Air Pollution and Post-COVID-19 Work Resumption: Evidence from China

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Air Pollution and Post-COVID-19 Work Resumption: Evidence from China

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Abstract

To cope with the coronavirus disease (COVID-19), national or subnational regions have carried out anti-pandemic measures such as locking down, which may improve their air quality. This paper examines the relation between air pollution and work resumption from a novel post-pandemic perspective. Using unique data on detailed industrial electricity consumption in China, this paper doesn't find a positive relation between post-COVID-19 work resumption and air pollution during the early-stage recovery. This result is obtained after controlling for province and date fixed effects, as well as local weather conditions. However, the positive relation is found for a particular subsample of large industrial enterprises and April. This finding indicates that large industrial enterprises may recover first, and the resumption is progressing gradually. Finally, several policy implications are provided, which are essentially helpful for other countries' post-pandemic recovery.

Keywords: Post-COVID-19; Air pollution; Work resumption; Electricity consumption; Coronavirus recovery; China

Declarations

- Ethics approval and consent to participate

  Not applicable

- Consent for publication

  Not applicable

- Availability of data and materials

  Not applicable

- Competing interests

  The authors declare that they have no competing interests

- Funding

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- Authors' contributions

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1. Introduction

To contain the COVID-19, a global public health crisis indeed(Wang et al., 2020), so many countries or regions have adopted various effective counter-virus measures to reduce person-to-person interaction, e.g., restricting transportation (private or public), encouraging social distancing, and even locking down cities (like China). Notwithstanding that the cost of these defensive measures is so huge, these measures still could bring some substantial social benefits(He et al., 2020). More specifically, environmental quality (air(Collivignarelli et al., 2020; Dantas et al., 2020; He et al., 2020; Kanniah et al., 2020) or water(Yunus et al., 2020)) improvement and the resulting health benefits(Chen et al., 2020) may to some extent offset the cost of these anti-pandemic measures.

Unlike previous studies using data before or during the pandemic(Dang and Trinh, 2021; Khomsi et al., 2021; Wang et al., 2021), this study creatively makes full use of a confidential official dataset to examine the relation of the COVID-19 and local air pollution from a "post-pandemic"[1] perspective. That is, the local disclosure of the data on post-pandemic work resumption gives us an excellent opportunity to conduct this research. Hence, the core question is whether or not the rapid work resumption in a post-pandemic short-window period has pushed up or restarted the ambient air pollution, and how does this impact differ at the aspects of enterprise size and time evolution.

The null hypothesis of this study is that the early-stage post-COVID-19 recovery has a negative effect on local air quality after controlling the impact of other factors. This may arise because the recovery reverse the unintended anti-pandemic improvement of air quality(Dang and Trinh, 2021; Kumar et al., 2021; Wang et al., 2021). The empirical analyses use a comprehensive dataset at

[1] This is a relative concept, which in this study mainly refers to the work resumption activities after the pandemic.

province-by-day level from March 3rd to April 21st in 2020. In particular, this study matches the official unique confidential data on post-COVID-19 recovery[2] provided by the China Southern Power Grid (CSG) to the air-quality data collected from the Ministry of Ecological Environment (MEE) and constructs a panel containing 250 province-dates. By using the fixed-effect panel regressions, this paper does not find a positive relation between the post-pandemic recovery and ambient air pollution so that rejecting the null hypothesis. This result is obtained after controlling for province and date fixed effects, as well as local weather conditions.

In addition, two various heterogeneous analyses are conducted from the perspective of enterprise-level characteristics and time evolution. Interestingly, the positive relation is found for a particular subsample of large industrial enterprises and April. On the one hand, this finding indicates that China's large industrial enterprises have undergone a remarkable recovery, hence no doubt throw a knock-down counterpunch to some news on faking recovery(Krawczyk, 2020; Yuan Ruiyang, 2020). This finding also suggests the success of China's powerful package of stimulating policies, as well as the wisdom of the street-stall and small-store economy. On the other hand, nearly all coefficients in the subsample of April have transformed into positive, which implies that China's domestic economy is gradually recovering over time. Furthermore, several additional tests are conducted to validate the robustness of the main results, mainly including substituting the measure variable of post-COVID-19 recovery by the resumption rate (RR), adjusting the study sample, and using the substitutable model settings. Overall, the core findings are insensitive to various robustness checks. Finally, some policy implications for other countries to recover during the post-pandemic era are provided.

[2] In this study, I mainly use the industrial electricity consumption to proxy the post-COVID-19 recovery.

China provides an ideal setting to test the hypothesis for two reasons. First, it is the first country afflicted with the COVID-19, and also the first one to embark on the work resumption. This work provides an indirect evaluation of China's public management policy during the post-pandemic era, which has received much attention by academics, industry representatives, and policymakers. Second, China is facing to some extent severe air-pollution problems, and more importantly it has been quantified the air quality improvements result from the COVID-19 outbreak in recent studies (e.g.,(Chen et al., 2020; He et al., 2020)).

This work sheds new light on the recent hot spots in the literature of the environmental impacts of public-health shocks (like the COVID-19). The contribution of this paper is threefold. First, although many existing studies have found that the COVID-19 has reduced ambient air pollution to some extent(Dang and Trinh, 2021; Khomsi et al., 2021; Wang et al., 2021), the existing methods without exception use the data during (or before) the pandemic for analysis. Instead, this paper uses the post-COVID-19 work resumption data for re-examination, thus enriching the strand of literature on examining the relation between public health events such as the pandemic and air quality. To my best knowledge, this is among the first in the literature to investigate the influence of the COVID-19 on air quality from a post-pandemic perspective. Second, from the perspective of economic development, the empirical results of this paper can not only provide an indirect test for China's powerful policy package on stimulating recovery but also provide policy implications for other countries that struggling to find a cure for domestic economic recovery. Third, this paper also contributes to the branch of literature on the economic recovery during the post-pandemic era. The current studies on post-COVID-19 economic recovery is relatively lacking. Thanks to its unique political advantage, China is the only major global economy to realize post-COVID-19 economic

recovery. Hence, making full use of the official post-COVID-19 electricity data in China, this study to some extent bridges this knowledge gap.

The remainder of this paper is organized as follows. The following section "Pandemic lockdown, work resumption in China" provides the background on China's virus containment as well as the status of post-pandemic recovery. Section 3 describes the data and discusses the variables and empirical strategy. Empirical findings are presented in section 4. The last section concludes.

