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Analysis

Clean air as an experience good in urban China

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Abstract

The surprise economic shutdown due to COVID-19 caused a sharp improvement in urban air quality in many previously heavily polluted Chinese cities. If clean air is a valued experience good, then this short-term reduction in pollution in spring 2020 could have persistent medium-term effects on reducing urban pollution levels as cities adopt new “blue sky” regulations to maintain recent pollution progress. We document that China’s cross-city Environmental Kuznets Curve shifts as a function of a city’s demand for clean air. We rank 144 cities in China based on their population’s baseline sensitivity to air pollution and with respect to their recent air pollution gains due to the COVID shutdown. The largest experience good effect should take place for cities featuring a high pollution sensitive population and where air quality has sharply improved during the pandemic. The residents of these cities have increased their online discussions focused on environmental protection, and local officials are incorporating “green” industrial subsidies into post-COVID stimulus policies.

1. Introduction

In recent years, China’s cities have enjoyed economic growth and declining urban air pollution. While economic growth rates varied across cities and regions, the nation’s economy as a whole was growing at a rate of roughly 6% per year over the last five years. Over the years 2015 to 2019, air pollution has declined annually by 6.9% in the average city and by 8.1% in the big cities.

In early 2020, urban air pollution sharply declined in China due to the COVID-19 induced economic shutdown (He et al., 2020). In the first three months of 2020, the PM2.5 concentration in 285 Chinese cities declined by 11.9% (with a standard deviation of 18.1%) relative to the same period in last year. These gains were not uniformly distributed. Some cities, such as Baoding and Xingtai in the Hebei Province, experienced large pollution reductions (roughly 25%) from an initial high pollution level of 80 μg/m3 in recent years.

In this paper, we study how the early 2020 economic shutdown influences urban China’s air quality, citizen environmental engagement, and the nation’s regulatory and industrial policy dynamics. A stationary Environmental Kuznets Curve (EKC) yields the empirical prediction that when a developing country economy experiences a “V” shaped economic recovery that pollution will follow similar dynamics and may even rise with ongoing economic growth (Grossman and Krueger, 1995). A local official in a developing country city might even choose to relax environmental regulations during an economic slowdown if he believes that such regulations hinder economic growth (Selden and
In contrast, if clean air is a valued experience good, then the reduction in pollution in spring 2020 could have persistent effects on future urban pollution levels even if the local economies fully recover from the recent recession. In China’s polluted cities, blue skies represent a new good. Until they experience persistent air quality gains, urban residents may under-estimate their own valuation of this new good. Research on experience goods have studied optimal pricing of such goods. Firms that market new products have incentives to initially price them at a low level to stimulate demand and to give consumers “a taste” of the new product (Riordan, 1986; Shapiro, 1983). We know of no analogous research exploring the implications of local public goods improvements as “experience goods”.

A “silver lining” of the COVID-19 pandemic is to offer millions of Chinese urbanites this clean air experience. While China does not hold direct elections, the Chinese people now have much more freedom to express their opinions online and in social media on environmental issues (which are not very sensitive as compared to other political topics). Urban leaders are increasingly held accountable to their citizens’ voice because of the rising information transparency. They are evaluated by the central government for political promotion. The criteria for promotion include social stability and environmental targets as well as local economic growth (Zheng et al., 2014). Both online and offline protests are regarded as threats to social stability. The local official performance criteria provides ambitious local leaders with career concerns to consider adopting “green policy”; especially if local residents increasingly desire such policies.

The clean air as an experience good hypothesis posits that the demand for increased regulation will take place in those cities that both enjoy increased short run access to cleaner air and where the population is more sensitive to pollution exposure. This experience effect can vary by city. In those cities where people exhibit a stronger demand for cleaner air, we predict an even greater experience effect as the COVID shutdown cleans up the air.

In a recent research, we have used the content of social media “tweets” in China to measure for each city, to what extent local air pollution lowers residents’ sentiment. Using this city level index to measure the local population’s pollution sensitivity, we identify those cities whose residents have revealed that they face the highest marginal sentiment cost due to pollution (Zheng et al., 2019).

In arguing that the COVID-19 induced shutdown may accelerate pollution reduction progress in China’s most polluted cities, we need to address the counter-factual of how pollution would have evolved in different Chinese cities if the COVID-19 shock had not occurred. We study this by first examining recent urban pollution dynamics over the years 2015 to 2019 across China. We explore the key roles of industrial activity, the transport sector and the home sector in driving these dynamics. We then build on the work of He et al. (2020) to explore how the recent COVID-19 shock affected pollution dynamics.

In the last section of the paper, we use several new data sets to explore the nascent demand for more intense environmental regulations. We rank 144 cities in China based on their population’s baseline sensitivity to air pollution and with respect to their recent air pollution gains due to the COVID shutdown. The largest experience good effect should take place for cities featuring a high pollution sensitive population and where air quality has sharply improved during the pandemic. For these cities, we document that in mid-2020 the local population has increased the discussion of environmental protection on the Internet, and local officials are incorporating “green” industrial subsidies into post-COVID stimulus policies. If these regulations are effective, then this will have long-lasting effects as they will induce a structural shift to the nation’s EKC curve and lead to a time series path featuring less pollution as economic development takes place (Dasgupta et al., 2002).

2. Recent trends in urban air pollution in China

We start by presenting recent trends in air pollution across China’s cities over the years 2015 to 2019. The pollution data reports each city’s PM$_{2.5}$ concentration level based on the real time platform managed by the China Environmental Monitoring Station network. The data are released daily. We calculate each city’s annual mean value. Cities with larger populations have higher average pollution levels at the start of the period but have enjoyed greater pollution reductions over time than smaller cities. Smaller cities have also enjoyed air pollution reductions. During a time of economic and population growth, China’s pollution levels have declined 15 μg/m$^3$ on a base of 55 μg/m$^3$ (See Fig. 1A).

