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Gone with the wind? Emissions of neighboring coal-fired power plants and local public health in China

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ABSTRACT

Based on a nationwide representative county-level dataset from China, this article empirically examines the spillover effects of air pollution from neighboring coal-fired power plants on local mortality rates due to cardiovascular and respiratory diseases. We combine data on power plants' industrial output with information on wind direction and speed to proxy for air pollution, and find that air pollution from neighboring power plants indeed has significant negative effects on local public health. The resulting treatment costs are also enormous. Our findings shed light on the necessity of intergovernmental cooperation in environmental governance.

1. Introduction

Since air pollution is a major health threat to people worldwide, estimating its effect on mortality is fundamental to environmental policymaking. Recently, a nascent strand of literature has investigated the effects of the cross-border externality of pollution on overall mortality (Luechinger, 2014; Anderson, 2015; Adhvaryu, Bharadwaj, Fenske, Nyshadham, & Stanley, 2019; Altindag, Baek, & Mocan, 2017; Beach & Hanlon, 2018; Deryugina, Heutel, Miller, Molitor, & Reif, 2019). In comparison, however, research on such effects on mortality due to specific diseases is still in its infancy. Yet these effects are of great policy interest for disease prevention and control. In this article, we focus on the mortality rate associated with two of the most sensitive diseases to air pollution—respiratory diseases and cardiovascular diseases (Zanobetti et al., 2003; Dominici et al., 2006; Jia & Ku, 2019) and examine the spillover effects of air pollution from coal-fired power plants in neighboring areas on local public health.[1]

China currently faces numerous environmental challenges (Ebenstein et al., 2015; Kahn & Zheng, 2016). Fewer than 1% of its 500 largest cities meet the air quality standards suggested by the World Health Organization (WHO) (Zhang and Crooks, 2012), and 99.6% of the Chinese population reside in areas with fine particle (PM2.5) concentrations above the WHO guideline of 10 μg/m^3 in 2003 (Brauer et al., 2016). Given the country's environmental degradation, public health policies for disease prevention and control are

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[1] We focus on the two diseases not only because of their sensitivities to the air pollution, but also because of their importance in Chinese residents' mortality structure. Fig. A1 of the Appendix A presents the proportions of mortality due to both respiratory diseases and cardiovascular diseases from 2002 to 2010. On average, deaths due to both diseases account for 50% of the total mortality over time.

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required. Accordingly, a comprehensive examination of the spillover effects of air pollution from coal-fired power plants—a major source of pollution—on local public health is a significant government and policy concern that warrants substantial research attention.

We assemble a dataset covering 161 counties called disease surveillance points (DSPs) in China in 2004 and 2008. It includes public health data extracted from the Center for Disease Control (CDC) and data on the air pollution generated by neighboring power plants (within 50 km of DSPs). The key to accurately estimating the spillover effects of air pollution is to construct an appropriate measure of cross-border externality—the air pollution from power plants transported by wind. Pollution levels depend not only on the scale of poisonous gases emitted by power plants in neighboring areas, but also on wind patterns, including the speeds and directions. Note that air pollution from neighboring areas will affect local public health only when the wind speed is moderate, and the prevailing wind direction is toward the area. We use the industrial output of coal-fired power plants in neighboring counties to measure their toxic gas emissions and calculate the downwind frequency—the proportion of the number of days per year in each county during which the wind is blowing at moderate speed downwind. By using the downwind frequency as weights, for each DSP, we employ the weighted output of power plants in neighboring counties to proxy for the cross-border externality of the air pollution.

On this basis, we find that the air pollution transported by wind from neighboring counties significantly affects the health of the population in DSPs: a 1% increase in the weighted output of neighboring power plants results in 0.108 and 0.042 extra deaths due to cardiovascular diseases and respiratory diseases, respectively, per 1000 population.[2] The results are robust to several important concerns for identification including avoidance behaviors and potential measurement errors. We conduct a series of placebo tests to strengthen the identification: by adjusting for the dependent variable of public health as deaths due to transport accidents, by adjusting for the industrial output of coal-fired power plants as that of hydroelectricity power plants, or by adjusting for moderate wind speed as low or high wind speed. The results corroborate the main findings. With regards to the heterogeneity, the negative health effects are more significant for men, young, and older groups, as well as people living in poor areas. By translating the point estimates into magnitudes, the results indicate that during 2003–2017 the DSP counties were exposed to 2.254 million tons of SO_2 emissions from power plants in neighboring areas, resulting in 2,517,000 and 979,000 extra deaths due to cardiovascular diseases and respiratory diseases, respectively. The related treatment costs were 1058.46 billion RMB (151.21 USD) for cardiovascular diseases and 468.50 billion RMB (66.93 USD) for respiratory diseases, accounting for 13% of the revenue of coal-fired power plants and around 10% of the treatment costs due to pollution from local sources.

This article contributes to two strands of literature. First, several previous studies have recognized that coal-firing is a major source of pollution in industrial production (Muller, Mendelsohn, & Nordhaus, 2011; Zhang and Crooks, 2012; Zheng & Kahn, 2013) and daily life (Cesur, Tekin, & Ulker, 2016, Cesur, Tekin, & Ulker, 2017).[3] Our estimates of the spillover effects of air pollution from power plants provide new insights for this subject. Moreover, calculating the treatment costs may help the government design the optimal regulatory policy and thresholds for particulate pollution, and provide valuable references for environmental compensation and health insurance.

Second, government intervention to protect the environment is based on the premise that the market cannot effectively internalize the negative externality of pollution, which is mainly driven by the free-riding behaviors of agents including local governments. A typical case is that governments in upwind or upstream areas free ride by moving pollution downwind or downstream.[4] Our article advances our understanding of the role of the government, indicating that better cooperation between local governments and coordination between the central and local levels are necessary to achieve good environmental governance.

The remainder of this article is organized as follows. Section 2 provides background information on China's air pollution, especially spillover pollution from power plants. The research design, data, and measurements are introduced in Section 3, and Section 4 presents the empirical results. Section 5 concludes.

2. Background and literature review

2.1. Air pollution of coal-fired power plants in China

China is one of the most polluted countries in the world, especially regarding levels of SO_2, NO_2, and particulates (World Bank, 2007). The coal-fired power industry has become the dominant pollution source: they contribute around 60% of the country's industrial pollution emissions (Zheng & Kahn, 2013, Zheng & Kahn, 2017; Zhang and Crooks, 2012). Panel A of Fig. 1 plots government

[2] For comparison, we roughly translate power plants' outputs into SO_2 concentration such that a 1 $\mu g/m^3$ increase in SO_2 concentration results in 0.06 and 0.002 extra deaths per 1000 people due to cardiovascular and respiratory diseases, respectively. The total effects, 0.062, are larger than those in Germany (0.045 according to Luechinger, 2014) and the United States (0.00061 according to Deryugina et al., 2018), which are described in Table A1 of the Appendix A. This is consistent with the conventional wisdom that, compared with developed countries, the health of residents of developing countries suffers more from pollution. The spillover effect is a little smaller than the local effects suggested by Chen et al. (2018), who find that a 1 $\mu g/m^3$ increase in SO_2 concentration results in 0.007 extra deaths per 1000 people due to respiratory diseases.

[3] Other related pollution sources mainly include traffic (Currie and Walker, 2011; Schlenker and Reedwalker, 2015; Viard & Fu, 2015; Knittel et al., 2016), wildfires (Jayachandran, 2009; Miller et al., 2017), dust (Adhvaryu et al., 2017; Jia and Ku, 2018), industrial pollution (Currie and Schmieder, 2009; Davis, 2011; Zheng, Cao, Kahn, & Sun, 2014; Currie, Davis, Greenstone, & Walker, 2015), and even China's winter heating policy (Chen et al., 2013b; Ebenstein, Fan, Greenstone, He, & Zhou, 2017).

[4] For the related literature, see Sigman (2002, 2005), Duvivier and Xiong (2013), Cai et al. (2016), Kahn et al. (2015), Monogan III, Konisky, and Woods (2017), Chen et al. (2018), Hatfield and Kosec (2018), He et al. (2018), DeCicca (2020).