2. Pandemic lockdown, work resumption in China

The rapid and widespread COVID-19 has had an immeasurable impact on China, the country with the second-largest economy and the largest population in the world. A rich set of regulations are implemented to counter the COVID-19, among which the policy of locking down cities is one of the most cost-effective and initiative. This section briefly reviews the outbreak of COVID-19, preventive measures, and the work resumption in China. More visually, the timing of China's anti-COVID-19 is mapped in Figure 1.

In December 2019, an unknown virus, later known as COVID-19, emerged in Wuhan, China(Lu et al., 2020; Zhu et al., 2020). After being aware of the person-to-person transmission of the virus, China's central government took the quick measure of locking down Wuhan City on January 23, 2020 to prevent its further spread. This may because China have learned valuable lessons from its 1911 battle against the pneumonic plague in Manchuria. With the exponential growth of confirmed cases, however, many other cities have begun to announce the implementation of closed management.[3]

[3] As of 12 February 2020, a total of 207 cities have taken measures of locking down cities.(wiki on COVID-19 pandemic lockdown in Hubei, accessed 03 October 2020);

There is no doubt that the pandemic outbreak has caused an unprecedented blow to the global major economies, including China. Thanks to China's unique political ecology, China's rapid powerful enforcement of a battery of anti-pandemic measures featuring the city locking down has yielded such great success that the pandemic has then gradually receded, even though China was one of the most affected economies in the early. Hence, with the effective control of the pandemic, restarting the economy becomes particularly pivotal to China's central government. From the date of 10 February 2020, one week after the Chinese Spring Festival holiday, many regions in China started to resume work, including the south-five provinces. In fact, the progress of work resumption is relatively slow in the initial stage. Besides, limited to the data availability, the time frame of this paper is from March 3rd to April 21st in 2020. Overall, the anti-epidemic tough measures such as locking down have a serious impact on people's lives, work, civic culture, etc. (Crossley et al., 2021; Durante et al., 2021; Engzell et al., 2021; Hensvik et al., 2021). Therefore, the domestic economic recovers as soon as possible is particularly critical in the post-pandemic era. Thanks to the innovation of public management policies, China has taken the lead in resuming work and achieved remarkable results among the global major economies.

Figure 1. Timing of China's anti-pandemic.

Note: Compiled by the author from publicly available figures. The sample period is from March 3, 2020 to April 21, 2020, with a purpose of capturing the effect, impact, and heterogeneity of the initial resumption in China.

https://en.wikipedia.org/wiki/COVID-19_pandemic_lockdown_in_Hubei

3. Data and method

This section mainly profiles the data and introduces the model setting. On the one hand, this paper integrate a unique dataset composed of three types of data, i.e., the local air quality data, the official work resumption data, and the local weather data. On the other hand, the main variables used and the empirical model are described in detail.

3.1 Data

To comprehensively study the influence of the COVID-19 pandemic (as discussed above, here mainly refers to “post-COVID” work resumption) on regional air quality and its impact mechanism, this paper synthesize multiple sets of statistical data and finally construct a unique confidential dataset at the province level with data for nearly two months (from March 3rd to April 21st in 2020). In particular, for the main empirical analysis, the comprehensive database principally includes the city-by-day air quality data, the province-by-day official statistical data for electricity consumption of industrial enterprises, as well as the city-by-day weather data. The details are as follows.

First, the urban air quality data -the main outcome variables in this paper- derives from the Ministry of Ecological Environment (MEE). Since 2001, the Ministry of Environmental Protection (MEP, reorganized to MEE in March 2018) has begun to officially disclose the daily air pollution data, which to some extent is also considered to be the beginning of the Chinese government's attention to its environmental issues. This daily indicator disclosed officially by the MEP is the Air Pollution Index (API). Since 2013, however, a more detailed renewed indicator -Air Quality Index (AQI)- has replaced the original API, which comprehensively considering the monitoring concentrations of six main air pollutants (i.e. SO_2, NO_x, CO, O_3, $PM_{10,}$ and $PM_{2.5}$) and consistent

with the calculation formula of AQI in the United States. The AQI monitoring data set is the most comprehensive, effective, and real-time official air quality data that reflects China’s air quality, which has been widely used by a battery of researchers (see, e.g. Li et al., (2018), H. Liu et al., (2017), Luo et al., (2020), Tong et al., (2016)).

Second, the official province-by-day panel data set on electricity consumption of industrial enterprises primarily derives from the China Southern Power Grid (CSG), one of the big two state-owned power grid enterprises in China. More specifically and accurately, this top-secret data was provided by the CNAO's Guangzhou Resident Office via a confidentiality deal, one of whose main responsibilities is to audit the operation of China's central enterprises including the CSG. After verification by the CNAO's Guangzhou Resident Office, this data set is more convincing, which provides an excellent opportunity to study the transmission mechanism behind the relation between the post-COVID-19 work resumption and the variations in local air quality.

Third and finally, the data on weather conditions at the city level -the main control variables in this paper- is collected from the National Climate Data Center, which is affiliated with the National Oceanic and Atmospheric Administration (NOAA). This study considers various weather variables, including the dew point temperature, wind speed rate, air temperature, and sea level pressure. Then, the three data sets are combine for the sample of province-dates. And one should note that, the mean values of city-by-day of the air quality and weather data for each province are calculated in order to match to the province-by-day industrial electricity consumption data.

3.2 Variables and description

Dependent variables. As mentioned above, some previous studies have investigated the

causation or correlation between the ambient air pollution (or quality) and the pandemic lockdown (or halting production). This paper, however, focuses on the influence of post-pandemic recovery on air quality. Realized this, following the method of other studies (Dang and Trinh, 2021; Khomsi et al., 2021; Wang et al., 2021), this paper takes the air quality as the dependent variables. More specifically, the natural logarithm of Air Quality Index (AQI), fine particulate matter (diameter ≤2.5 microns (PM2.5) and diameter ≤10 microns (PM10)), ozone (O3), nitrogen dioxide(NO2), sulfur dioxide (SO2), and carbon monoxide(CO) are used as the measures of the air quality. It is worth noting that, the lower the AQI, the higher the air quality; while the lower the other six indicators, the lower the air quality. At the same time, the ambient AQI is calculated based on the other six air pollutants following the technical regulation promulgated by the MEE[4]. Unlike some other studies, however, this work not only includes the AQI but also includes the six other air pollutants. Taking into consideration of the calculation rules of AQI and the Chinese environmental setting as well as China's environmental context, more attention to the PM have been paid compared to the other pollutants. While the results of all the six pollutants are provided in this study.

