhood. Environ. Res. 95 (2), 198–206.

Shan, Y., Liu, J., Liu, Z., Xu, X., Shao, S., Wang, P., Guan, D., 2016. New provincial CO2 emission inventories in China based on apparent energy consumption data and updated emission factors. Appl. Energy 184, 742–750.

Sharma, D., 2003. The multidimensionality of electricity reform—an Australian perspective. Energy Policy 31 (11), 1093–1102.

Sharma, P., Sharma, P., Jain, S., Kumar, P., 2013. An integrated statistical approach for evaluating the exceedence of criteria pollutants in the ambient air of megacity Delhi. Atmos. Environ. 70, 7–17.

Shiu, A., Lam, P.-L., 2004. Electricity consumption and economic growth in China. Energy Policy 32 (1), 47–54.

Streets, D., Waldhoff, S., 2000. Present and future emissions of air pollutants in China:: SO2, NOx, and CO. Atmos. Environ. 34 (3), 363–374.

Tang, C.F., 2008. A re-examination of the relationship between electricity consumption and economic growth in Malaysia. Energy Policy 36 (8), 3077–3085.

Tao, S., Zheng, T., Lianjun, T., 2008. An empirical test of the environmental Kuznets curve in China: a panel cointegration approach. China Econ. Rev. 19 (3), 381–392.

Urpelainen, J., Yang, J., Liu, D., 2018. Power sector reforms and technical performance: good news from an instrumental variable analysis. Rev. Pol. Res. 35 (1), 120–152.

Vallero, D., 2014. Chapter 29 - air pollutant emissions. In: Vallero, D. (Ed.), Fundamentals of Air Pollution, fifth ed. Academic Press, Boston, pp. 787–827.

Wang, K., Tian, H., Hua, S., Zhu, C., Gao, J., Xue, Y., ... Zhou, J., 2016. A comprehensive emission inventory of multiple air pollutants from iron and steel industry in China: temporal trends and spatial variation characteristics. Sci. Total Environ. 559, 7–14.

Wang, X., Lin, B., 2017. Electricity subsidy reform in China. Energy Environ. 28 (3), 245–262.

Wang, Y., Ying, Q., Hu, J., Zhang, H., 2014. Spatial and temporal variations of six criteria air pollutants in 31 provincial capital cities in China during 2013–2014. Environ. Int. 73, 413–422.

WHO, 2018. Ambient (outdoor) air quality and health. Retrieved from. http://www.who.int/en/news-room/fact-sheets/detail/ambient-(outdoor)-air-quality-and-health May 2, 2018.

Williams, J.H., Ghanadan, R., 2006. Electricity reform in developing and transition countries: a reappraisal. Energy 31 (6–7), 815–844.

Wolde-Rufael, Y., 2006. Electricity consumption and economic growth: a time series experience for 17 African countries. Energy Policy 34 (10), 1106–1114.

Xu, D., Liu, Y., 2018. Understanding China's Overcapacity. Peking, China. Springer, Singapore.

Yuan, J., Zhao, C., Yu, S., Hu, Z., 2007. Electricity consumption and economic growth in China: cointegration and co-feature analysis. Energy Econ. 29 (6), 1179–1191.

Yuan, X., Mi, M., Mu, R., Zuo, J., 2013. Strategic route map of sulphur dioxide reduction in China. Energy Policy 60, 844–851. https://doi.org/10.1016/j.enpol.2013.05.072.

Zhang, B., Cao, C., Hughes, R.M., Davis, W.S., 2017. China's new environmental protection regulatory regime: effects and gaps. J. Environ. Manag. 187, 464–469.

Zhang, B., Fei, H., He, P., Xu, Y., Dong, Z., Young, O.R., 2016. The indecisive role of the market in China's SO2 and COD emissions trading. Environ. Pol. 25 (5), 875–898.

Zhang, K.-m., Wen, Z.-g., 2008. Review and challenges of policies of environmental protection and sustainable development in China. J. Environ. Manag. 88 (4), 1249–1261.

Zhang, L., 2012. Electricity pricing in a partial reformed plan system: the case of China. Energy Policy 43, 214–225.

Zhang, S., Worrell, E., Crijns-Graus, W., 2015. Evaluating co-benefits of energy efficiency and air pollution abatement in China's cement industry. Appl. Energy 147, 192–213.

Zhang, X.-P., Cheng, X.-M., 2009. Energy consumption, carbon emissions, and economic growth in China. Ecol. Econ. 68 (10), 2706–2712.

Zhang, Y.-F., Parker, D., Kirkpatrick, C., 2008. Electricity sector reform in developing countries: an econometric assessment of the effects of privatization, competition and regulation. J. Regul. Econ. 33 (2), 159–178.

Zhao, Y., Wang, S., Nielsen, C.P., Li, X., Hao, J., 2010. Establishment of a database of emission factors for atmospheric pollutants from Chinese coal-fired power plants. Atmos. Environ. 44 (12), 1515–1523.