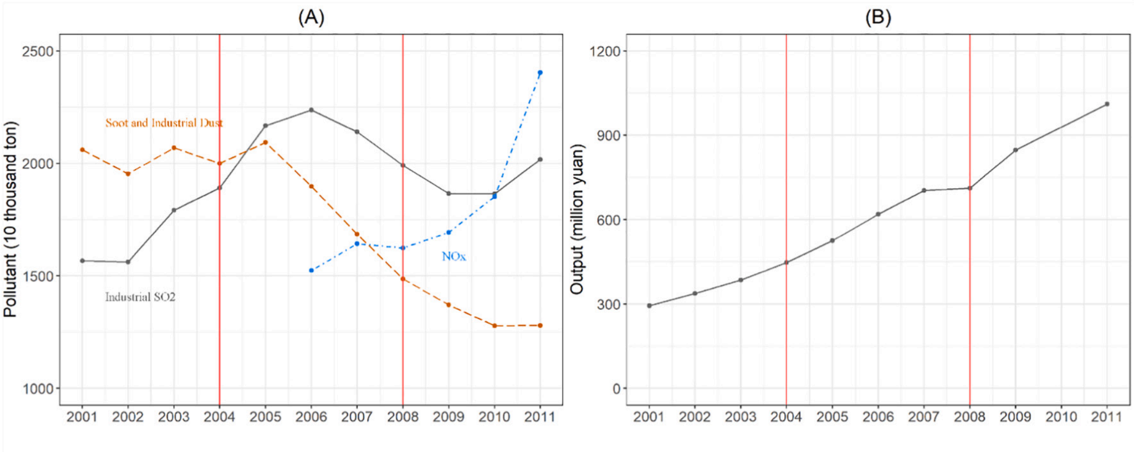

Fig. 1. Air pollution and industrial output of power plants in China (2001–2011).

reported industrial SO_2, NOx, and soot and industrial dust emissions between 2001 and 2011, which are over 15 million tons for most of the period. Panel B of Fig. 1 plots the industrial output of power plants over year.

Given the severe pollution, a series of policies have been implemented to improve air quality, and there is no exception in the field related to the production of coal-fired power plants. For example, since 2004, most provinces started to provide price subsidies to encourage the utilization of desulfurization equipment and reduce SO_2 emission (Shi, Zhou, Zheng, & Zhang, 2016); during the 11th Five-Year Plan, a policy called *Shang Da Ya Xiao* was implemented by promoting large generators and closing down small ones, which are fuel-intensive and highly polluted.[5]

2.2. *Spillover effects of air pollution*

Pollutants can travel via wind or the flow of rivers. In a nascent area of research, scholars have demonstrated that US residents are affected by pollution from upstream highways, airports, and coal-combustion activities (Schlenker & Walker, 2016; Yang and Chou, 2018; Anderson, 2015; Deryugina et al., 2019). Similar spillover effects related to wind are also found in other countries: Beach & Hanlon, 2018 examine such effects in Britain and find that a one standard deviation increase in coal use raises infant mortality by 6–8%; in Germany, 0.045 infant lives (per 1000 live births) are saved for every 1 $\mu g/m^3$ reduction in SO_2 concentration (Luechinger, 2014); and in West Africa, additional exposure of 10 $\mu g/m^3$ of PM 2.5 during each month of gestation on average decreases infant survival by 2.3 percentage points (Adhvaryu et al., 2019).

The spillover effects are also common at the international level. For example, Jia and Ku (2019) document the impact of cross-border air pollution from China to South Korea due to yellow dust and show that China's air pollution causes extra deaths due to respiratory and cardiovascular diseases in South Korea. We summarize these findings in Table A1 of the Appendix A.

2.3. *Spillover effects of air pollution in China*

In China, a few studies have demonstrated the spillover effects of pollution. For instance, studies on water pollution indicate that Chinese local governments are likely to keep pollution out of their “backyards” by moving pollution-intensive industries or polluting activities downstream or to the border of an area (Cai, Chen, & Gong, 2016; Chen, Li, & Yao, 2018; He, Wang, & Zhang, 2018; Kahn, Li, & Zhao, 2015). Similarly, air pollution can be blown across regions by wind. For instance, Beijing's air quality is deteriorated by both the yellow dust from northern Inner Mongolia and the pollution particles from the neighboring Hebei Province. Around 10% of Beijing's $PM_{2.5}$ can be attributed to pollution from Hebei (Ecns.cn, 2016). The industrial toxic smog from Zhaoqing, Qingyuan, and Heyuan is also dispersed by wind to Hong Kong (Edgilis, 2009). A systematic analysis of 303 China's cities between 2014 and 2016 shows that the percentage contributions of PM2.5 pollution from upwind cities to local PM2.5 levels can be as large as 50% (Chen & Ye, 2019). Unfortunately, current studies on health effects of air pollution do not fully consider the influence of pollution spillover. We use a representative sample to empirically explore the spillover effects of air pollution from coal-fired power plants on deaths due to cardiovascular and respiratory diseases.[6]

[5] See http://www.gov.cn/gongbao/content/2007/content_534198.htm.

[6] Some scholars have explored the spillover effects of air pollution on housing prices or morbidity costs (Barwick, Li, Rao, & Zahur, 2018; Zheng et al., 2014).

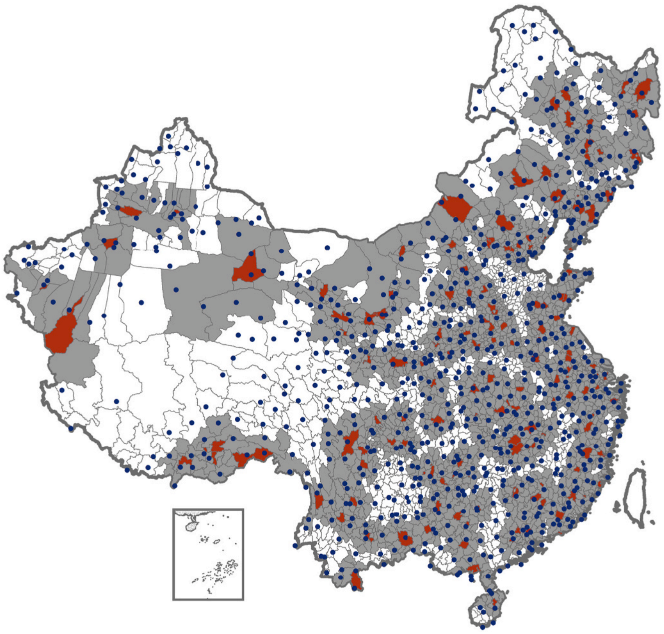

Fig. 2. Spatial distribution of samples.

3. Research design and data

3.1. Mortality

This article explores how the air pollution from power plants affects public health through the wind. In terms of public health, we mainly focus on mortality rates of cardiovascular and respiratory diseases and pay attention to 161 representative counties for which we can access such mortality information.

Specifically, such mortality information is extracted from the annual reports of the Diseases Surveillance Points (DSPs) system. The DSPs contain mortality and morbidity information for 10 million (a little under 1% of the Chinese population) residents along with their gender and age group (Yang et al., 2005). The surveillance was conducted at 161 voluntary sites in urban and rural areas. Our dataset consists of all 161 counties covered in the surveillance (indicated in red on Fig. 2; hereafter, we refer to these 161 counties as DSP counties). We employ the mortality rates due to cardiovascular and respiratory diseases as the dependent variables. Note that the mortality rates vary across gender groups, age groups, and counties.

3.2. Power plants' outputs and wind patterns

The main treatment is the cross-border air pollution transported by wind from power plants, which depends on the total emissions of poisonous gases from power plants in neighboring areas conditional on wind patterns. We follow previous studies and employ power plants' industrial output values to proxy for levels of air pollution (Clay, Lewis, & Severnini, 2015; Davis, 2011).[7] Thus, the pollution is captured by the total output of coal-fired power plants located within 50 km of DSP counties from the Chinese Industrial Enterprises Database (1998–2013). And the actual pollution is a part of the total output, which is conditional on the wind patterns. Fig. 2 plots the spatial distribution of samples including DSP counties and neighboring counties within 50 km.