Since big cities are richer, local leaders are more likely to enforce stringent environmental regulations (Grossman and Krueger, 1995; Selden and Song, 1995). When cities differ with respect to their environmental regulatory enforcement, this raises the possibility that footloose polluting industries will relocate to poorer cities that have less stringent regulations, which leads to the “domestic pollution haven” problem (Zheng et al., 2014). In Fig. 1B, we document the decline in the share of local output from manufacturing in both big and small cities. Big cities have experienced a larger decline. The transition to services and high tech in China’s major cities is an important factor that mirrors the transition that occurred in U.S cities (Kahn, 1999). The nation’s industrial policy has contributed to this geographic shift. The 13th Five-Year Plan (2016–2020) offers forward guidance in determining the spatial distribution of industrial growth. Given that air pollution has declined in recent years in both big and small cities and in rich and poor cities, this suggests that any industrial composition shifts has been offset by technique effects such that pollution per unit of economic activity declines.

To explore recent changes in the urban population’s exposure to pollution, we calculate the urban population’s distribution of pollution exposure in 2015 and 2019. In each year, we tabulate the annual weather-adjusted pollution data$^4$ and weight the data by the city’s population. Fig. 2 reports these two cumulative distribution functions (CDF). Define X80 as the 80th percentile of the CDF in 2015. X80 indicates that 20% of the total urban population lived in a city whose average pollution level was equal to or greater than X80. We find that there have been large reductions in pollution exposure to the dirtiest air.

In the year 2015, roughly 20% of Chinese urbanites were exposed to less than 40 units of PM$_{2.5}$. In the year 2019, this percentage grew to almost 50%. The median Chinese urbanite was exposed to just over 50 μg/m$^3$, a large improvement in urban air pollution quality. The average size of cities in the year 2015 and 2019 are roughly 100,000 and 200,000 respectively. The pollution in larger cities has declined by 15 μg/m$^3$ due to the COVID shutdown.

$^4$ The quality of China’s official air quality data has been improved significantly in the last few years, as documented by recent studies. For instance, Liang et al. (2016) found that the US PM$_{2.5}$ monitors show measured values highly consistent with those measured at China’s Ministry of Environmental Protection PM$_{2.5}$ monitors located nearby. Stoerk (2016) compared the air quality data via Benford’s Law which suggests that misreporting of air quality data for Beijing has likely ended in 2012.

$^5$ According to the plan, large cities and cities in the eastern region focus on the development of high-tech industries, while middle-sized and small cities and cities in the central and western regions are responsible for the traditional manufacturing industry. From 2015 to 2018, the average drop in the share of manufacturing in total GDP of Chinese cities was 3 percentage points (equals to 6.8% of the mean manufacturing share in 2015). 178 cities experienced decline, and 99 cities experienced increase in this share. More than half of the cities with an increasing manufacturing share are in the western region.

$^6$ To obtain the weather-adjusted pollution level, we use key weather variables (temperature, precipitation) to normalize air pollution concentration data by running city-year-specific regression of PM$_{2.5}$ on these two key weather variables (with their standardized values) and extract the (residual + constant) for all our city-year observations.
Fig. 1. Trends in the PM\(_{2.5}\) concentration and the GDP share from industrial sector in big and small cities.
Notes: Big cities include 35 major cities in China: Beijing, Tianjin, Shijiazhuang, Taiyuan, Hohhot, Shenyang, Dalian, Changchun, Harbin, Shanghai, Nanjing, Hangzhou, Ningbo, Hefei, Fuzhou, Xiamen, Nanchang, Jinan, Qingdao, Zhengzhou, Wuhan, Changsha, Guangzhou, Shenzhen, Chongqing, Chengdu, Guiyang, Kunming, Xi’an, Lanzhou, Yinchuan, Urumqi; Small cities include other 250 cities in China.

Fig. 2. Cumulative distribution function of population pollution exposure in 2015 and 2019 (weighted by 2015 population).
Notes: The air pollution used for this figure is the (residual + constant) from running a city-year-specific regression of PM\(_{2.5}\) on temperature and precipitation (with their standardized values). Units of pollution in 2015 while the median person was exposed to 35 units in 2019.\(^7\) The large distance between the two cumulative distribution functions highlights the significant pollution gains enjoyed by those who live in moderately polluted areas (by way of comparison Los Angeles features a PM\(_{2.5}\) average level of roughly 20). The Figure highlights that even at the high quantiles of the pollution exposure distribution that there has been significant air pollution exposure progress.

3. Increasing public demand for clean air and the demand for regulation

3.1. Measuring clean air demand using internet search data

Traditional revealed preference methods rely on annual data such as real estate prices or survey data asking people to state their quality of life priorities. Scholars have also studied the demand for self-protective goods such as masks and air filters and studied how the demand varies across China (Sun et al., 2017; Ito and Zhang, 2020; Barwick et al., 2018). Rising access to real time “big data” provides new facts about how local pollution and climate conditions affect our quality of life. In recent research, we have used billions of social media messages posted on the equivalent of China’s Twitter to explore how the population’s sentiment (expressed happiness) is affected by pollution and heat (Zheng et al., 2019). People from different cities in China vary with respect to how sensitive they are to air pollution. Zheng et al. (2019) measures this by estimate a city specific partial derivative of happiness (as revealed by social media content analysis) with respect to that city/day PM\(_{2.5}\) (the “sentiment-pollution” elasticity).\(^8\)

In that study, the researchers use their 144 city sample to estimate a second stage regression to understand the correlates of this pollution sensitivity. The relationship between city income and pollution sensitivity is monotonically positive – people are more sensitive to pollution in richer cities. At the same time, very dirty and clean cities have a relatively higher elasticity compared to cities in the intermediate

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\(^7\) It is important to note that these calculations do not incorporate private averting behavior (Sun et al., 2017). We also do not incorporate within city variation in pollution and the geographic distribution of people within the city.

