Gone with the Wind? Emissions of Neighboring Coal-fired Power Plants and Local Public Health in China[1]

Abstract: Based on a nationwide representative county-level dataset from China, this paper 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.

Key words: Wind; Air pollution; Coal-fired power plants

JEL: I10, O13, Q53

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1. Introduction

Since air pollution is a major health threat to people worldwide, estimating its effect on mortality is fundamental to environmental policy-making. Recently, a nascent strand of literature has investigated the effects of the cross-border externality of pollution on overall mortality (Luechinger, 2014; Anderson, 2016; Adhvaryu *et al.*, 2017; Altindag *et al.*, 2017; Beach and Hanlon, 2017; Deryugina *et al.*, 2018). 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 and Ku, 2018) and examine the spillover effects of air pollution from coal-fired power plants in neighboring areas on local public health.[2]

China currently faces numerous environmental challenges (Ebenstein *et al*., 2015; Kahn and 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 ($PM_{2.5}$) 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 required. Accordingly, a comprehensive examination of the spillover effects of air pollution from coal-

[2] 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. Figure 1A of the Appendix presents the proportions of mortality due to both respiratory diseases and cardiovascular diseases from 2002 to 2012. On average, deaths due to both diseases account for 50% of the total mortality over time.

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 from 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 speed and direction. 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. The exogeneity of such wind patterns indicates that our research design is a "quasi-natural experiment" (Dominici *et al*., 2014), which mitigates the endogeneity bias associated with air pollution. 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.[3] 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

[3] For example, the downwind frequency of a county with 30 days per year of moderate speed wind would be 30/365 or 0.082.

output of neighboring power plants results in 0.108 and 0.042 extra deaths due to cardiovascular diseases and respiratory diseases, respectively, per 1,000 population.[4] 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 1,058.46 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.

This paper contributes to two strands of literature. First, several previous studies have recognized that coal-fired power plants are a major source of pollution (Muller *et al.*, 2011;

[4] For comparison, we roughly translate power plants' outputs into SO_2 concentration such that a 1 μg/m^3 increase in SO_2 concentration results in 0.06 and 0.002 extra deaths per 1,000 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. 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 μg/m^3 increase in SO_2 concentration results in 0.007 extra deaths per 1,000 people due to respiratory diseases.

Zhang and Crooks, 2012; Zheng and Khan, 2013).[5] 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.[6] Our paper 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 paper 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.

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[5] Other related pollution sources mainly include traffic (Currie and Walker, 2011; Schlenker and Reedwalker, 2015; Viard and 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 *et al*., 2014; Currie *et al*., 2015), and even China's winter heating policy (Chen *et al*., 2013; Ebenstein *et al*., 2017).

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

2. Background

2.1 Air Pollution of Coal-fired Power Plants in China

China is the most polluted country in the world, especially regarding levels of SO_2 and particulates (World Bank, 2007a). The coal-fired power industry has become the dominant pollution source: they contribute around 60% of the country's industrial SO_2 emission and particulates (Zheng and Khan, 2013, 2017; Zhang and Crooks, 2012). Figure 1 plots government-reported industrial SO_2 emissions between 2001 and 2011, which are consistently over 15 million tons.

Figure 1: Industrial SO_2 Emissions in China (2001–2011)

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 and Walker, 2015; Anderson, 2016; Beach and Hanlon, 2017). Such spillover effects are also common at the international level. For example, Jia and Ku (2018) 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.

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 go to extreme lengths to keep pollution out of their "backyards", for example by moving pollution-intensive industries or polluting activities downstream or to the border of an area (Cai *et al*., 2016;

Kahn *et al*., 2015; Chen *et al*., 2018; He *et al*., 2018). 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). Unfortunately, current studies on the 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.[7]

3. Research Design and Data

3.1 Research Design

This paper estimates the spillover effects of air pollution from power plants on public health by using exogenous wind directions and speeds as weights. The main obstacle associated with accurately estimating such effects is constructing an appropriate measure of cross-border air pollution transported by wind from power plants. It depends on the total emissions of poisonous gases from power plants in neighboring areas conditional on wind patterns. To capture the emissions of poisonous gases, we employ power plants' industrial output values to proxy for levels of air pollution, which has been widely used in previous studies (Davis, 2011; Clay *et al*., 2015).[8]

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[7] Some scholars have explored the spillover effects of air pollution on housing prices or morbidity costs (Zheng *et al.* 2014; Barwick *et al.* 2018).

[8] 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*., 2012; Ghanem and Zhang, 2014), data on the output of industrial firms are much more reliable and have been

We then consider the effect of wind patterns, including directions and speeds. We believe air pollution will 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 (Beaufort scale 2–5, or 6–10.7 km/h). Otherwise, the effects will be limited.[9] 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. Finally, we build our independent variable—air pollution—by exploiting the production capacities of power plants, coupled with information on wind directions and speeds.