We consider the effect of wind patterns, including directions and speeds. Existing literature holds that wind can be too slow to spread pollutants. Therefore, we draw our attention to wind speed no less than Beaufort scale 2 (Kim, Lee, Woo, & Bae, 2015; Kozawa,

[7] The ideal measure would be the amount of air pollution directly produced by the power plants. We use the current strategy for two reasons. First, given the potential manipulation and falsification of China's pollution data (Andrews, 2008; Chen et al., 2013a; Ghanem & Zhang, 2014), data on the output of industrial firms are much more reliable and have been widely used in existing research (Brandt, Van Biesebroeck, Wang, & Zhang, 2017; Brandt, Van Biesebroeck, & Zhang, 2012, 2014; Hsieh & Song, 2015). Second, although an alternative dataset (e.g. China's Environmental Survey and Reporting (ESR) database) is available, the Chinese Industrial Enterprises Database, from which we obtain our industrial output information, more comprehensively maps China's industries. For example, the Chinese Industrial Enterprises Database covers 276,474 firms in 2004 and 411,407 in 2008, whereas ESR only covers 70,457 firms in 2004 and 108,598 in 2008. Meanwhile, for ESR, the reliability of pollutant emission information reported by firms themselves requires more evaluation in the future.

Winer, & Fruin, 2012). We exclude the wind speed higher than Beaufort scale 5, as the pollutants in the air would be diluted. The validity of the interval (moderate speed, Beaufort scale 2–5, or 6–10.7 km/h) will be evaluated empirically later. In terms of directions, we only focus on the wind from neighboring counties since it can bring pollutants to DSP counties. Thus, we construct a measurement of wind patterns: downwind frequency, or the proportion of the number of days per year in each county during which the wind is blowing at moderate speed downwind.[8] We believe air pollution would only affect local public health in a given area when a power plant is located upwind of the area and the wind speed is moderate. Data on wind speeds and directions are from the National Meteorological Information Center (http://data.cma.cn/), which covers 824 weather stations across the country (see Fig. 2). We match the locations of weather stations with each county and calculate the proportions of time spent each wind speed and wind direction in the whole year.[9]

We use the relevant proportions to calculate the actual pollution. The actual pollution is proxied as

$$Capacity_{it} = \sum_{j \in D} Z_{ijt} s_{ijt} \tag{1}$$

where Z_{ijt} denotes the total output of coal-fired power plants in direction j of county i in year t,[10] s_{ijt} denotes the proportion of the number of days of moderate-speed wind blowing from direction j to county i in year t,[11] and $j \in D \equiv \{\text{N, NNE, NE, ENE, E, ESE, SE, SES, S, SSE, SW, WSW, W, WNW, NW, NNW}\}$.

We also control for meteorological and socioeconomic factors to mitigate concerns of omitted variable bias. The meteorological condition variables include the mean atmospheric pressure, temperature, rainfall, sunlight, and humidity. The socioeconomic factors consist of population density, GDP per capita, and fiscal revenue per capita, which are compiled from the Financial Statistics of Cities and Counties of China, provincial statistical yearbooks, and Wind database. All the economic variables are deflated by the 2003 CPI index. Finally, we assemble a panel dataset across age groups, gender groups, and counties covering the years 2004 and 2008 for analysis. A brief statistical summary of all the variables are presented in Table 1.

4. Empirical analysis

4.1. Basic results

We use the following econometric specification to estimate the spillover effects of air pollution from power plants on local public health:

$$mortality_{igat} = \alpha^{*} capacity_{it} + C^{'}\beta + county_i + gender_g + age_a + year_t + \varepsilon_{igat} \tag{2}$$

where i, g, a, t refer to county, gender, age group, and year, respectively. *mortality* is the dependent variable including cardiovascular and respiratory mortality. The key independent variable, $capacity_{it}$, denotes the total output of power plants weighted by wind speeds and directions. The vector C' includes proxies for other mentioned variables including socioeconomic factors and meteorological condition variables. We also consider several fixed effects to mitagate the potential ommited variable bias. We consider county fixed effects $county_i$ to capture time-invariant factors, gender fixed effects $gender_g$ to control for gender-invariant factors, age fixed effects age_a to control for age-invariant factors, and year fixed effects $year_t$ to capture factors that influence the entire sample over time such as the economic cycle and macroeconomic policies. ε_{igat} represents the error term, and standard errors are clustered at the county level.

Table 2 reports the regression results. The key dependent variable is the mortality rates from cardiovascular diseases (Columns 1 to 3) and respiratory diseases (Columns 4 to 6). The results show that in the one-way fixed effect model that only considers county fixed effects (Columns 1 and 4), air pollution from power plants in neighboring counties damages local public health. Such spillover effects are robust, as expected, after controlling for year, gender, and age fixed effects. Specifically, a 1% increase in the total output of power plants weighted by the wind speeds and directions results in 0.108 (Column 3) and 0.042 (Column 6) extra deaths per 1000 people due to cardivacular and respiratory diseases, respectively.[12] We also control for the local output to deal with the potential spatial

[8] The wind directions distinguish wind from 16 directions: North, North-North-East, North-East, East-North-East, East, East-South-East, South-East, South-South-East, South, South-South-East, South-West, West-South-West, West, West-North-West, North-West, and North-North-West.

[9] For counties in which at least one weather station is located, we directly assign the wind information of the station(s) to this county; for counties with no weather station, we match this county with the closest station. If a county contains more than one weather station, we average the records of these stations.

[10] We also use inverse geographical distance between upwind direction power plants and the focal county center as alternative weights, through replacing Z_{ijt} with Z_{ijt}/d_{ij} in Eq. (1), where d_{ij} denotes the geographic distance. The results are robust and presented in Columns 2 and 4 of Table A2 of the Appendix A. To illustrate the necessity of weights of wind pattern and justify our research design, we run the regressions by taking the weights out, and as expected, we do not find significant results (Columns 1 and 3 of Table A2).

[11] For county i, we can get $\sum_{j \in D} s_{ijt} + d_r/d_t = 1$, where d_t is the total number of days in year t, d_r represents the number of days with non-moderate wind speed, and we have neglected days with wind information missing. We illustrate s_{ijt} with a specific example: for county A, in 2004 there are 100 days when the wind speed exceeds the moderate range, 100 days when the moderate wind blows from north to south, and 166 days when the moderate wind blows from south to north. Then, we can calculate $s_{A,N,2004} = 100/366$, $s_{A,S,2004} = 166/366$, and $Capacity_{A,2004} = s_{A,N,2004} \times Z_{A,N,2004} + s_{A,S,2004} \times Z_{A,S,2004}$.

[12] The results are robust after clustering the standard error at prefecture level (See Table A3 of the Appendix A).

Table 1
Statistical description.

Variable	Obs	Mean	S.D.	Min	Max
Dependent Variables					
Mortality of cardiovascular diseases per 1000 population [A]	3864	4.165	8.637	0	46.904
Mortality of respiratory diseases per 1000 population [A]	3864	1.669	4.096	0	37.686
Mortality of transport accidents [B]	3864	33.58	62.64	0	647.400
Independent Variables					
Output (ln) of coal-fired power plants [C]	3864	7.914	5.185	0	14.608
Output (ln) of Hydraulic power plants [C]	3864	5.191	4.213	0	15.303
Asset (ln) of coal-fired power plants [C]	3864	8.565	5.525	0	14.865
Income (ln) of coal-fired power plants [C]	3864	7.895	5.182	0	14.629
The number of employees (ln) of coal-fired power plants [C]	3864	3.159	2.388	−1.789	7.560
Economic control variables					
Population density (ln) [D]	3360	−3.553	1.642	−8.579	1.191
GDP per capita (ln) [D]	3336	0.120	0.884	−2.234	2.460
Revenue per capita (ln) [D]	3240	−3.182	1.048	−5.579	0.125
Weather control variables					
Average air pressure (0.1 hPa) [E]	3864	9562	823.2	6236	10,168
Average temperature (0.1 °C) [E]	3864	138.719	49.593	5.421	247.544
Rainfall from 20 pm to 20 pm(0.1 °C) [E]	3864	24.272	13.240	0.512	74.546
Average sunlight (0.1 h) [E]	3864	57.591	15.003	24.180	94.350
Average humidity (100%) [E]	3864	0.658	0.101	0.359	0.840

Data Source:
A: The Chinese Disease Surveillance Points (DSP) System.
B: Yearbook of China Transportation and Communications (*Zhongguo Jiaotong Nianjian*).
C: Chinese Industrial Enterprises Database (1998–2013).
D: National Prefecture and County Finance Statistics Compendium (*Quanguo Di Shi Xian Caizheng Tongji Ziliao*), Provincial Statistic Yearbooks, Wind Database.
E: National Meteorological Information Center (http://cdc.nmic.cn).

correlation. The local output refers to the industrial output of local power plants in the sample county multiplies by the proportion of the number of days with low wind speed (below scale 2) per year. Table A4 of the Appendix A reports both spillover and local effects of pollution on health. For mortality of cardiovascular and respiratory diseases, the effect of local pollution is 20% and 50% higher than that of cross-border pollution, respectively.