\(^8\) In Zheng et al. (2019), they divide the full sample of city-day observations into 144 city subsamples and estimate the following equation using a fixed effect regression approach for each city \(i\). This procedure generates a marginal city-specific partial derivative of sentiment with respect to PM\(_{2.5}\) - the “sentiment-pollution” elasticity, \(\varphi_{s,t}\). It is expected to be negative – all else equal, people are more likely to be unhappy on days when their city’s pollution level is higher.

\[
\text{Sentiment}_t = \varphi_{0} + \varphi_{1}\text{Pollution}_t + \varphi_{2}\text{Weather}_t + \text{date fixed effects} + \nu_t
\]

\(\text{Sentiment}_t\) and \(\text{Pollution}_t\) represent the sentiment measure and the pollution level (PM\(_{2.5}\) concentration) of this city \(i\) on day \(t\), respectively. We include other variables \(\text{Weather}_t\) which represents the city’s weather conditions, and date fixed effects.
pollution range. One explanation for this fact is that people who dislike air pollution most move and live in cleaner cities, and at the same time, people in dirtier cities come to recognize the health risks associated with the long-term pollution exposure.

Using these city specific estimates of the sentiment-pollution elasticity, we divide cities into above median and below median elasticity groups, and test whether the time trends are equal for the two sets of cities over the years 2015 to 2019.

We estimate Eq. (1) using city/year data to test whether cities with above median sentiment for avoiding pollution have a steeper negative time trend. Intuitively, we test if we observe a steeper decline in air pollution most move and live in cleaner cities, and at the same time, people in dirtier cities come to recognize the health risks associated with the long-term pollution exposure.

\[
\text{Trends in the PM}_{2.5} = \alpha_0 + \alpha_1 \times \text{Trend} + \alpha_2 \times \text{HS} \times \text{Trend} + \lambda \times X_s + \text{city fixed effects} + \nu
\]

In Eq. (1), HS is a dummy variable, which equals 1 if the “sentiment-pollution” elasticity of city i is higher (than the median value), and 0 otherwise. The sample is restricted to the 144 cities whose “sentiment-pollution” elasticities have been estimated by Zheng et al. (2019).

The regression results are presented in Table 1. As shown in columns (1) and (2), PM_{2.5} declined by 8.0% per year on average in these 144 cities from 2015 to 2019. The decline rate is 7.5% per year in lower sentiment-pollution elasticity cities and 8.8% in the high elasticity cities. The results suggest that cities where the population is more susceptible to pollution have experienced a larger improvement in air quality. The high anti-pollution sentiment cities tend to be the relatively rich cities.

As Chinese urbanites have grown richer and more educated, this group should increasingly demand “blue skies”. The subset of urbanites who live in the most pollution sensitive cities should be most responsive and place more pressure on local leaders (Zheng et al., 2014).

To explore this hypothesis, we use Internet data to measure the bottom-up push from the public for environmental protection and how this varies across time by city. We use “environmental protection” as the keyword to create an environmental attention index (Baidu_index) at the city level using Baidu platform (http://index.baidu.com/v2/index).

Table 1

| Dependent variables: | (1) | (2) | (3) | (4) |
|----------------------|-----|-----|-----|-----|
| Trend                | -0.080*** | -0.073*** | 0.000** |       |
|                      | (0.004) | (0.005) | (0.000) |       |
| HighSentiment*Trend  | -0.013**  | 0.001**   |       |       |
|                      | (0.007) | (0.000) |       |       |
| Baidu_index          |       |       | -2.288*** |       |
|                      |       |       | (0.732) |       |
| Lag of Baidu_index   |       |       | 0.527*** |       |
|                      |       |       | (0.048) |       |
| Lag of lnPM2.5       |       |       |       |       |
| Control variables    | Y   | Y   | Y   | Y   |
| N                    | 718 | 718 | 718 | 574 |
| R²                   | 0.950 | 0.951 | 0.460 | 0.942 |

Notes: Columns (1), (2) and (4) report results from estimating fitting version of Eq. (1); column (3) reports results from estimating Eq. (2). Control variables include temperature, rainfall, and city fixed effects. Robust standard errors clustered at the city level are reported in parentheses. * p < 0.10, ** p < 0.05, *** p < 0.01.

Specifically, the Baidu_index = total entries of the key word “environment protection” in the Baidu search engine divided by the total population. This variable is measured in the number of entries per million people. This index reflects the public attention devoted to environment protection for each city in a given year.

We study the yearly environmental attention index’s dynamics using Eq. (2) (with the same specification as Eq. (1)). In column (3) of Table 1, we find that it increases from 2015 to 2019 after controlling for climate and a city’s inherent characteristics, and urbanites in cities featuring a higher sentiment-pollution elasticity are paying more and more attention to environmental protection. In column (4), we document that in the cities with a larger higher environmental attention index, they have experience an air quality improvement in the next year.

\[
\text{Baidu_index}_{it} = \beta_0 + \beta_1 \times \text{Trend} + \beta_2 \times \text{HS} \times \text{Trend} + \gamma \times X_s + \text{city fixed effects} + \mu
\]

3.2. The dynamic environmental kuznets curve

In this section, we will use the pre-2020 COVID data to present empirical evidence on the Environmental Kuznets Curve (EKC) in Chinese cities, and highlight the role of public awareness as a demand-side factor that may trigger structural changes that gradually shift the EKC. We are not "blind adherents" to the theory that economic growth first causes pollution and then "cures" pollution once a city’s per-capita income exceeds a threshold. At the same time, we do view the EKC as a useful statistical approach for testing for how the reduced form relationship between a city’s pollution and per-capita income shifts over time.

We test if the cities with a greater environmental awareness have an earlier EKC turning point such that subsequent economic growth is negatively correlated with pollution. Following the research design in Zheng et al. (2014), we estimate Eq. (3) below in order to examine how the shape of the EKC and in particular the GDP "turning point" varies as a function of the public sentiment-pollution elasticity and their demand for environmental protection. In Eq. (3), the unit of analysis is a city/year. Following the EKC literature, we include a quadratic in a city’s per-capita real GDP. These variables proxy for the city’s enforcement of environmental regulation and the quality of the local capital stock. We expect that in richer cities that environmental regulations are more stringent and that the capital stock is newer and more energy efficient.

\[
\text{Pollution}_{it} = \gamma_0 + \gamma_1 \times \ln(\text{GDPPC}_{it}) + \gamma_2 \times \ln(\text{GDPPC}_{it})^2 + \gamma_3 \times \ln(\text{POP}_{it}) + \lambda \times X_s + \text{year fixed effects} + \epsilon
\]

In Eq. (3), we also control for the city’s population level (the scale of activity) and the weather conditions in that city/year and year fixed effects to control for the macro conditions of the economy at that time.