Independent variables. Notwithstanding that a rich data set on China's post-pandemic work resumption is provided by the CNAO's Guangzhou Resident Office, this paper mainly focuses on two key indicates on the industrial electricity consumption in view of reflecting the economic recovery directly. More specifically, the province-by-day total daily electricity consumption of industrial enterprises (ELE)[5] is used as the barometer of industrial enterprises' recovery in the baseline models. Meanwhile, this paper also constructs a proportional index -the enterprise's resumption rate (PR)- as an alternative measure in Section 4.3. The PR equals the ELE divided by

[4] Refer to: https://www.mee.gov.cn/ywgz/fgbz/bz/bzwb/jcffbz/201203/t20120302_224166.shtml.
[5] Actually, the natural logarithm of ELE (ln(ELE)) is used in the baseline models.

the average daily electricity consumption in December 2019. Obviously, the higher the two values, the better the degree of resumption of enterprises in the corresponding province. Generally speaking, the electricity consumption is more proper as the measure of the work resumption than any other indicators such as back-to-work persons, since it directly links to the production activities. Another reason is that some other statistical indicators are rough enough when counting whether one factory has resumed work. For instance, even if only one or two persons return to work, it is considered that the factory has resumed work in some cases. So, the other indicators are abandon and the more effective indicator of electricity consumption are chosen as the measure of work resumption in this study.

Control variables. To control the confounding influences of any other factors on the ambient air quality, this paper introduces two types of control variables. On the one hand, a number of studies contend that the weather conditions can affect the ambient air quality (see, e.g., (Clancy et al., 2002; Cropper et al., 1997; Kelsall et al., 1997; Zhong et al., 2021)). Thus the weather conditions (Weather) are controlled in the empirical models, mainly including the air temperature (AT), dew point temperature (DPT), sea level pressure (SLP), wind direction (WD), and wind speed rate (WSR). On the other hand, the thermal power generation in which coal-fired power generation accounts for a large proportion may also confound the regressions (Du et al., 2020; Sheehan et al., 2014; Yuan et al., 2018). Hence, the province-month-level thermal power generations (TPG) are included in the empirical models.

Descriptive analysis. Table 1 shows a brief description of the main variables, its acronyms used in the analysis, main summary statistics, as well as the number of observations for the total sample. From the descriptive statistics, one could easily get the following preliminary findings. First,

222 the province-daily electricity consumption of large industrial enterprises is not surprisingly even
223 larger than that of general ones, with a magnitude of around 11,320 kWh on average. Second,
224 judging from the official electricity consumption data obtained, the work resumption is quite
225 encouraging in the sample period, with a resumption rate at 73.1%. Third, the work resumption
226 seems to be in good condition on the surface, which also could be seen from Figure A1. While the
227 air quality does not seem to change from good to bad. Because, whether by province or not, the AQI
228 has reached the first (good) level[6] on average (see Table A1 for details). The only exception is
229 Yunnan province, whose AQI (63.163) however is only slightly higher than the threshold of the first
230 level. Meanwhile, another detailed violin profile of electricity consumption and AQI by province
231 are displayed in appendix Figure A2.
232

[6] The classification standards of the AQI and air pollution levels are: 0-50 (good), 51-100 (moderate), 101-150 (Unhealthy for Sensitive Groups), 151-200 (unhealthy), 201-300 (very unhealthy), >300 (Hazardous).

Table 1. Summary statistics and description of variables.

Variables	Obs.	Mean	S.D.	Variables	Obs.	Mean	S.D.
ln(ELE)	250	9.980	1.117	ln(NO2)	250	2.802	0.405
(province-daily electricity consumption of enterprises, 10,000 kWh)				(nitrogen dioxide)			
ln(ELE_L)	250	9.632	1.292	ln(O3)	250	4.480	0.359
(province-daily electricity consumption of large industrial enterprises, 10,000 kWh)				(ozone)			
ln(ELE_G)	250	8.500	1.085	ln(CO)	250	-0.418	0.221
(province-daily electricity consumption of general industrial enterprises, 10,000 kWh)				(carbon monoxide)			
PR	250	73.1	13.6	ln(WSR)	250	3.243	0.339
(enterprises' resumption rate, %)				(wind speed rate, m/s)			
ln(AQI)	250	3.752	0.432	ln(AT)	250	5.193	0.251
(air quality index)				(air temperature, ℃)			
ln(PM2.5)	250	3.152	0.514	ln(DPT)	250	4.782	0.496
(fine particles, designated PM2.5, with a diameter of 2.5 μm or less)				(dew point temperature, ℃)			
ln(PM10)	250	42.34	17.09	ln(SLP)	250	9.147	0.0530
(inhalable coarse particles, designated PM10, which are coarse particles with a diameter of 10 μm or less)				(sea level pressure, hPa)			
ln(SO2)	250	1.981	0.467	ln(TPG)	250	4.266	0.917
(sulfur dioxide)				(province-month-level thermal power generation, 100 million kWh)			

Note: Unit of observation is the province-day. Data source: The information on post-pandemic recovery comes from the CNAO's Guangzhou Resident Office; data on air quality and weather are from the Ministry of Ecological Environment (MEE) and National Climate Data Center of NOAA, respectively.

3.3 Empirical model

This paper runs fixed-effect panel regressions to test the relation between ambient air pollution and early-stage post-COVID-19 work resumption. And, the industrial electricity consumption are used as a proxy measure for the post-COVID-19 work resumption. The main regression takes the following form.

$$Y_{it}^{P} = \beta_0^P + \beta_1^P WR_{it} + X_{it}^P + \gamma_i^P + \lambda_t^P + \in_{it}^P \quad (1)$$

where i and t index province and designated day separately. The dependent variable Y_{it}^P consists of seven strands of outcomes, i.e. AQI, PM2.5, PM10, O3, NO2, and CO, which is represented by P equals 1, 2, 3,...7, respectively. And, the logarithmic form of the above seven outcome variables are used in the specifications. The independent variable WR_{it} indicates work resumption, which is defined as either the province-daily electricity consumption of enterprises (logarithm, in the baseline model) or the resumption rate (in the robustness model). X_{it}^P is a vector of controls at the province-date level, including the natural logarithm of province-day-level weather conditions (ln(WSR), ln(AT), ln(DPT), ln(SLP)), and province-month-level thermal power generation (ln(TPG)). β is the coefficient, and ε is the random error term. Besides, this paper takes advantage of the panel-data nature of the dataset to include province fixed effects (γ_i^P) as well as date fixed effects (λ_t^P) in the model specifications. These fixed effects can eliminate many potential sources of omitted-variable bias that may confound the inferences. In particular, the province fixed effects γ_i^P subsume province-specific characteristics that are time-invariant, such as economic and geographical conditions, industrial structure and policies, and environmental policies. While the date fixed effects λ_t^P absorb common shocks to all provinces on a given day.