The above interpretation of baseline results may have selection bias induced by avoidance behaviors such as residents in DSP counties might move to "upwind" areas in response to severe local pollution (Fan, 2005a, 2005b; de Brauw & Giles, 2017).[13] Ignoring such factors may lead to the mismeasurement of air pollution exposure and further bias the estimation (Graff Zivin, Neidell, & Schlenker, 2011; Janke, 2014; Neidell, 2009). Three strategies are employed to address the issue: first, we restrict the sample to residents older than 65 in "healthy areas" who have a low willingness of moving (Zhu & Chen, 2009; Liu & Xu, 2017) in Columns 1 and 4 of Table 3.[14] Second, we consider the effects of air pollution in places with poor socioeconomic conditions in Columns 2 and 5, measured by whether a county is classified as a national poverty county,[15] because it is difficult for residents in these areas to afford migration costs. Finally, we estimate the subsample of counties with wind divergence, since if the wind is divergent, it is difficult for residents to choose an "upwind" area to move to.[16] The related results are reported in Columns 3 and 6 of Table 3. Across all the subsamples, air pollution from power plants weighted by wind patterns is significantly positively related to the mortality due to cardiovascular and respiratory diseases.[17]

We conduct a series of robustness checks to consider the measurement errors of the independent variable. Table 4 shows that the baseline results are not sensitive to the measurement choices when we employ other commonly used measurements of scales of power plants like total assets, income, or the number of employees (Axtell, 2001; Fujiwara, Di Guilmi, Aoyama, Gallegati, & Souma, 2004;

[13] Other alternative avoidance behaviors include wearing masks, buying air purifiers, purchasing health insurance, etc. (Zhang & Mu, 2018; Ito & Zhang, 2016; Chang et al., 2018; Sun, Kahn, & Zheng, 2017). Due to data limitations, we mainly consider migration here.
[14] Based on 20% sample of the 2005 1% mini-census, we obtain the average health status of the elderly in each area. Specifically, this census asked individuals about their health status. We calculate the proportion of individuals whose replies are "healthy" in the group of people older than 65 in each area and define areas where the proportions are larger than the mean value as the "healthy areas". We thank the anonymous reviewer for the suggestion.
[15] For detailed information on national poverty counties, see http://www.cpad.gov.cn/. For observations in 2004, we use the list of national poverty counties of 1994. For 2008, we use the 2006 list.
[16] In our empirical analysis, we calculate the fraction of time spent in each wind direction for the whole year and their standard deviation. We choose the counties in which the fractions are smaller than the means of standard deviation as the subsample.
[17] Compared with the findings of Table 2, the results of Table 3 suggest that our baseline findings are the lower bound of the health effects of air pollution, and that residents indeed employ migration to avert pollution.

Table 2
Spillover effects of air pollution.

	Mortality of Cardiovascular Diseases			Mortality of Respiratory Diseases		
	(1)	(2)	(3)	(4)	(5)	(6)
Output(ln)	0.108**	0.108**	0.108**	0.040*	0.042*	0.042*
	(0.048)	(0.047)	(0.047)	(0.024)	(0.025)	(0.025)
Economic control variables	Yes	Yes	Yes	Yes	Yes	Yes
Weather control variables	Yes	Yes	Yes	Yes	Yes	Yes
County fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects		Yes	Yes		Yes	Yes
Gender and age fixed effects			Yes			Yes
Observations	3228	3228	3228	3228	3228	3228

Notes: *, **, and *** denote significance at the 90%, 95%, and 99% levels, respectively. Standard errors are in parentheses and have been clustered at the county level. The constant term is included but not reported. Economic control variables contain population density (ln), GDP per capita (ln), and revenue per capita (ln). Weather control variables contain average air pressure, average temperature, rainfall from 20 pm to 20 pm, average sunlight, and average humidity.

Hart & Oulton, 1996).[18] We then aggregate 16 wind directions into 8 directions and 4 directions separately.[19] The results, reported in Panel A of Fig. 3, are consistent with our expectation. To check the rationale of choosing power plants within 50 km of DSP areas, we test alternative thresholds of 30 km, 40 km, 60 km, and 70 km. Panel B of Fig. 3 displays the results, which indicate that the spillover effects of air pollution have consistent and stable effects on mortality. Concerning power plants may produce and emit more air pollution in summer and less in winter, we then use wind information in summer (Columns 1 and 3 in Table 5) or excluding the wind information in winter (Columns 2 and 4 in Table 5) to construct the independent variable. The results are still robust.

Another concern is whether policies of pollution reduction will threaten the validity of our estimations. As we have mentioned in section 2.1, during the 11th Five-Year Plan, the government implemented policy of *Shang Da Ya Xiao* and provided price subsidies for the desulfurization. *Shang Da Ya Xiao* admitted the lower efficiency and more pollution from small plants and encouraged to promote the output of large power plants, which will mix our assumption of proxying pollution with output. Thus, we check the robustness of the results when small generators are excluded and the output and pollution are "closely related," which is measured by the difference between the growth rates of output and pollution.

We first construct our independent variable by focusing on power plants whose size, measured by their output, is above the mean value, and then calculate the difference between the growth rates of output and air pollution.[20] The absolute value of the difference can measure the extent to which the output and pollution are closely related. We re-run the regressions based on subsamples from below 10 percentile to below 100 percentile of the absolute value of the difference. The results are reported in Fig. 4. As expected, the results are robust when we concern the policy of *Shang Da Ya Xiao*.

We also concern the effects of desulfurization technology. The desulfurization technology may threat our assumption that more output increases pollution.[21] Thus, we address this issue by focusing on observations where desulfurization technology is rarely utilized. Specifically, we obtain data on industrial SO_2 emission and industrial SO_2 removal in each prefecture and calculate the proportions by dividing industrial SO_2 removal by the sum of industrial SO_2 emission and industrial SO_2 removal. We run the regressions based on subsamples from below 10 percentile to below 100 percentile of the SO_2 removal, and report the results in Fig. 5. The results are still robust as expected.

4.2. *Pollution as mechanism*

In this section, we provide more evidence to justify the mechanism through which the output has effects on public health is the air pollution. We refer to the satellite-derived SO_2 data and apply a 2SLS-style analysis to show the role of SO_2 pollution. The satellite-derived SO_2 data come from National Earth System Science Data Center and National Science & Technology Infrastructure of China (http://www.geodata.cn). Since data are derived from satellite observations, we concern less about data manipulation. In the 2SLS-style analysis, we use the outputs of neighboring power plants as an instrument of the satellite-derived SO_2, and then regress the county's mortality on the predicted SO_2 at the second stage. The results are reported in Table 6. Column 1 shows the positive and significant correlation in the first stage. The *F*-statistic is far larger than 10, indicating that there is no weak instrument problem.

[18] The effects on deaths due to respiratory diseases are marginally significant. The *p* value of Asset (ln) in Column 4 is 0.116, and the *p* value of the number of employees (ln) in Column 6 is 0.161. We also report results concerning migration using a subsample of counties with wind divergence in Table A5 of the Appendix A, and the significance increases greatly.

[19] Although this classification helps us to accurately capture the wind directions, it may be biased by the research design. For instance, the toxic gas emissions of power plants in the north may travel to the DSP areas through north wind, as well as north-north-east or north-north-west wind. But the latter two are ignored in our calculation.

[20] The air pollution is measured by the industrial SO_2 emission at prefecture level from China City Statistical Yearbook.