In column (1) of Table 2, the results are based on the sample of 285 cities. We find evidence of an inverted-U relationship between the city’s PM_{2.5} concentration and per-capita GDP. The turning point is about 48.8
thousand Yuan (7839 US dollars, in 2015 constant price).

Estimates of the urban environmental Kuznets curve.

Table 2

|                      | (1) All cities | (2) High sentiment | (3) Low sentiment | (4) High BaiduIndex | (5) Low BaiduIndex |
|----------------------|----------------|-------------------|-------------------|---------------------|-------------------|
| ln(GDP_pc)           | 0.783***       | 0.571***          | 0.677***          | 0.429***            | 0.699***          |
|                      | (0.078)        | (0.148)           | (0.296)           | (0.155)             | (0.160)           |
| ln(GDP_pc)^2         | −0.247****     | −0.173****        | −0.218**          | −0.163***           | −0.175***         |
|                      | (0.024)        | (0.038)           | (0.089)           | (0.039)             | (0.063)           |
| Turning point (RMB in 2015) | 48,829        | 49,041            | 47,373            | 37,423              | 73,786            |
| Number, (%) of cities passing the Turning Point | 527 (47.0%) | 236 (82.2%) | 173 (60.5%) | 474 (83.9%) | 20 (3.6%) |
| Control variables    | Y              | Y                 | Y                 | Y                   | Y                 |
| N                    | 1121           | 287               | 286               | 565                 | 556               |
| $R^2$                | 0.393          | 0.466             | 0.340             | 0.401               | 0.383             |

Notes: This Table reports results from estimating Eq. (3). Control variables include population, temperature, rainfall, and year fixed effects. Robust standard errors clustered at the province/year level are reported in parentheses. * p < 0.10, ** p < 0.05, *** p < 0.01.

Dependent variable: ln(PM2.5).

4. The impact of the COVID induced shutdown on pollution dynamics

4.1. Estimating the air pollution decline during the COVID induced shutdown in China

We use the variation induced by the COVID shutdown to provide new insights about the distribution of pollution dynamics across China’s cities. Fig. 3A shows the timeline around the 2020 Chinese New Year (CNY). The traditional CNY holiday (when almost all production activities pause) would end seven days since the CNY’s Eve, which is Jan 31st in year 2020. However, due to the COVID pandemic, 29 provinces (out of 31 provinces) in China mandated businesses to not resume work before Feb 10th at the earliest. This unexpected post-CNY holiday shutdown provides us with the opportunity to identify the determinants of air pollution in China.

Fig. 3B presents the trends of air pollution before and after the Chinese New Year in 2017 through 2020. Air pollution since the CNY’s Eve of 2020 was significantly lower than that of the same periods of 2017–2019. This divergence becomes much larger after the end of traditional CNY holiday.

To quantify the reduction in pollution associated with the shutdown, we use city/year/day pollution data and present an event study in a difference-in-differences setting (Eqs. (4) and (5)):

$$ Pollution_{it} = \theta_0 + \theta_1 \cdot \text{Shutdown}_t + \theta_2 \cdot \text{Shutdown}_t \times \text{year}_{2020} + \text{fixed effects} + \epsilon_{it} $$ (4)

We restrict the sample to twenty days before and sixteen days after the CNY’s Eve (until Feb 10th, the first day of re-open). In Eq. (4), $\text{Shutdown} = 1$ indicates the seventeen days since the CNY’s Eve. $\text{year}_{2020} = 1$ indicates year 2020. We choose 2018 and 2019 as the benchmark years. In Eq. (5), $\text{SF}_h = 1$ indicates the eight days since the CNY’s Eve, also the regular CNY holiday, so this period for all the three years has very little production activity. $\text{Covid}_h = 1$ indicates the 8th to 16th days since the CNY’s Eve, which are the unexpected shutdown days in 2020 due to COVID, but they are regular workdays in 2018 and 2019. Therefore, the extra decline of air pollution in the first period in 2020 was mainly due to the complete pause of holiday activities such as driving for family reunion, net of the possible increase of home cooking (which might add pollution); while the extra decline in the second period was attributed to the shutdown of production activity and the associated travel demand decline, net of the home cooking effect.

We assume there is no difference in air pollution between the pre-CNY days in 2020 and 2018/2019 after controlling for city fixed effects, year fixed effects, month fixed effects, day of month fixed effects, and day of week fixed effects. The regression results are reported in Table 3. Compared to the years before 2020, air pollution significantly decreased by 14.9%–16.6% in the sixteen days after the CNY’s Eve (Panel A, columns (1) and (3)). After we decompose this post-CNY period into the regular CNY holiday (1st to 7th day after CNY eve) and the unexpected COVID shutdown period (8th to 16th day after CNY eve), the first period a 27.5% larger decline in pollution relative to 2018 and 2019, and this extra drop in the second period was 7.1%–9.7% (Panel A, columns (2) and (4)).

By estimating Eq. (5) for each city, we obtain 285 estimates of $\delta_0$ and $\delta_5$. These measure the changes in air pollution during the CNY holiday and COVID shutdown days of 2020 relative to 2018 and 2019, respectively. Fig. 4 present the changes in PM2.5 concentration during the CNY holiday and COVID shutdown days across cities in 2020. Most of Chinese cities (190 out of 285) experienced decreases in air pollution.  

$^{12}$ $1$ = RMB 6.23, in 2015.

$^{13}$ The left two provinces (Qinghai and Tibet) set Feb 3th as the earliest day of resuming work, and the actual first day depended on the city-specific situation around that time.

$^{14}$ Air pollution in cities in northeast and northwest China increased in CNY holiday of 2020, which might due to some meteorological factors and the weak impact of the initial COVID outbreak.
4.2. Understanding why pollution declined in early 2020 in many cities

We focus on three main determinants of air pollution – driving, industrial activities, and cooking, which were impacted by the COVID shutdown. First, the majority of the trips were cancelled, which would reduce the emission of air pollutants from vehicles. Second, factories were forced to close. This led to a significant reduction in industrial pollutant emissions. Third, the closure of restaurants and the ban on gatherings greatly reduced people’s dining out activities. During this time people could only cook at home, and this might lead to increased air pollution due to the decentralized low-efficient use of solid fuels (Chafe et al., 2014).