We focus on the 161 representative counties for which we have mortality data (called DSP counties, which is explained in more detail below). We match the industrial output of each coal-fired power plant in neighboring counties to DSP counties and assign wind directions and speeds using this match. We calculate the spillover effect for each neighboring county by multiplying the industrial output value by the downwind frequency. For each DSP county, we aggregate the spillover effects from all neighboring counties to measure the cross-border air pollution.

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widely used in existing research (Brandt *et al*., 2012, 2014; Hsieh and Song, 2015; Brandt *et al*., 2017). 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.

[9] When the wind speed is low, the poisonous gas emissions from power plants cannot spread downwind. When the wind speed is high, the pollutants in the air will be diluted.

3.2 Data and Variables

Three types of data were used in this research: (1) mortality rates of cardiovascular and respiratory diseases as the dependent variables, (2) industrial output of power plants, as well as wind speeds and directions to construct the independent variable, and (3) weather and socioeconomic conditions serving as control variables.

The micro data on mortality rates are extracted from the annual reports of the Diseases Surveillance Points (DSPs) system. The DSPs contain mortality and morbidity information for 1 million (a little under 1% of the Chinese population) residents along with their gender and age group. 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 Figure 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.

The independent variable is constructed from two parts. First, we collect data on the total output of coal-fired power plants located within 50 km of DSP counties from the Chinese Industrial Enterprises Database (1998–2013). Second, we gather data on wind speeds and directions from the National Meteorological Information Center (http://data.cma.cn/), which covers 824 weather stations across the country. 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.[10] The air pollution of DSP counties should be the sum of annual industrial output of power plants in all neighboring counties, weighted by the downwind

[10] 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.

frequencies in that year.[11] Figure 2 plots the spatial distribution of samples including DSP counties, neighboring counties within 50 km, and weather stations.

Figure 2: Spatial Distribution of Samples

We also control for some meteorological and socioeconomic factors. 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 covering the years 2004 and 2008 for analysis. A brief statistical summary of all the variables are presented in Table 1.

Table 1: Statistical Description

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:

$$mortality_{igat} = \alpha * capacity_{it} + X'\beta + county_i + gender_g + age_a + year_t + \varepsilon_{igat} ;$$

[11] 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.

(1)

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, $capacity$, denotes the total output of power plants weighted by wind speeds and directions. The vector X' includes proxies for other mentioned variables including socioeconomic factors and meteorological condition variables. We also 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 increases of 0.108 (Column 3) and 0.042 (Column 6) extra deaths per 1,000 people due to cardivacular and respiratory diseases, respectively.

Table 2: Spillover Effects of Air Pollution

The findings reported in Table 2 assume that power plants' industrial output can capture air pollution emissions quite well. But the output may not affect public health only through air pollution. Thus, we employ a series of placebo tests. 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, or (3) adjusting for wind frequencies with moderate speed as that above or below would not produce similar results as the baseline results. Table 3 presents the estimates of the placebo tests. The dependent variable is the mortality rate associated with transport accidents in Column 1.[12] As expected, the coefficient of power plants' total output is insignificant. In Columns 2 and 3, we adjust for the independent variable of the baseline model as the total output of hydroelectric power plants.[13] The results are insignificant, suggesting that the spillover effects presented in Table 2 are indeed caused by air pollution rather than others.

Table 3: Spillover Effects of Air Pollution on Placebo Measures

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 reported in Table 2. Panel A of Figure 3 checks the validity of this assumption and shows that low and high wind speeds indeed do not generate similar significant effects.

[12] 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.

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

Figure 3: Spillover Effects of Air Pollution

4.2 Robustness Checks

The spillover effects of air pollution on mortality are conditional on choices about the behaviors of the affected population and the appropriate spatial bandwidths, etc. In this section, we explore our estimates' sensitivity to these behaviors and choices and conduct a series of robustness checks to test the relationship between mortality and downwind exposure.

We first consider the measurement errors induced by avoidance behaviors such as moving to "upwind" areas in response to severe local pollution (Fan, 2005a, 2005b; De Brauw and Giles, 2008).[14] Ignoring such factors may lead to the mismeasurement of air pollution exposure and further bias the estimation (Neidell, 2009; Graff Zivin *et al*., 2011; Janke, 2014). Two strategies are employed to address this issue. First, we restrict the sample to residents older than 65 who have a low intention of moving (Zhu and Chen, 2010; Liu and Xu, 2015). Second, 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.[15]

Table 4 presents the results for the subsample analysis: Columns 1 and 3 are the subsample of people over 65, and Columns 2 and 4 are the subsample of counties with wind divergence.

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[14] Other alternative avoidance behaviors include wearing masks, buying air purifiers, purchasing health insurance, etc. (Zhang and Mu, 2016; Ito and Zhang, 2016; Chang *et al.*, 2018; Sun *et al*., 2017). Due to data limitations, we mainly consider migration here.

[15] 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.