[21] One possible mechanism is the plants with larger output may apply desulfurization technology more intensively, as they can get more subsidies.

Table 3
Spillover effects of air pollution concerning migration.

	Mortality of Cardiovascular Diseases			Mortality of Respiratory Diseases		
	65+ years old in "healthy areas"	National Poverty Counties	Divergent Wind Directions	65+ years old in "healthy areas"	National Poverty Counties	Divergent Wind Directions
	(1)	(2)	(3)	(4)	(5)	(6)
Output (ln)	0.809***	0.253**	0.162***	0.502**	0.200***	0.085**
	(0.281)	(0.098)	(0.046)	(0.221)	(0.069)	(0.035)
Economic control variables	Yes	Yes	Yes	Yes	Yes	Yes
Weather control variables	Yes	Yes	Yes	Yes	Yes	Yes
County fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Gender and age fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	248	444	2076	248	444	2076

Notes: *, **, and *** denote significance at the 90%, 95%, and 99% levels, respectively. Standard errors are in parentheses and have been clustered at the county level. The constant term is included but not reported. Economic control variables contain population density (ln), GDP per capita (ln), and revenue per capita (ln). Weather control variables contain average air pressure, average temperature, rainfall from 20 pm to 20 pm, average sunlight, and average humidity. Data of heathy status come from the 20% sample of the 2005 1% mini-census provided by the National Bureau of Statistics.

Table 4
Spillover effects of air pollution on alternative measures.

	Mortality of Cardiovascular Diseases			Mortality of Respiratory Diseases		
	(1)	(2)	(3)	(4)	(5)	(6)
Asset (ln)	0.094**			0.037		
	(0.042)			(0.024)		
Income (ln)		0.115**			0.047*	
		(0.049)			(0.025)	
The number of employees (ln)			0.234**			0.083
			(0.104)			(0.059)
Economic control variables	Yes	Yes	Yes	Yes	Yes	Yes
Weather control variables	Yes	Yes	Yes	Yes	Yes	Yes
County fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Gender and age fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3228	3228	3228	3228	3228	3228

Notes: *, **, and *** denote significance at the 90%, 95%, and 99% levels, respectively. Standard errors are in parentheses and have been clustered at the county level. The constant term is included but not reported. Economic control variables contain population density (ln), GDP per capita (ln), and revenue per capita (ln); Weather control variables contain average air pressure, average temperature, rainfall from 20 pm to 20 pm, average sunlight, and average humidity.

Columns 2 and 3 report the results of the second stage: one DU increase of SO_2 leads to 37 and 19 extra deaths per 1000 people due to cardivacular and respiratory diseases, respectively.[22]

We then employ a series of placebo tests to justify the role of pollution. If the effects of the industrial output of coal-fired power plants on public health were indeed only through air pollution, (1) adjusting for the dependent variable as the mortality not caused by air pollution, or (2) adjusting for coal-fired power plants as other lower-polluting power plants would not produce similar results as the baseline results. Table 7 presents the estimates of the placebo tests. The dependent variable is the mortality rate associated with transport accidents in Column 1.[23] As expected, the coefficient of power plants' total output is insignificant. In Columns 2 and 3, we use the total output of hydroelectric power plants as the independent variable.[24] The results are insignificant, suggesting that the spillover effects presented in Table 2 are indeed caused by air pollution.

In addition, our baseline model assumes that only when the wind speed was moderate (scale 2–5) would air pollution affect public health in DSP areas. If this is the case, using wind speeds below 2 or above 5 as weights would not produce similar results as those

[22] DU (Dobson Units) is the unit of satellite derived SO_2. 1 DU is equivalent to 2.69×10^{16} molec/cm^2. In our sample, the average level of satellite derived SO_2 is 0.26 DU with standard deviation 0.19. We thank the anonymous reviewer for the suggestion on the 2SLS-style analysis.

[23] The China Transport Statistical Yearbooks provide the number of deaths due to transport accidents by province. We calculate the county-level mortality of transport accidents based on the proportion of each county's roadway-lane in each province.

[24] The data on the output of hydroelectric power plants are from the Industrial Census Database.

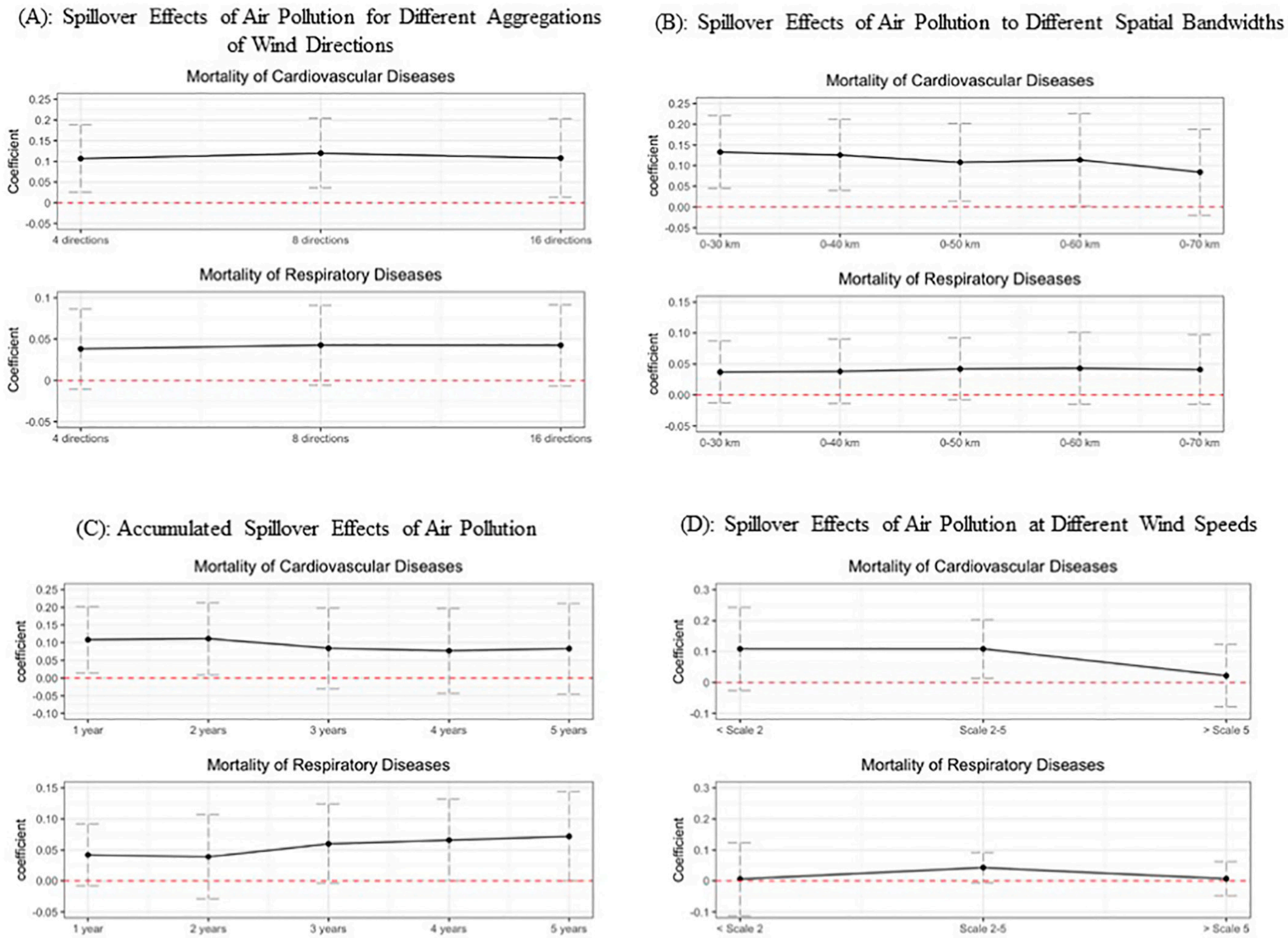

Fig. 3. Spillover effects of air pollution.

Table 5
Spillover effects of air pollution in selected months.