To decompose recent pollution dynamics into key urban fundamentals, we construct three variables to reflect the driving, industrial activities, and cooking activities in Chinese cities. They are the total number of private cars (in log, Vehicle), GDP share from industrial sector (Industry), and the employment in the accommodation and restaurant industry (in logs, Cooking). We use the pre-COVID levels of the three variables to reflect the city’s scale in these three activities. We posit that cities featuring greater levels of transport, industry and cooking before the COVID shutdown would feature higher levels of air pollution.

\begin{equation}
\Delta \text{Pollution}_i = \rho_0 + \rho_1 \cdot \text{Vehicle}_i + \rho_2 \cdot \text{Industry}_i + \rho_3 \cdot \text{Cooking}_i + \text{region fixed effects} + \epsilon_i
\end{equation}

The results are reported in Panel B in Table 3. We find that among the three activities, cooking mainly contributes to the changes in air pollution in the regular CNY holiday. This result is plausible as most of the production activities stopped during every year’s CNY holiday. Therefore, the PM$_{2.5}$ change in this year relative to the previous years in this regular holiday window was not correlated with the production scale. However, in the post-CNY COVID shutdown days which only existed in year 2020, cities with more private cars, a larger share of the industrial production in the urban economy, and fewer people employed in the restaurant sector experienced a larger decrease in air pollution.

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We do not include coal consumption in explaining the air pollution changes to avoid double counting. Coal is the raw materials of production and living activities. The three activities that we focus on (driving, industrial activities, and cooking) represent the major activities for which coal is used. According to the energy balance sheet of China in 2017, the industrial production itself consumed 94.8% coal in China. This consumption also includes the coal used for generate power which is used by industrial sector.

Necessary production activities such as power supply, water supply and heating, and production activities of medical supplies related to epidemic control did not stop.
Table 3
The effects of the economic shutdown on air pollution and the determinants of air pollution changes.

Panel A: The effects of the shutdown on air pollution

| Dependent variable: ln(PM$_{2.5}$) | 29 province sample | 28 province sample (drop Hubei) |
|-----------------------------------|--------------------|---------------------------------|
| **Shutdown**                     | $-0.130^{***}$     | $-0.120^{***}$                  |
|                                  | (0.022)            | (0.022)                         |
| **Shutdown × year2020**          | $-0.149^{***}$     | $-0.166^{***}$                  |
|                                  | (0.026)            | (0.027)                         |
| **SF_holiday**                   | $-0.092^{***}$     | $-0.086^{***}$                  |
|                                  | (0.019)            | (0.019)                         |
| **COVID_shutdown**               | $-0.347^{***}$     | $-0.331^{***}$                  |
|                                  | (0.032)            | (0.034)                         |
| **SF_holiday × year2020**        | $-0.275^{***}$     | $-0.276^{***}$                  |
|                                  | (0.030)            | (0.031)                         |
| **COVID_shutdown × year2020**    | $-0.071^{*}$       | $-0.097^{**}$                   |
|                                  | (0.037)            | (0.038)                         |
| Control variables                |                    |                                 |
| Y                                |                    |                                 |
| Y                                | 31,376             | 31,376                          |
| Y                                | 0.392              | 0.399                           |
| N                                | 31,376             | 30,044                          |
| R$^2$                            | 0.399              | 0.391                           |
|                                   |                    | 0.397                           |

Panel B: The determinants of air pollution changes

| Dependent variables | 29 province sample | 28 province sample (drop Hubei) |
|---------------------|--------------------|---------------------------------|
| ln(Vehicle)         | $-0.114^{***}$     |                                 |
|                     | (0.035)            |                                 |
| ln(Industry_share)  | $-0.268$           | $-0.583^{***}$                  |
|                     | (0.233)            | (0.220)                         |
| ln(Restaurant_emp)  | $0.078^{***}$      | $0.095^{***}$                   |
|                     | (0.028)            | (0.027)                         |
| Region fixed effects| Y                  | Y                               |
| Constants           | 0.509              | 2.345^{***}                     |
|                     | (0.541)            | (0.522)                         |
| N                   | 269                | 269                             |
| R$^2$               | 0.462              | 0.301                           |
|                     |                    | 0.452                           |

Notes: In Panel A, columns (1) and (3) report results from estimating Eq. (4); columns (2) and (4) report results from estimating Eq. (5). Dependent variable is log of PM$_{2.5}$ concentration. Control variables include city fixed effects, year fixed effects, month fixed effects, day of month fixed effects, and day of week fixed effects. Robust standard errors clustered at city level are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Fig. 4. Changes in PM$_{2.5}$ during the COVID shutdown days.

A. Changes in PM$_{2.5}$ during the Chinese New Year Holiday of 2020 ($\delta_4$ of equation (5))

B. Changes in PM$_{2.5}$ during the COVID Shutdown Days of 2020 ($\delta_5$ of equation (5))
Fig. 5. The impact of the COVID induced shutdown on pollution dynamics.
A. The Relationship between Decrease in PM$_{2.5}$ and Number of Private Cars.
B. The Relationship between Decrease in PM$_{2.5}$ and GDP Share from Industrial Sector.
C. The Relationship between Decrease in PM$_{2.5}$ and Cooking.
5. Blue skies as an experience good

5.1. The demand for clean air

We now compare a subset of Chinese cities to the rest of the cities. We focus our attention on the subset of cities that meet two criteria. The first criteria is that the city experienced a 2020 air pollution decline in the COVID pandemic (based on the city-specific estimate of $\theta_{2}$ in Eq. (4)). The second criteria is that the city’s anti-pollution sentiment is greater than the median (based on the estimates from Zheng et al. (2019)).

We divide the 144 Chinese cities into four quadrants based on their sentiment-pollution elasticity and the PM$_{2.5}$ change during the COVID shutdown. As shown in Fig. 6A, the 49 cities in quadrant I are those where air pollution significantly declined and the population is more sensitive to air pollution. These cities are defined to be the “treated cities”. We examine whether their population exhibits a high demand for clean air. We study this using the Baidu data.