Hence, the β_1^P is the most concerned coefficient in this paper, which captures the influence of

the post-COVID-19 work resumption on ambient air pollution. If coefficient β_1^P is statistically significantly positive, thus one can infer that the post-pandemic work resumption pushes up or restarts the ambient air pollution.

Overall, the comprehensive data set and empirical models in this study have two notable advantages for the analysis. First, the post-COVID-19 work resumption data is derived from the CSG and also double-checked by the CNAO's Guangzhou Resident Office, which provides enough confidence to precisely capture the post-pandemic recovery, especially in the industry sectors. Besides, electricity is a barometer of the whole economy, and all indicators in this study are based on electricity consumption. Second, the fixed-effect panel regressions allow us not only to control all unobserved province-specific time-invariant characteristics that influence the dependent variables, but also all general macroeconomic factors affecting all province over time.

4. Empirical Results

This section mainly first describes the results of the baseline models. Next, two various heterogeneity analyses are shown, from the perspective of enterprise scale and sample period. Finally, a battery of robustness checks are performed to defend the main findings, including an alternative measure of post-pandemic recovery, an adjusted sample, and two different model settings.

4.1 Air Pollution and Work Resumption

The main results from the baseline empirical models corresponding to Eq. (1) for the relation between the air pollution and post-COVID-19 work resumption are depicted in Figure 2. The dependent variable is the logarithm of seven ambient air quality indicators, i.e., AQI, PM2.5, PM10,

O3, NO2, and CO, which are plotted with different symbols[7]; and the independent variable is the logarithm of industrial electricity consumption.

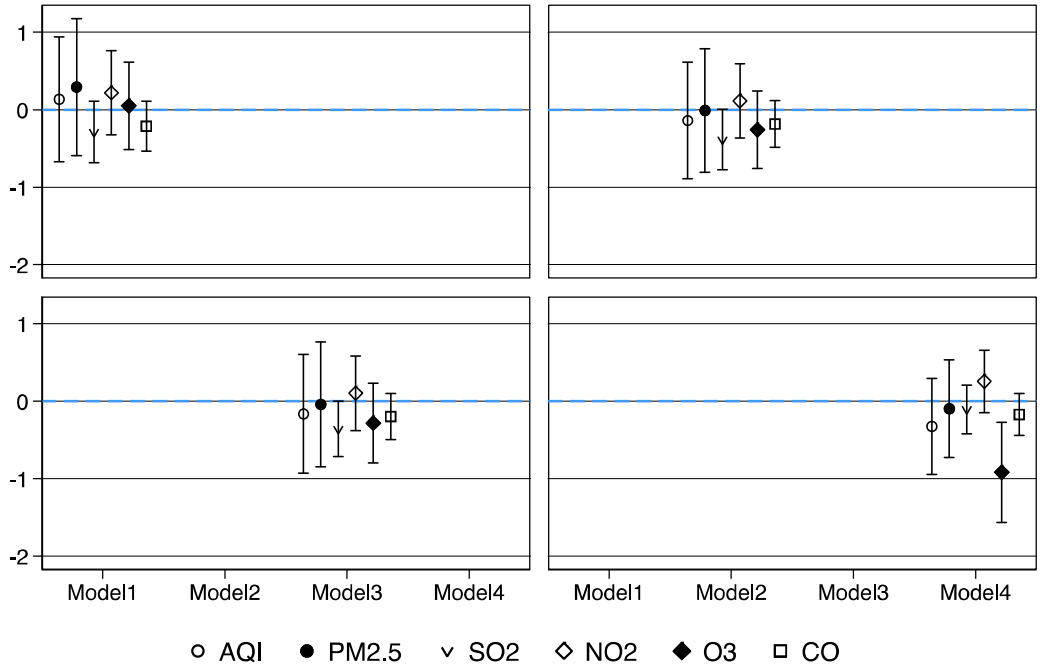


Figure 2. Regression results for post-COVID-19 recovery and air quality.

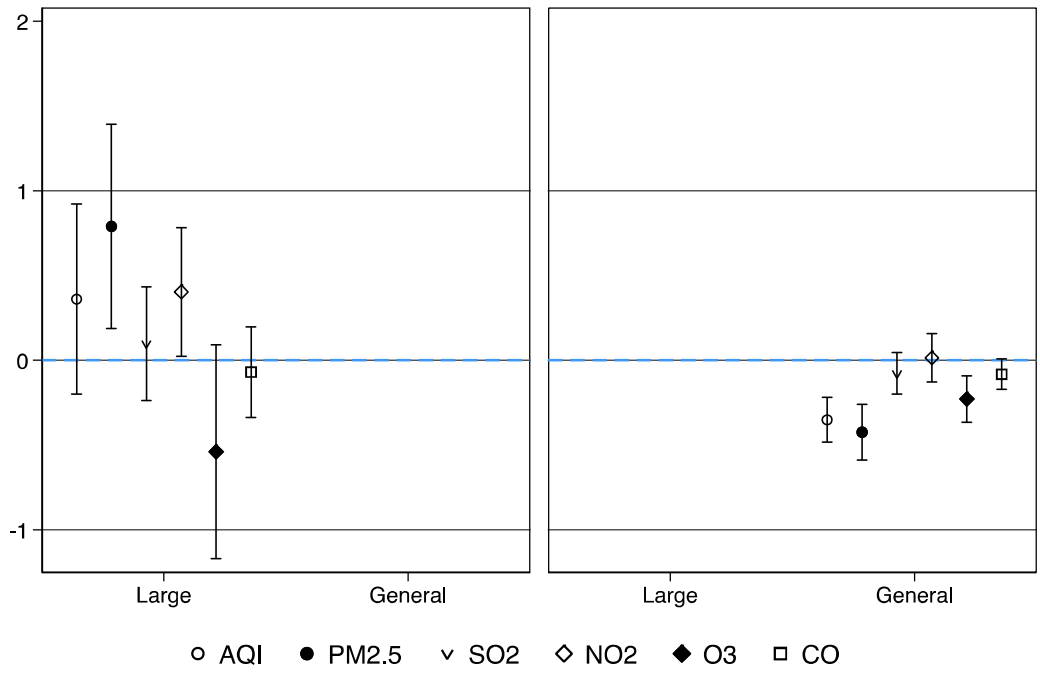
Note: The figure shows the regression results of four various models. Specifically, Model 1 is one simple OLS model, Model 2 controls the weather conditions (including WSR, AT, DPT, and SLP), Model 3 further controls the thermal power generation, and Model 4 further controls the time trend (including the day and week trends). Unit of observation is the province-day. Sample period 03/03/2020 - 21/04/2020. All models have controlled the province and day fixed effects, and the dependent variables of which are all the electricity consumption. Six independent variables are included in the plot, with different symbols. (The regression results of PM_{10} are not included because of the wider confidence interval.) The dependent and independent variables in all models are all in logarithms. The estimated coefficients and their 95% confidence intervals (error bars) are plotted. The detailed tabulated form can be available from the author.