	Mortality of Cardiovascular Diseases		Mortality of Respiratory Diseases	
	Keep June –September	Drop November –February	Keep June –September	Drop November –February
	(1)	(2)	(3)	(4)
Output (ln)	0.086**	0.104**	0.038*	0.051**
	(0.043)	(0.045)	(0.022)	(0.023)
Economic control variables	Yes	Yes	Yes	Yes
Weather control variables	Yes	Yes	Yes	Yes
County fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Gender and age fixed effects	Yes	Yes	Yes	Yes
Observations	3228	3228	3228	3228

Notes: *, **, and *** denote significance at the 90%, 95%, and 99% levels, respectively. Standard errors are in parentheses and have been clustered at the county level. The constant term is included but not reported. Economic control variables contain population density (ln), GDP per capita (ln), and revenue per capita (ln). Weather control variables contain average air pressure, average temperature, rainfall from 20 pm to 20 pm, average sunlight, and average humidity.

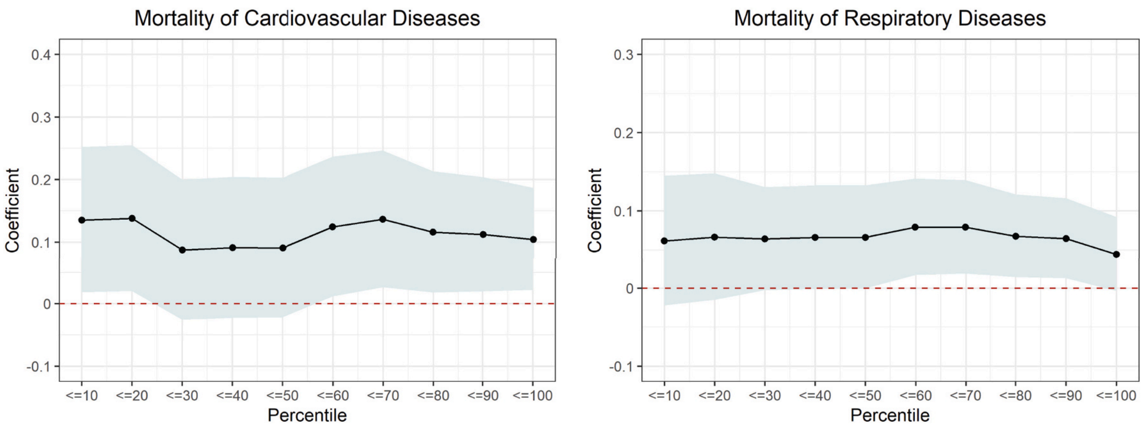

Fig. 4. Spillover effects of air pollution concerning Shang Da Ya Xiao.

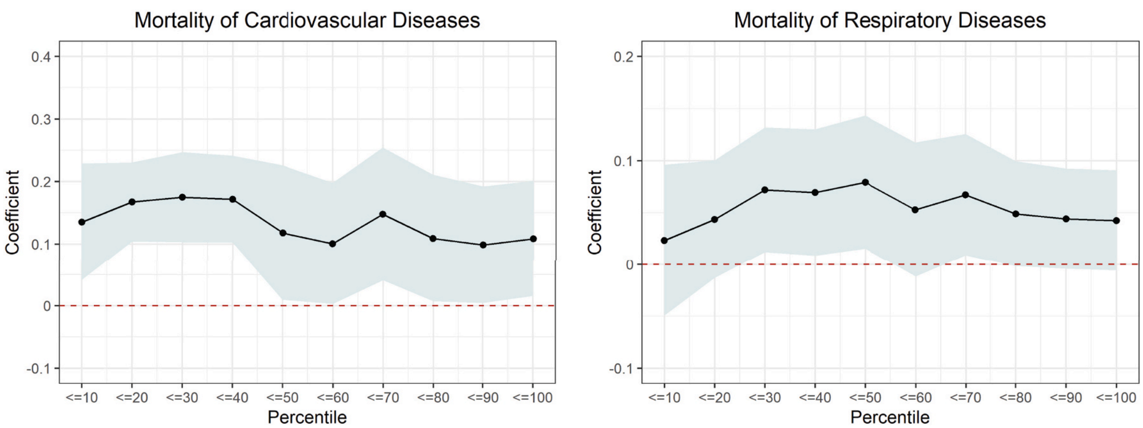

Fig. 5. Spillover effects of air pollution concerning SO_2 removal.

Table 6
2SLS-Style analysis.

	(1)	(2)	(3)
	First Stage (SO_2)	Second Stage	
		Mortality of Cardiovascular Diseases	Mortality of Respiratory Diseases
SO_2		37.318**	18.769*
		(18.609)	(10.674)
Output(ln)	0.002***		
	(0.001)		
Economic control variables	Yes	Yes	Yes
Weather control variables	Yes	Yes	Yes
County fixed effects	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes
Gender and age fixed effects	Yes	Yes	Yes
Number of Clusters	110	110	110
Observations	2640	2640	2640
F-statistics	11.66		

Notes: *, **, and *** denote significance at the 90%, 95%, and 99% levels, respectively. Robust standard errors are reported in parentheses. The constant term is included but not reported. Economic control variables contain population density (ln), GDP per capita (ln), and revenue per capita (ln). Weather control variables contain average air pressure, average temperature, rainfall from 20 pm to 20 pm, average sunlight, and average humidity.

Table 7
Spillover effects of air pollution on placebo measures.

	Mortality of Transport Accidents	Mortality of Cardiovascular Diseases	Mortality of Respiratory Diseases
	(1)	(2)	(3)
Output of coal-fired power plants (ln)	−0.094		
	(0.307)		
Output of hydroelectric power plants (ln)		−0.032	−0.020
		(0.042)	(0.026)
Economic control variables	Yes	Yes	Yes
Weather control variables	Yes	Yes	Yes
County fixed effects	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes
Gender and age fixed effects	Yes	Yes	Yes
Observations	3228	3228	3228

Notes: *, **, and *** denote significance at the 90%, 95%, and 99% levels, respectively. Standard errors are in parentheses and have been clustered at the county level. The constant term is included but not reported. Economic control variables contain population density (ln), GDP per capita (ln), and revenue per capita (ln). Weather control variables contain average air pressure, average temperature, rainfall from 20 pm to 20 pm, average sunlight, and average humidity.

reported in Table 2. Panel D of Fig. 3 confirms the validity of this assumption and shows that low and high wind speeds do not generate similar significant effects.

Finally, as the effects of air pollution on health can be cumulative (Cheung, He, & Pan, 2020), we justify the role of pollution by evaluating the cumulative effects. We replace annual output of power plants with aggregated output of past 1 to 5 years, which can represent the long-term exposure to pollution and is less likely to be intervened by local officials.[25] Panel C of Fig. 3 reports the accumulated spillover effects of air pollution on public health. The "1-year" dot indicates the average estimated spillover effects in the sample years (2004 and 2008), the "2-year" dot denotes the aggregate estimated effects based on the observations in both sample years and one year before the sample year (i.e. 2003–2004 and 2007–2008) and so forth. The results are as expected and show that air pollution really matters.

4.3. Heterogeneity analysis

In this section, we conduct the heterogeneity analysis. The conventional epidemiologic literature has found that different groups of people have varying risks of developing cardiovascular and respiratory diseases: the prevalence of both types of diseases is higher in men, and older people are susceptible to cardiovascular diseases, whereas young people are more likely to contract respiratory diseases

[25] The local officials' average tenure in China is three years (Chen & Kung, 2016; Li & Zhou, 2005). They have no long-term incentive to intervene industrial activities for four or five years.

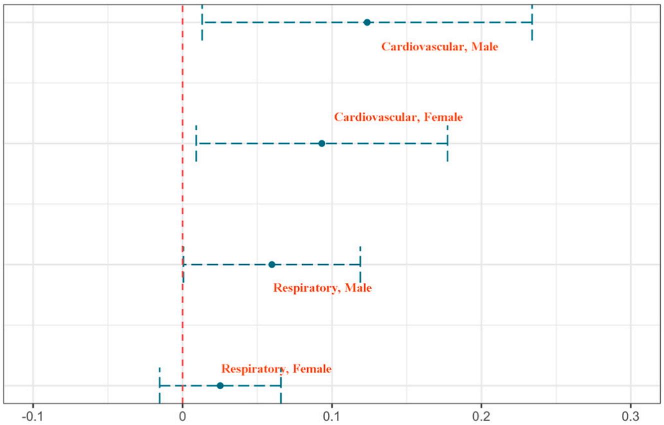

Fig. 6. Spillover effects of air pollution by gender.