Here we construct a daily Baidu environmental attention index, and estimate the following DID model for city/year/day data.

$$\text{baidu}_{i,t} = \eta_0 + \eta_1 \text{Treat}_{i} + \text{Post}_{t} + \text{fixed effects}_i + \mu_u$$

In Eq. (7), the dependent variable is the daily count of the keyword “environmental protection” in the Baidu search engine by city $i$ at date $t$. The $\text{baidu}_{i,t}$ in Eq. (7) is standardized by dividing it over its mean value. This makes the number comparable across different keywords. $\text{Treat}$ equals 1 for the cities in quadrant I in Fig. 6A and equals zero for the cities in the other quadrants. City fixed effects and date fixed effects are included in the regression.

The trends in Fig. 6B show that the quantity of Internet discussion activity mentioning “environmental protection” in Chinese cities in quadrant I increased by more than one time in other cities during the same time period. The regression results confirm that this Baidu index in those cities increased 1.5 times of its mean higher than the other cities (see Table A2). The local population in the quadrant-I cities is increasingly interested in environmental protection and they seek more information about what the local officials are doing to further improve the local environment.

5.2. Local government post-COVID stimulus

Whether the short-run improvement in air quality persists over time as the local economy recovers hinges on how such a bottom-up push pressure from the local popile nudges the local government to enact credible anti-pollution policies. In this section we investigate whether local governments in 2020 redesigned their environmental strategies and whether this “green push” is stronger for cities in quadrant I.

Since February 2020, both the central and local governments have issued many different “stimulus” policies aiming to re-boost the economy and make up the economic loss due to the COVID shutdown. Some of the stimulus policies highlight the “greenness” and “sustainability”, while others do not. For instance, on March 4, 2020, the Standing Committee of the Political Bureau of the CCP Central Committee issued a guideline on speeding up the construction of “new infrastructure”, e.g., 5th generation mobile communication technology (5G), internet of things (IoT), big data center, etc., which are much greener than the old infrastructure such as highways and power plants. On Feb 27, 2020, Guangzhou city government issued the stimulus policy of providing financial subsidy measures for the promotion and application of new energy buses. While in Yinchuan city, on Mar 2, 2020, the city government issued a stimulus policy to boost and stabilize the industrial growth after the COVID pandemic aiming to fulfill the economic growth target set originally.

We collected the policy documents issued by local governments from February 2020 to May 2020 from Baidu ThinkTank (http://www.baihuazhiku.com/policy/adlist), and extracted the stimulus policies related to industrial development. Here we focus on three types of “green industrial policies” – new energy vehicles, industrial upgrading (toward low energy intensity) and new internet technology (IT) infrastructure. Fig. 6C shows the statistical results for the four groups of cities presented in Fig. 6A. We find that those cities in quadrant I have a larger share of their documents mentioning the “green industrial policies”. While those cities in quadrant IV have the very low share of pro-environment documents. This is suggestive evidence that the local governments for the quadrant-I cities are responding to their citizens’ demand for blue sky and are taking actions to strike a balance between stimulating the economy and protecting the environment.

It is an open question whether those green stimulus policies will be effectively implemented and whether their effects will persist over time. In China, local governments have a strong “visible hand” in setting the priorities in local economic growth and allocating resources to implement their growth strategies. They are very good at implementing those industrial policies in a timely fashion (Zheng and Kahn, 2017). Therefore, it is highly likely that those stimulus policies will be implemented as stated. Here we provide some early-stage evidence by collecting new 2021 data to document ongoing pollution reduction progress. Our regression results show (see Table A3), after controlling for city, month, day-of-week fixed effects, the PM$_{2.5}$ concentration level in the same period (from CNY Eve to 17 days after) in 2021 enjoyed a further 4% decline relative to 2020. For the cities in quadrant I (those that experience the largest experience good effect), this further decline from year 2020 is even much larger – 10.2%. These facts suggest that the greener post-COVID stimulus policies for those quadrant-I cities has contributed to the ongoing air pollution progress from 2020 to 2021. We recognize that a stronger test of this hypothesis will be available as time passes and more post-COVID 2020 data is available.

6. Conclusion

In early 2020, cities all over the world have experienced an economic shutdown in order to reduce the contagion risk. A silver lining of this shutdown is that previously very dirty cities experienced blue skies. We posit that clean air is an experience good.

The private sector often produces new goods such as electric vehicles

17 Source: [http://cpc.people.com.cn/s1/2020/0305/c64094-3167516.html](http://cpc.people.com.cn/s1/2020/0305/c64094-3167516.html)

18 Source: [http://www.gz.gov.cn/gfxwj/sbmgfxwj/gzsjtysj/content/post_5680165.html](http://www.gz.gov.cn/gfxwj/sbmgfxwj/gzsjtysj/content/post_5680165.html)

19 Source: [http://www.yinchuan.gov.cn/xxgk/bmxqgml/szfbgt/xxgml_1841/zwj/yzb/202003/t20200304_1978593.html](http://www.yinchuan.gov.cn/xxgk/bmxqgml/szfbgt/xxgml_1841/zwj/yzb/202003/t20200304_1978593.html)

20 The policies we consider are all officially published with clearly Issued Numbers. All subordinate offices will receive this document and have to carry out the work following the guidance of the policy document.