[7] It's worth noting that the regression results of PM_{10} are not included because of the wider confidence interval, and the detailed tabulated form including the results of PM_{10} can be available from the author.

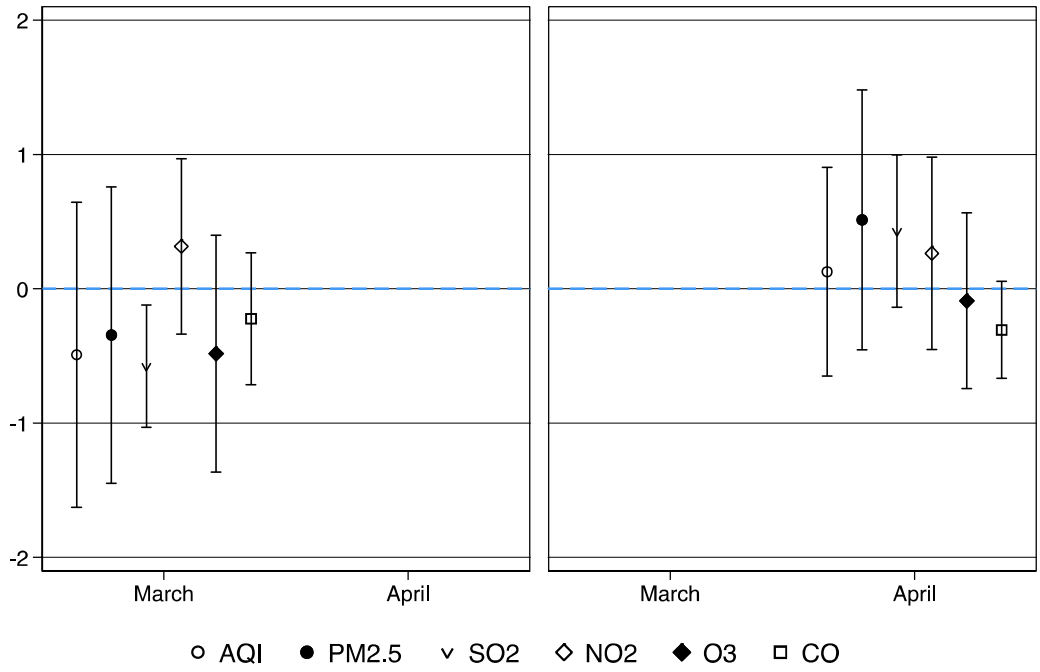
Surprisingly, the most interested coefficient β_1^P are all not significantly positive in the four different models, which casts doubt that there is no or weak influence of post-COVID-19 work resumption on ambient air pollution. More specifically, Model 1 in Figure 2 presents the regression results after controlling only province and day fixed effects but not the other variables. One can find that although the coefficients for the four indicators are positive, statistically insignificant. Not to mention that the coefficient for the other two indicators are negative. Considering the systematically complex influence of weather conditions on ambient air pollution, Model 2 in Figure 2 further controls four weather variables. It shows that except for NO_2, the other five all turn to negative. Coal-fire power generation plays an important role in China's power system, which also affects the ambient air quality so that confusing the identification. Realized this, Model 3 in Figure 2 further controls the province-month thermal power generation, which indicates similar results as in Model 2. Finally, given the date effects, Model 4 in Figure 2 further controls the day and week trends, which also show similar results as before. Combined, One cannot find a statistically significant positive influence of the post-COVID-19 work resumption on ambient air pollution.

4.2 Heterogeneity analysis

Scale of enterprises. With information on the electricity consumption of large and general industrial enterprises in the data set, this paper can investigate the possible heterogeneous effects across differential enterprises' size. Panel a in Figure 3 shows the regression results of the two subgroups, which shows that there is a positive influence between the electricity consumption of large industrial enterprises and the ambient air pollution, especially for AQI, PM2.5, PM10, and NO2. However, a nearly reverse effect is found in the subgroup of general industrial enterprises.



(a) Enterprise scale



(b) Sample period

Figure 3. Heterogeneity effect.

Note: The figure depicts the results of two heterogeneity effects, i.e., different enterprise scale (a) and sample

period (b). All models control the weather conditions, thermal power generation, day and week trends, as well as the province and day fixed effects. The explanations of dependent and independent variables are the same as Figure 2. The estimated coefficients and their 95\% confidence intervals (error bars) are plotted. And, the detailed tabulated form can be available from the author.

March and April. As mentioned above, the data set in this paper includes the resumption information for March and April 2020. This is because that the CNAO's Guangzhou Resident Office only collects and checks the statistical information of the two months. Hence, the analyses in this study are mainly intended to reveal the relation between the ambient air pollution and the post-pandemic work resumption in the early stage. Besides, considering the fact that as time goes by, the work resumption will get better and better, so this study regresses the sample in March and April 2020 respectively. As shown in Panel b in Figure 3, from March to April 2020, the influence changes from negative to positive in general.

4.3 Robustness checks

Alternative measure of post-pandemic recovery. Making full use of the data set, this study gives another regression result based on an alternative measure of the post-pandemic work resumption, i.e. resumption rate (RR). Specifically, the RR indexes the proportion of enterprises whose electricity consumption exceeds 30% of its average daily electricity consumption in December 2019, which to some extent indicates the variation of post-pandemic recovery.