Table 8
Spillover effects of air pollution on different age groups and gender.

	Mortality of Cardiovascular Diseases			Mortality of Respiratory Diseases		
	Whole sample	Male	Female	Whole sample	Male	Female
	(1)	(2)	(3)	(4)	(5)	(6)
Output (ln)	0.077*	0.097*	0.056	0.072***	0.094***	0.050**
	(0.046)	(0.054)	(0.041)	(0.025)	(0.029)	(0.021)
Age group (20–34) × Output (ln)	−0.002*	−0.001	−0.003**	0.008***	0.008***	0.008***
	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)
Age group (35–49) × Output (ln)	−0.010*	−0.010	−0.010*	0.004**	0.004*	0.004***
	(0.005)	(0.007)	(0.005)	(0.002)	(0.002)	(0.001)
Age group (50+) × Output (ln)	0.101	0.084	0.119**	−0.095**	−0.108**	−0.081**
	(0.063)	(0.070)	(0.059)	(0.042)	(0.047)	(0.039)
Economic control variables	Yes	Yes	Yes	Yes	Yes	Yes
Weather control variables	Yes	Yes	Yes	Yes	Yes	Yes
County fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Gender and age fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3228	1614	1614	3228	1614	1614

Notes: *, **, and *** denote significance at the 90%, 95%, and 99% levels, respectively. Standard errors are in parentheses and have been clustered at the county level. The constant term is included but not reported; the individual terms of age groups are also included but not reported. Economic control variables contain population density (ln), GDP per capita (ln), and revenue per capita (ln). Weather control variables contain average air pressure, average temperature, rainfall from 20 pm to 20 pm, average sunlight, and average humidity. The reference group is age group (1–19).

(Anderson, 1986; Uemura & Pisa, 1988; Yang et al., 2012). Fig. 6 plots the estimated effects of air pollution on each type of disease by gender. For both diseases, men are more vulnerable to air pollution than women.

Columns 1 and 4 of Table 8 present the estimated results for different age groups. Regarding cardiovascular diseases, people over 35 are more susceptible to the effects of air pollution, and this susceptibility increases with age. The effects of air pollution for people over 50 are 16 times larger than for those aged 35–49 (Column 1). For respiratory diseases, young people (under 20) are more sensitive (Column 4). The remaining columns of Table 8 (Columns 2–3 and Columns 5–6) consider the heterogeneity of gender and age groups simultaneously, and the results are still robust.

4.4. Treatment costs estimation

In this section we evaluate the total treatment costs including pollutant emissions, health expenditure, and lives loss based on the estimated coefficients and parameters from statistical yearbooks. We mainly focus on SO_2 emissions since these are the main pollutant generated by coal-fired power plants and represent the main environmental threat in China.[26] As SO_2 is not the only pollutant generated by coal-fired plants, our estimation should be treated as the lower bound of the potential costs.

We conduct the estimation for our sample years, 2004 and 2008. Based on the China Statistical Yearbook on Environment, the total SO_2 emissions from coal-fired power plants were 19.2492 million tons in 2004 and 2008. And based on the Industrial Census, the total industrial output value of the coal-fired electric power industry for these two years was 1169 billion RMB. Thus, we calculate the ratio as 60,766RMB/1 ton. We translate the 26.372 million RMB industrial output of power plants in our sample into 433,993 tons of SO_2 emissions. We also consider SO_2 loss during the dispersal. At a wind speed of about 25 km/h, SO_2 emissions will lose 6% per hour on average (Chen et al., 2005). As the power plants in our sample are located within 50 km of DSP areas, around 12% of SO_2 emissions will be lost and about 381,914 tons will remain (=433,944 × (1 − 12%)). In short, in 2004 and 2008, DSP counties would have received 381,914 tons of SO_2 from neighboring coal-fired power plants.

In addition, we calculate the magnitude of lives lost and the corresponding health expenditure. Based on the coefficients of 0.108 for cardiovascular diseases and 0.042 for respiratory diseases, we find that SO_2 emissions from neighboring power plants caused the deaths of 255,702 people due to cardiovascular diseases and 112,105 due to respiratory diseases in 2004 and 2008. This represents an average case fatality rate of 2.55% and 0.90%, respectively, which we use to calculate that 10.03 million people have cardiovascular diseases and 12.46 million have respiratory diseases.[27] We calculate that 10.03 million people have cardiovascular diseases and 12.46 million have respiratory diseases. Second, given that the average treatment expense was 5469.94 RMB for cardiovascular diseases and 2535.43 RMB for respiratory diseases in these two years, the total treatment costs would have been 54.85 billion RMB (7.84 billion USD) for cardiovascular diseases and 31.58 billion RMB (4.51 billion USD) for respiratory diseases, accounting for 7.4% of the revenue of the coal-fired power plants generating the spillover pollution and around 10% of the treatment costs due to pollution from local sources.[28] Thus, ignoring pollution spillovers would lead to the underestimation of the treatment costs by at least 10%.

We also estimate the lives lost and treatment costs for the period 2003–2017, and find that SO_2 emissions from neighboring power plants led to 2,517,000 deaths due to cardiovascular diseases and 979,000 deaths from respiratory diseases. The total treatment costs were 1058.46 billion RMB (151.21 billion USD) for cardiovascular diseases and 468.50 billion RMB (66.93 USD) for respiratory diseases, accounting for 13% of the revenue of coal-fired power plants.[29]

5. Conclusion

This analysis draws on a nationwide representative county-level dataset from China in 2004 and 2008. It uses industrial output from coal-fired power plants to proxy for air pollution, and wind directions and speeds as weights, to empirically examine the spillover effects of air pollution from coal-fired power plants on public health. The results reveal that air pollution from neighboring power plants indeed has significant negative effects on local public health, and the resulting treatment costs are enormous.

Estimating the health effects of air pollution on specific diseases helps the government design optimal environmental policies and distribute scarce resources most effectively. It also provides a valuable reference for the government to promote industrial restructuring for energy industries and the related health care policies. Finally, cross-border air pollution highlights the necessity of cooperation and collaboration among local governments and coordination between the central and local levels of government.

Funding source

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Declaration of Competing Interest

The authors declare that they have no conflict of interest.

Appendix A

[26] Based on the China Statistical Yearbook on Environment, SO_2 emissions from power plants accounted for 54% of the total SO_2 emissions from scaled industrial enterprises. SO_2 emissions also accounted for 77% of the total toxic air pollutants generated by power plants in 2004 and 2008. Thus coal-fired power plants contribute a very large share of the country's total SO_2 emissions. Similarly, based on the China Statistical Yearbooks, the ratios of the amount of SO_2 reduction to the amount of SO_2 emissions are very low in 2004 and 2008 for both scaled industrial enterprises as a whole and for the electric power generation industry in particular. Thus, the volume of SO_2 emissions is very large, and very difficult to reduce.

[27] Data on case fatality rate are from the China Health Statistics Yearbook.

[28] According to Chen et al. (2018), the total health expenditure for respiratory diseases due to SO_2 is around 300 billion RMB on average between 2000 and 2010. This magnitude is also consistent with Chen and Ye (2019)'s finding that the percentage contributions of PM2.5 pollution from upwind cities to local PM2.5 levels is between 0 and 50%.

[29] We also calculate the magnitude of lives lost and treatment costs year by year from 2003 to 2017 and report the results in Table A6 of the Appendix A.

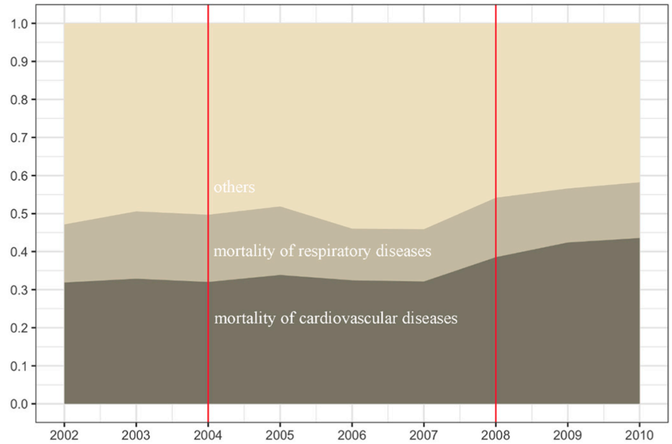

Fig. A1. Proportions of mortality due to various diseases. (Source: China Health and Family Planning Statistical Yearbook.)