21 As pointed out by a referee, an alternative explanation for why quadrant-I cities have enjoyed greater recent pollution progess may be that these areas face more stringent Central government regulation to comply with the national air quality targets. The following two pieces of evidence suggest that this is unlikely to be the case. First, to regulate air pollution, the central or provincial governments usually set a specific pollution reduction target (in terms of pollution change, not pollution level) for each city government (such as the “Air Pollution Prevention and Control Action Plan”, the “Five-Year Plan”, etc.). Under this policy, the cities needing to devote greater effort to meet the national target (before the pandemic) would experience greater pollution reductions before 2020. We do not observe this pattern for the cities in quadrant I. Over the years 2015 to 2019, we estimate that there is a 26.1% pollution reduction for quadrant-I cities and 24.2% for non-quadrant-I cities (they are not significantly different from each other). Second, the city-specific “sentiment-pollution” elasticity (measuring the extent to which a city’s local residents are sensitive to pollution) is not monotonically positive or negative correlated with air quality. Instead, people in both relatively cleaner and also relatively dirtier cities are more sensitive to pollution, relative to the cities in the middle (see Fig. 3b in Zheng et al. (2019)).
or science fiction movies. Before a person experiences such a good, they may under-value it. Anticipating this issue, sellers of such new products will engage in advertising and offer initially low prices to attract consumers. In contrast to a private good, a city’s air quality is a local public good. It is produced as a byproduct of the activities of emissions within the airshed and that blow into the airshed. A byproduct of China’s development fueled by coal and heavy industry production is that there are many cities where ordinary people have not experienced clean air for decades. The 2020 shutdown offered an opportunity to trigger a potential structural change.

The Environmental Kuznets Curve (EKC) describes how the structural factors shape the relationship between economic growth and pollution in the long-run. If this COVID shock would not lead to some structural change, later the recovery of the old-fashion macro economy would predict that air pollution would return to its previous high levels in cities in polluted developing nations such as China. If they can be implemented effectively and persistently, those green policies will have long-lasting effects as the EKC will be shifted down due to structural change. One caveat pertains to future economic recessions. When these events occur in the future, city leaders will face tradeoffs balancing economic growth and environmental protection. This happened after the 2008 Global Financial Crisis. A clear policy implication is that, in China’s political system, the central government should send clear signals to city leaders and also design the right mechanisms (for instance, adjusting the relative weights of GDP growth and quality of life indicators in the promotion criteria; and providing tax and subsidy incentives), to effectively incentivize local leaders to continue their effort in regulating pollution and promoting green investment and consumption.

### Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.
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Appendix 1: Data appendix

A.1. PM$_{2.5}$ data

We collect the data of PM$_{2.5}$ concentration from the real time release platform of national urban air quality of China Environmental Monitoring Station. The data is daily released since May 13th, 2014.

The air pollution data of China in early time was found to be manipulated by local government and inaccurate (Ghanem and Zhang, 2014). However, since 2013, the central government of China has issued a series of policies to ensure the quality of air monitoring and avoid data manipulation. More recent studies have documented the improvement of air pollution data quality of Chinese cities. For example, Liang et al. (2016) found that the US PM$_{2.5}$ monitors show measured values highly consistent with those measured at China’s Ministry of Environmental Protection PM$_{2.5}$ monitors located nearby. Stoerk (2016) compared the air quality data via Benford’s Law which suggests that misreporting of air quality data for Beijing has likely ended in 2012.

A.2. COVID information

The number of death from COVID comes from the Big Data Analysis Platform of Global COVID Epidemic Situation (https://www.zq-ai.com/#/fe/xgfybigdata).

A.3. Economic and social data

The data of city-year GDP, population, % of GDP from industrial sector, number of employment in accommodation and restaurant industry come from China City Statistical Yearbook. The data city-year number of private cars comes from the statistical yearbooks of each province. The data of city-year mortality comes from the statistical yearbooks of each city.

A.4. Temperature and rainfall

The city-year average temperature and total rainfall is calculated based on the hourly monitoring data of automatic ground stations uploaded by National Meteorological Information Center.

A.5. Baidu index

The Baidu keyword search index is created from the Web tools (http://index.baidu.com/v2/index.html#/). It provides the city-day entries of each key word in https://www.baidu.com/. The index reflects the public attention on the event corresponding to the key word.

A.6. Industrial policy information

The policy documents issued by local governments from February 2020 to May 2020 from are download from Bailu ThinkTank (http://www.bailuzhiku.com/policy/adlist). We employ the text analysis tool to extract the stimulus policies related to industrial development and identify if they are environmentally friendly.

22 On September 10, 2013, the State Council issued the “Air Pollution Prevention and Control Action Plan” (APPCAP), emphasizing the government’s objective of establishing a centrally-managed national air quality monitoring network, which includes the construction of urban stations, background stations, and regional stations. The Plan aims to enhance the management of the quality of monitoring data, objectively reflect the air quality status, strengthen the construction of the online monitoring system for primary pollution sources and promote the application of environmental satellites. By 2015, all cities, at the prefecture-level and above, were equipped with monitoring stations for fine particulate matter and stations under government supervision. Remote quality control systems had been set up in 1436 national control monitoring stations, with the function of data recording and alarm systems under abnormal circumstances. Fu Deqian, Deputy Head of China National Environmental Monitoring Center, noted that “there are several monitoring stations in one city and the data from all stations should be similar. If the data reported in one station is inconsistent with the others”, the alarm will be triggered.” (see http://www.chinanews.com/sh/2016/12-10/8089501.shtml) According to the statistics of the Environmental Monitoring Department of the Ministry of Ecology and Environment, in 2015, there were no cases of data falsification. The “Measures for Environmental Monitoring Data Falsification” issued by the Ministry in December 2015 required local environmental departments to carry out inspection of environmental data quality and punish data falsifications. In July 2016, the Chinese Academy of Engineering organized a mid-term assessment of the implementation of APPCAP and carried out quality control on the monitoring data, especially the PM$_{2.5}$ data. By integrating the data from the Ministry of Ecology and Environment, the Chinese Academy of Sciences, the China Meteorological Administration, and relevant scientific research institutes on long-term ground-based positioning observations, comprehensive observations of typical processes, and satellite remote sensing inversion, a variety of technical methods had been used to assess air quality conditions, pollution trends across the country. By comparing the synchronous data of 28 monitoring stations of the Chinese Academy of Sciences, China Meteorological Administration, and other institutions, it is found that the multi-party monitoring data of similar stations indicate good consistency, reveal that the monitoring data is systematic and comparable, and is suitable for evaluation. (see http://www.gov.cn/xinwen/2016-07/06/content_5088795.htm) In November 2016, the Ministry issued the “Thirteenth Five-Year Plan - Environmental Monitoring Quality Management Work Plan” and “Work Plan About Strengthening the Quality Management of Ambient Air Automatic Monitoring”, required 1436 state-controlled monitoring stations in 338 prefecture-level cities nationwide to transfer their monitoring rights. Through public bidding, the third party firm which wins the bid, will be responsible for the project’s operation and maintenance. Meanwhile, all stations are required to install video surveillance systems to plug the loopholes of manipulated data falsification.
Appendix 2: Table appendix