As shown in the first panel (Top left) of Figure 4, all coefficients for the six indicators are negative. Not surprisingly, one still cannot get a result supporting the null hypothesis which assuming the post-pandemic recovery causes the deterioration of air quality. That is, the main results

in this subsection are generally consistent with the baseline model.

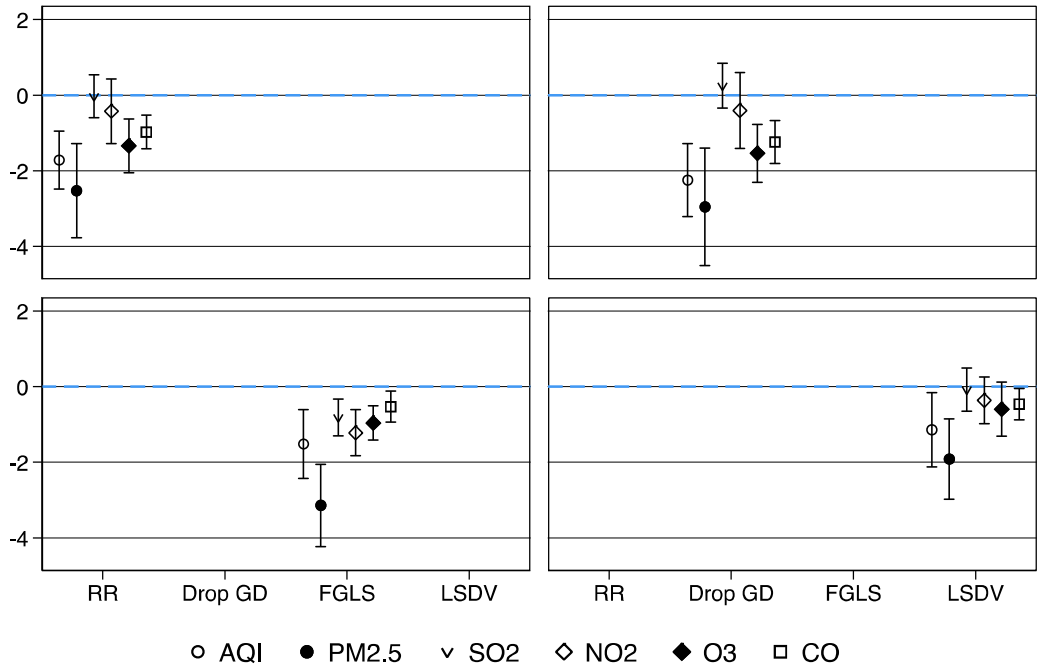


Figure 4. Robustness Checks.

Note: The figure shows four panels of robustness checks. More specifically, the first panel (Top left) depicts the results of an alternative measure of post-pandemic recovery, i.e., the resumption rate. The second panel (Top right) depicts the results of adjusted sample, i.e., dropping the data of Guangdong province. The third panel (Bottom left) depicts the results of FGLS model, while the last panel (Bottom right) depicts the results of LSDV model. All models control the weather conditions, thermal power generation, day and week trends, as well as the province and day fixed effects. The estimated coefficients and their 95% confidence intervals (error bars) are plotted. And, the detailed tabulated form can be available from the author.

Adjusting sample. Among the provinces in the data set, Guangdong province is somewhat heterogeneous. This heterogeneity mainly includes but not limited to: 1) As a megacity in China, Guangdong province is more sensitive to the work resumption because of the larger proportion of the foreign population. 2) Guangdong province is located in the Guangdong-Hong Kong-Macao

Greater Bay Area, with the largest economy among the provinces of the data set. 3) After the work resumption started, the pandemic in Guangdong province has rebounded to some extent, which has affected its further work resumption. Therefore, the sample excluded Guangdong province is used to regress the baseline model again. The second panel (Top right) of Figure 4 shows the result, which still rejects the hypothesis assuming the post-pandemic recovery caused the deterioration of air quality.

Different model setting. Considering that the data in this paper is a long panel, the assumption of independently and identically distribution (i.i.d.) of the random error terms in the short panel thus can be relaxed. More specifically, considering the possible heteroscedasticity, intra-group autocorrelation, or inter-group simultaneous correlation in the error terms, the full feasible generalized least squares (FGLS) method is used to estimate the model again. The results are shown in the third panel (Bottom left) of Figure 4. Moreover, this study also uses the least squares dummy variable (LSDV) model to include indicator variables for each panel-unit, and the results are shown in the fourth panel (Bottom right) of Figure 4. Undoubtedly, the main results of the two models are still robust enough

Another concern about the analyses is the problem of endogeneity, which may mainly come from the measurement error or missing variables. Notwithstanding that it is difficult to provide a perfectly clean causal identification, the results of correlation are also enough.

5. Further discussion

Thus far, using unique official electricity consumption data of south-five provinces in China, the relation between the post-COVID-19 work resumption and the ambient air quality has been

estimated. Counter-intuitively, however, one cannot find any empirical evidence to support the null hypothesis which assumes a negative relation between the post-COVID-19 recovery and ambient air quality. And the results are robust enough to several robustness checks. Hence, why one cannot find a positive relation between the post-pandemic electricity consumption and ambient air pollution? And how to explain this counterintuitive phenomenon?

The possible explanations given are as follows: First, notwithstanding that one has not observed a positive relation between the post-COVID-19 electricity consumption and the ambient air pollution in the full sample, a statistically significant positive relation has been found in the subgroup of large industrial enterprises as shown in section 4.2.1. On the one hand, these results indicate that large industrial enterprises have undergone a remarkable recovery, which not only owing to the relatively large proportion of State-owned enterprises (SOEs) but also a powerful package of policies such as the new infrastructure, supportive electricity prices, ensuring 'six priorities' and stability in six areas and so on. On the other hand, the results also indicate that general industrial enterprises may have not experienced a significant recovery during my study period, which may be the starting point of the street-stall and small-store economy.

Second, from the view of time evolution, nearly all coefficients in the subgroup of April have turned positive as shown in section 4.2.2, although statistically not significant. This to some extent implies that China's domestic economy is gradually recovering over time, which owing to a strong package of post-pandemic stimulating policies and also in line with my intuition.