Table A1
A brief summary of recent research on spillover effects of pollution.

Authors	Period of Study	Site	Health Outcome	Main Finding
Schelnker and Walker, 2016	2005–2007	California, U.S.	Asthma	A one standard deviation increase in daily pollution explains roughly one third of average daily admissions for asthma problems.
Anderson, 2020	1999–2001	Los Angeles, U.S.	All-cause mortality rate, cardio-respiratory mortality rate and lung cancer mortality	A one standard deviation increase in downwind frequency raises all-cause mortality rate by 0.8–0.9 percentage points, raises the cardio-respiratory mortality rate by 0.4–0.5 percentage points, and raises lung cancer mortality by 0.1 percentage points.
Yang and Chou, 2018	2004–2010	New Jersey, U.S.	Low birth weight	For mothers who live as far as 20 to 40 miles away but downwind of the power plant, being exposed to power plant emissions during the first month of pregnancy could increase the likelihood of having full-term babies but with low birth weight by 42%.
Deryugina et al., 2019	1999–2011	U.S.	Death and emergency room (ER) visits	A 1 μg/m^3 increase in PM 2.5 exposure for one day causes 0.61 additional deaths per million elderly individuals and increases three-day ER visits by 2.3 per million beneficiaries and ER spending by over $15,000 per million.
Beach & Hanlon, 2018	1851–1660	British	Infant mortality	A one standard deviation increase in coal use raised infant mortality by 6–8%.
Luechinger, 2014	1985–2003	Germany	Infant mortality	0.045 infant lives (per 1000 live births) are saved for every 1 μg/m^3 reduction in SO_2 concentration.
Jia & Ku, 2019	2000–2011	South Korea	Respiratory and cardiovascular mortality	If China's average AQI increases by one standard deviation, respiratory and cardiovascular mortality rates in South Korea increase by 0.040 per 100,000.
Altindag et al., 2017	2003–2011	South Korea	Birth weight	A one μm/m^3 increase in average exposure to PM10 during pregnancy leads to about 0.8 g reduction in newborn's birth weight.
Adhvaryu et al., 2017	1986–2006	Twelve low-income countries in West Africa	Infant mortality	Additional exposure of 10 μg/m^3 of PM 2.5 during each month of gestation on average decreases infant survival by 2.3 percentage points.

Note: The reviewed literature is listed based on their use of wind to capture pollution spillovers.

Table A2
Spillover effects of air pollution weighted by inverse geographical distance.

	Mortality of Cardiovascular Diseases		Mortality of Respiratory Diseases	
	(1)	(2)	(3)	(4)
Output(ln): $\sum_{j\in D}(Z_{ijt}/d_{ij})$	0.193 (0.174)		0.024 (0.094)	
Output(ln): $\sum_{j\in D}(Z_{ijt}/d_{ij}) \times s_{ijt}$		0.188** (0.077)		0.075** (0.037)
Economic control variables	Yes	Yes	Yes	Yes
Weather control variables	Yes	Yes	Yes	Yes
County fixed effects	Yes	Yes	Yes	Yes

(continued on next page)

Table A2 (*continued*)

	Mortality of Cardiovascular Diseases		Mortality of Respiratory Diseases	
	(1)	(2)	(3)	(4)
Year fixed effects	Yes	Yes	Yes	Yes
Gender and age fixed effects	Yes	Yes	Yes	Yes
Observations	3228	3228	3228	3228

Notes: *, **, and *** denote significance at the 90%, 95%, and 99% levels, respectively. Standard errors are in parentheses and have been clustered at the county level. The constant term is included but not reported. Economic control variables contain population density (ln), GDP per capita (ln), and revenue per capita (ln). Weather control variables contain average air pressure, average temperature, rainfall from 20 pm to 20 pm, average sunlight, and average humidity.

Table A3
Spillover effects of air pollution at alternative cluster levels.

	Mortality of Respiratory Diseases	Mortality of Respiratory Diseases
	(1)	(2)
Output (ln)	0.108**	0.042*
	(0.047)	(0.025)
Economic control variables	Yes	Yes
Weather control variables	Yes	Yes
County fixed effects	Yes	Yes
Year fixed effects	Yes	Yes
Gender and age fixed effects	Yes	Yes
Observations	3228	3228

Notes: *, **, and *** denote significance at the 90%, 95%, and 99% levels, respectively. Standard errors are in parentheses and have been clustered at the prefecture level. The constant term is included but not reported. Economic control variables contain population density (ln), GDP per capita (ln), and revenue per capita (ln). Weather control variables contain average air pressure, average temperature, rainfall from 20 pm to 20 pm, average sunlight, and average humidity.

Table A4
Spillover effects of air pollution conditional on local effect.

	Mortality of Cardiovascular Diseases	Mortality of Respiratory Diseases
	(1)	(2)
Output of coal-fired power plants (ln)	0.104**	0.044*
	(0.042)	(0.024)
Local output (ln)	0.125**	0.067
	(0.061)	(0.048)
Economic control variables	Yes	Yes
Weather control variables	Yes	Yes
County fixed effects	Yes	Yes
Year fixed effects	Yes	Yes
Gender and age fixed effects	Yes	Yes
Observations	3228	3228

Notes: *, **, and *** denote significance at the 90%, 95%, and 99% levels, respectively. Standard errors are in parentheses and have been clustered at the county level. The constant term is included but not reported. Economic control variables contain population density (ln), GDP per capita (ln), and revenue per capita (ln). Weather control variables contain average air pressure, average temperature, rainfall from 20 pm to 20 pm, average sunlight, and average humidity.

Table A5
Spillover effects of air pollution on alternative measures with subsample.

	Mortality of Cardiovascular Diseases			Mortality of Respiratory Diseases		
	(1)	(2)	(3)	(4)	(5)	(6)
Asset (ln)	0.114***			0.083**		
	(0.043)			(0.036)		
Income (ln)		0.144***			0.101**	
		(0.050)			(0.043)	
The number of employees (ln)			0.242**			0.117
			(0.116)			(0.098)
Economic control variables	Yes	Yes	Yes	Yes	Yes	Yes
Weather control variables	Yes	Yes	Yes	Yes	Yes	Yes
County fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Gender and age fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2016	2016	2016	2016	2016	2016

Notes: *, **, and *** denote significance at the 90%, 95%, and 99% levels respectively. Standard errors are in parentheses and have been clustered at the county level. The constant term is included but not reported. Economic control variables contain population density (ln), GDP per capita (ln), and revenue per capita (ln). Weather control variables contain average air pressure, average temperature, rainfall from 20 pm to 20 pm, average sunlight, and average humidity. Here we use subsample of counties without clear upwind area.

Table A6
Life loss magnitudes and treatment costs.

	Life Loss Magnitude of Cardiovascular Diseases	Life Loss Magnitude of Respiratory Diseases	Treatment Cost of Cardiovascular Diseases	Treatment Cost of Respiratory Diseases
2003	12.497	4.860	39.912	14.272
2004	13.135	5.108	26.394	14.357
2005	13.678	5.319	32.962	16.798
2006	13.554	5.271	26.636	15.836
2007	14.342	5.577	39.047	18.752
2008	14.457	5.622	33.397	15.874
2009	14.584	5.672	47.449	19.150
2010	15.101	5.873	55.974	23.797
2011	15.072	5.861	61.672	26.371
2012	15.055	5.855	67.866	28.444
2013	15.187	5.906	102.834	38.519
2014	14.456	5.622	97.767	31.442
2015	14.492	5.636	135.576	46.007
2016	14.591	5.674	150.480	51.064
2017	14.699	5.716	168.444	57.160

Notes: the unit for life loss magnitude is 10 thousand, and the unit for treatment cost is billion RMB. All the costs have been adjusted by CPI with 2003 as the reference year.

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