Table A1
EKC results based on a more flexible functional form for per-capita income.

|                | (1)       | (2)       | (3)       | (4)       | (5)       | (6)       | (7)       |
|----------------|-----------|-----------|-----------|-----------|-----------|-----------|-----------|
|                | All cities| Low sentiment | High sentiment | All cities| Low sentiment | High sentiment | All cities|
| X1             | 1.292     | 1.131     | 1.719     | 1.105     | 2.613**   | -2.729    | 2.427**   |
|                | (1.077)   | (1.006)   | (2.378)   | (0.968)   | (1.132)   | (2.521)   | (1.027)   |
| X2             | -2.854*** | -0.300    | -4.065**  | 0.566     | -1.262    | -2.799**  | -1.105    |
|                | (0.829)   | (1.069)   | (1.584)   | (0.961)   | (1.173)   | (0.957)   |           |
| X3             | 0.678***  | -2.575*** | 0.425     | -2.498**  | -0.701    | 0.037     | -1.017*** |
|                | (0.255)   | (0.629)   | (0.288)   | (0.620)   | (0.355)   | (0.475)   |           |

|                | X1 × High Sentiment | X2 × High Sentiment | X3 × High Sentiment | High Sentiment | High_Baidu_index | X1 × High_Baidu_index | X2 × High_Baidu_index | X3 × High_Baidu_index | High_Baidu_index |
|----------------|---------------------|---------------------|---------------------|---------------|------------------|----------------------|----------------------|----------------------|------------------|
|                | 0.192               | 4.035**             | 2.145***            | 2.602         | -2.951           | 3.286                | -2.319               | 1.555                | 0.773            |
|                | (2.750)             | (2.026)             | (0.701)             | (12.059)      | (15.178)         | (1.061)              | (1.100)              | (0.988)              | (0.681)          |

ln(population) 9.734*** 8.484*** 10.354*** 9.632*** 12.948*** 5.904*** 10.901***

|                | (1.006)           | (1.082)           | (1.160)           | (0.874)       | (1.270)         | (2.161)         | (1.100)         | (1.090)         | (15.178)         |

Temperature -0.345 0.143 -0.745*** -0.324 -0.029 -0.914*** -0.414**

|                | (0.209)           | (0.204)           | (0.239)           | (0.204)       | (0.259)         | (0.201)         | (0.198)         | (0.199)         | (0.198)         |

Rainfall -0.000*** -0.000*** -0.000*** -0.000*** -0.000*** -0.000*** -0.000***

|                | (0.000)           | (0.000)           | (0.000)           | (0.000)       | (0.000)         | (0.000)         | (0.000)         | (0.000)         | (0.000)         |

Year fixed effects Y Y Y Y Y Y Y

|                | Constant          | 1.612*** 1.790*** | 2.8038*** 48.593*** | -11.042 |
|----------------|-------------------|-------------------|--------------------|---------|
|                | (6.146)           | (8.876)           | (10.989)           | (7.186) |

|                | 2.383             | -0.804            | -28.038*** 48.593*** | -11.042 |
|----------------|-------------------|-------------------|--------------------|---------|
|                | (2.867)           | (10.989)          | (10.989)           | (10.989)|

|                | 2.793             | 285               | 288                | 573     |
|----------------|-------------------|-------------------|--------------------|---------|
|                | (4.16)            | (0.416)           | (0.348)            | (0.348) |

|                | 0.425             | 0.334             | 0.355              | (0.355) |
|----------------|-------------------|-------------------|--------------------|---------|
|                | 0.691             | 0.522             |                    |         |

Note: Robust standard errors clustered at province/year level are reported in parentheses. * p < 0.10, ** p < 0.05, *** p < 0.01.

Dependent variable: PM$_{2.5}$.

Table A2
Baidu environment attention index (city-day data, January 24th, 2020-April 5th, 2020).

|                | (1)       | (2)       |
|----------------|-----------|-----------|
| Key words:     | Environment protection | Non-environmental words |
| Treat × Post   | 1.467**   | 0.145     |
|                | (0.593)   | (0.252)   |
| City fixed effects | Y         | Y         |
| Date fixed effects | Y         | Y         |
| Constant       | 1.612***  | 1.790***  |
|                | (0.159)   | (0.068)   |
| N              | 13,156    | 65,780    |
| R$^2$          | 0.339     | 0.355     |

Note: This Table reports results from estimating Eq. (7). Robust standard errors clustered at city level are reported in parentheses. * p < 0.10, ** p < 0.05, *** p < 0.01.

Dependent variable: Baidu_index.

We present one placebo test to address concerns about omitted variables that simultaneously affected air pollution and people’s environmental attention might bias our DID estimations. To address this endogeneity concern, we further create another five Baidu search index using keywords that are not related with air pollution: COVID-19, pneumonia, education, medical treatment, health. Column (2) of Table A2 shows the results of this placebo test. We find a small and insignificant effect on Baidu searches for non-environmental words.

Table A3
The persistent effects of the economic shutdown on air pollution (2020 and 2021).

|                | (1)       | (2)       |
|----------------|-----------|-----------|
| Dependent variable: ln(PM$_{2.5}$) | (continued on next page) |
Table A3 (continued)

| Dependent variable: ln(PM$_{2.5}$) | (1)         | (2)         |
|-----------------------------------|-------------|-------------|
| All cities                        | Year 2021   | Year 2021   |
|                                   | $-0.040^{**}$ | $-0.102^{**}$ |
|                                   | (0.018)     | (0.043)     |
| Control variables                  | Y           | Y           |
| $N$                                | 9656        | 1632        |
| $R^2$                              | 0.397       | 0.529       |

Notes: Dependent variable is log of PM$_{2.5}$ concentration. Control variables include city fixed effects, month fixed effects, and day of week fixed effects. Robust standard errors clustered at city level are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

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