Combined, my results can help to understand the policies issued for recovery more systematically. After revisiting China's unique political regime and political ecology, I then plot the potential mechanism of stimulating post-COVID-19 recovery which is shown in Figure 5. Under

the pressure of the anti-pandemic and Sino-US trade war, the central government of the P.R.C has issued a series of policies to promote work resumption after the COVID-19, including cut electricity prices. Because of the political hierarchy in China, the pressure is partly transferred to the local governments. Among the response manners, the local governments may assign concrete targets or indicators (e.g., targets of back-to-work and electricity consumption) to district enterprises, as well as implementing other local management decisions. In a word, China's central and local governments have taken series of strong measures to help enterprises recover, whose effects are gradually emerging.

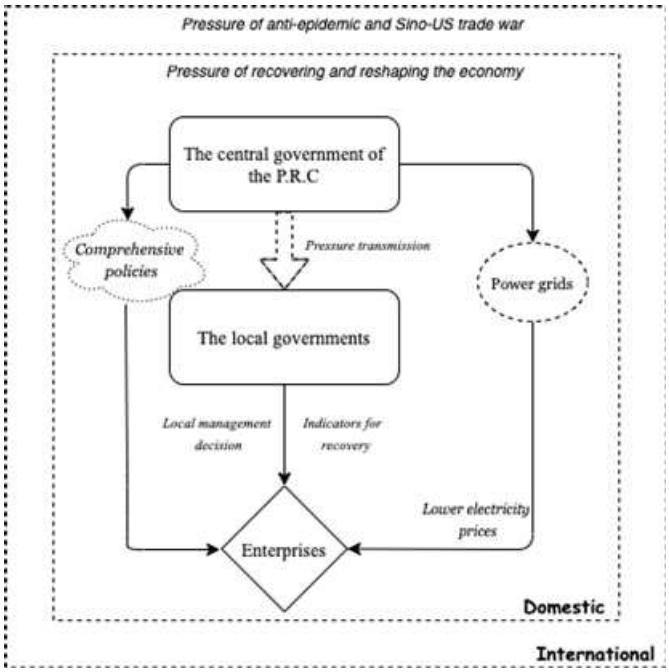


Figure 5. Mechanism of stimulating post-COVID-19 recovery.

Note: Compiled by authors from publicly available figures. Comprehensive policies include the new infrastructure, street-stall economy, and ensuring 'six priorities' and stability in six areas, etc.

Some policy implications for other countries, which would seek an effective cure to restart the economy in the post-COVID-19 era, are as follows: (i) The post-COVID-19 work resumption is not only an economic activity but also a management behavior. It is necessary to pay attention to the effective connection between economic and management science. (ii) Pay attention to policy flexibility. The large industrial enterprises may be the breakthrough and forerunner of the post-pandemic recovery. While the policy-makers should sidestep the curse of attending to one thing and losing another, i.e., taking targeted measures to help general industrial enterprises recover. (iii) One of the most effective means may be to reduce the pressure on enterprises' operating costs, such as lower electricity prices. (iv) Green stimulus packages should focus more on highly polluting and highly energy-wasting large-scale industrial enterprises, which also plays an important role in coping with climate change. (v) The last point is to consider the actual national conditions. At the

level of policy implementation (local government) in China, the number of large industrial enterprises is small, and almost all state-owned enterprises fall into this category, so the implementation of recovering policies is relatively easier; while the number of general industrial enterprises is larger, including many small workshops and enterprise of the service industry. Given this, on the one hand, it is relatively easier to implement the resumption policy with large industrial enterprises as the entry point, and it has a more obvious role in promoting the recovery of the overall economy; on the other hand, promoting the recovery of general industrial enterprises requires innovative policy mechanisms, such as China's specific and targeted economy policy of the street-stall and small-store. The developing countries, which are still in the developing stage and dominated by the secondary industry, are similar to China's national conditions. Therefore, this paper can provide a useful reference for their innovation of public management policies.

6. Conclusion and Outlook

Based on a battery of studies(Dang and Trinh, 2021; Khomsi et al., 2021; Wang et al., 2021), this study firstly proposes a hypothesis -controlling the impact of other factors, post-COVID-19 work resumption has a negative effect on ambient air quality- which provides a novel perspective to reevaluate the comprehensive impact of the pandemic and also promotes the policy-making of greening the post-pandemic recovery. By using unique official electricity data of south-five provinces in China, no empirical evidence, however, is found to support this hypothesis. In fact, using the unique data of work resumption across provinces in China, some positive effects in different model settings even has been found. Overall, the results are robust to a series of robustness checks on the measure index, study sample, and different model settings.

However, this study provides econometric evidence that local air quality does respond to the post-COVID recovery in China, in the heterogeneous analysis. On the one hand, a statistically significant positive relation has been found in the subgroup of large industrial enterprises, which shows that the large industrial enterprises have undergone a remarkable recovery, hence maybe indicate the success of China's powerful package of stimulating policies and the wisdom of the street-stall and small-store economy. On the other hand, nearly all coefficients in the subgroup of April 2020 have turned positive, which implies that China's domestic economy is gradually recovering over time. Finally, some policy implications for other countries to recover during the post-pandemic era are provided.

Potentially fruitful areas for future research include a comparison of the effects of differential recovery policies. This includes not only different recovery policies within the same economy but also among various economies. More detailed (e.g., city- or even facility-level) and longer time-scale data can be applied to the analysis of recovery policy assessment, from the standpoint of dynamic evolution. Finally, the assessment of policies in the green recovery dimension should be given more attention.

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544 # Appendix

545 **Table A1. Mean values of seven air quality indicators over south-five provinces in China.**

Province	AQI	PM	PM10	SO2	NO2	O3	CO
Guangdong	41.619	23.903	38.823	7.916	24.756	92.334	0.688
Guangxi	46.711	26.792	44.010	9.642	19.980	74.248	0.797
Guizhou	49.127	27.837	41.296	10.604	16.498	94.827	0.574
Hainan	27.204	12.435	25.898	3.231	9.102	80.074	0.519
Yunnan	63.163	37.639	55.960	8.181	17.974	123.198	0.773
Total	45.565	25.721	41.197	7.915	17.662	92.936	0.670

546 *Note:* The table shows the mean values of the key air quality indicators over provinces in the dataset, while the population mean values are

547 reported in the last row. Data source: The Ministry of Ecological Environment (MEE) and National Climate Data Center of NOAA.

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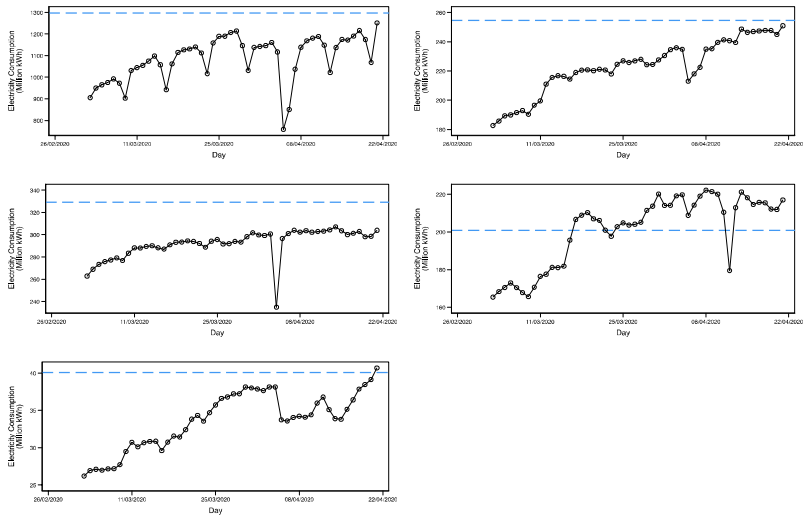
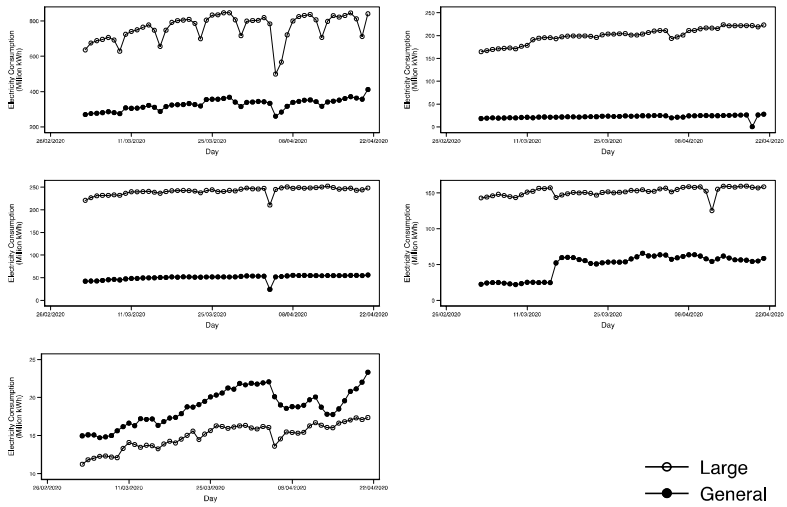


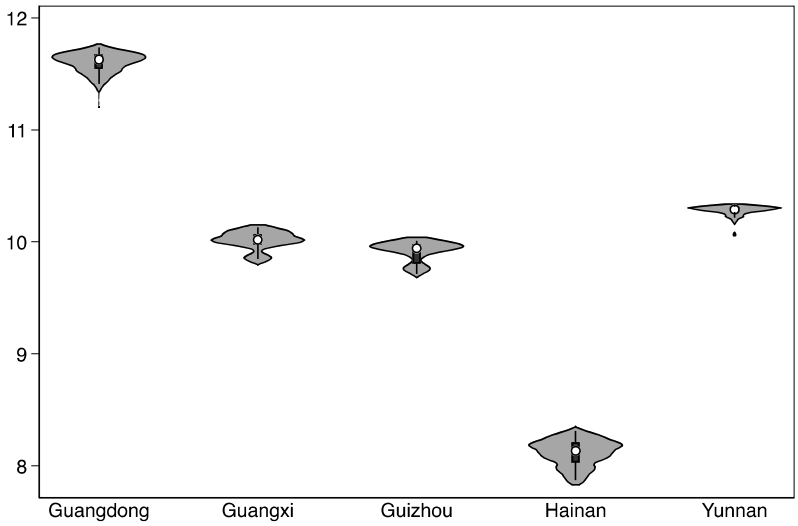
(a) Electricity consumption by province



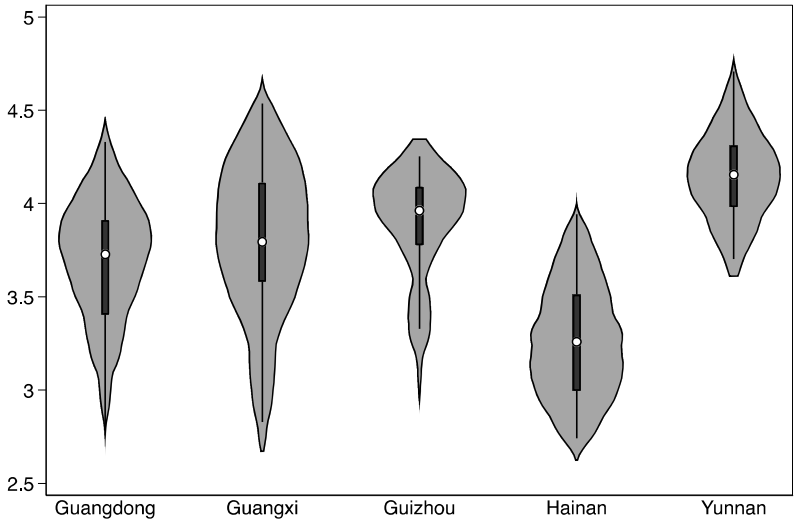
(b) Electricity consumption by province and scale

Fig A1 Time trend of electricity consumption

Note: Panel a shows the day-evolution trends of electricity consumption for Guangdong (top left), Guangxi (top right), Yunnan (middle left), Guizhou (middle right), and Hainan (bottom left). The dash blue lines in Panel a mark the provinces' average daily electricity consumption in December 2019. Panel b shows the day-evolution trends of electricity consumption, further divided into large (white dots) and general (black dots) industrial enterprises, and the same provinces' order as Panel a. Data source: The CNAO's Guangzhou Resident Office, and the China Southern Power Grid (CSG).



(a) Violin plot of electricity consumption



(b) Violin plot of AQI

Fig A2. Distributions of electricity consumption and AQI.

Note: The figure depicts distributions of log-transformed electricity consumption (a) and AQI (b) for south-five provinces, which merge both kernel density and box plots. The inside box boundaries indicate the 25th (lower hinge) and 75th (upper hinge) percentiles; the white dots represent the median values; and the whiskers represent the upper- and lower-adjacent values; while, the outside distribution clouds show the data distributions and their probability density).