Across both subsamples, air pollution from power plants weighted by wind patterns is significantly positively related to the mortality due to cardiovascular and respiratory diseases. Compared with the findings in Table 2, the results in Table 4 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 4: Spillover Effects of Air Pollution Concerning Migration

We then consider the measurement error of the independent variable, which consists of three parts: industrial output, downwind frequency, and neighborhood distance of 50 km. Table 5 tests the validity of the measurement of industrial output by showing 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 (Hart and Oulton, 1996; Axtell, 2001; Fujiwara et al., 2004), the results basically corroborate our baseline findings, although the effects on deaths due to respiratory diseases are marginally significant.[16]

Table 5: Spillover Effects of Air Pollution on Alternative Measures

The original data on downwind frequencies provide daily wind information on 16 directions. Although this classification helps us to accurately capture the wind directions, it may be biased by our research design. For instance, the toxic gas emissions of power plants in the

[16] 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. In Appendix Table A2, we also report corresponding results using a subsample of counties without a clear upwind area as coded before, and the significance increases greatly.

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. Therefore, we aggregate 16 directions into 8 directions and 4 directions separately to test the robustness. The results, reported in the Panel B of Figure 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 C of Figure 3 displays the results, which indicate that the spillover effects of air pollution have consistent and stable effects on mortality. Thus, the choice of 50 km is a reasonable one, and our findings are robust to alternative distances.

Finally, we test the robustness of our findings over the long term. A blossoming literature has shown that long-term exposure to air pollution results in negative health outcomes (Dockery *et al*., 1993; Pope *et al*., 2009; Anderson, 2016). We seek to broaden the scope of this literature by examining the spillover effects on long-term public health. Panel D of Figure 3 reports the accumulated spillover effects of air pollution on public health from the short term to the long term. The horizontal axis represents the number of years since the sample year of 2004 and 2008. The vertical axis represents the estimated coefficients of 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 show that air pollution has both short- and long-term spillover effects.

4.3 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 (Anderson, 1986; Uemura and Pisa, 1988; Yang *et al*., 2012). Figure 4 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.

Figure 4: Spillover Effects of Air Pollution by Gender

Columns 1 and 4 of Table 6 present the estimated results for different age groups. With regard to 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 6 (Columns 2–3 and Columns 5–6) consider the heterogeneity of gender and age groups simultaneously, and the results are still robust.

Table 6: Spillover Effects of Air Pollution on Different Age Groups and Gender

Moreover, one mechanism through which air pollution affects mortality is socioeconomic status. Previous studies have examined the role of socioeconomic status in differentiating the health effects of air pollution (Currie and Hyson, 1999; Neidell, 2004; Graff Zivin and Neidell, 2013). Therefore, we consider the effects of air pollution in places with different socioeconomic conditions, measured by whether a county is classified as a national poverty county.[17] The estimated coefficients are larger than the estimation of Table 2: the estimated effect on death due to cardiovascular diseases is 0.253, which is 2.34 times larger than the result of the baseline regression (=0.108). The same estimation for respiratory diseases is 0.200 and 4.76 times larger than the baseline result (=0.042). We also employ an interaction term between national poverty county dummy and the key independent variable in Appendix Table A3 and find similar results. Note that the results are consistent with previous studies that highlight how poor socioeconomic conditions can undermine public health.

Finally, air pollution and environmental regulation policies such as the two-control-zone policy (TCZ) have improved public health and reduced infant mortality (He *et al*., 2002; Tanaka, 2015). We use a difference-in-differences method to evaluate the effects of the policy and augment the models with an interaction term between the policy-related term and the key independent variable.[18] For both types of diseases, the SO_2 control policy significantly reduces the mortality. The estimated effect of the interaction term on death due to cardiovascular diseases and respiratory diseases are 0.37 and 0.244, respectively. In areas with more air pollution carried by wind, the effects of this policy decrease, suggesting that the policy should take spillover effects into account.

[17] 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 from 1994. For 2008, we use the 2006 list.

[18] The standard difference-in-differences interaction term consists of two parts: the first difference is whether an area is categorized as a SO_2 control zone or not, and the second difference is whether the year is within the period (1998–2005) when the TCZ policy was implemented. When constructing the first difference, we focus on SO_2 emissions because it is the main pollutant of coal-fired power stations; when constructing the second difference, we use 2004 as the treatment year since the TCZ policy was active at that time, and 2008 as the temporal control group since the policy had been informally abandoned by then.

4.4 Treatment Costs Estimation

We 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.[19] 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 1,169 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 (=433,993*(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. To calculate the treatment costs, we first estimate the number of people with cardiovascular and respiratory diseases based on the case fatality rates of 2.55%

[19] 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.

and 0.90%, respectively.[20] 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 5,469.94 RMB for cardiovascular diseases and 2,535.43 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 such spillover pollution.

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 1,058.46 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.[21]

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 exogenous wind directions and speed 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.

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[20] Data on case fatality rate are from the China Health Statistics Yearbook.
[21] We also calculate the magnitude of lives lost and treatment costs year by year from 2003 to 2017 and report the results in Table A4 of the Appendix.

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 between local governments and coordination between the central and local levels of government.

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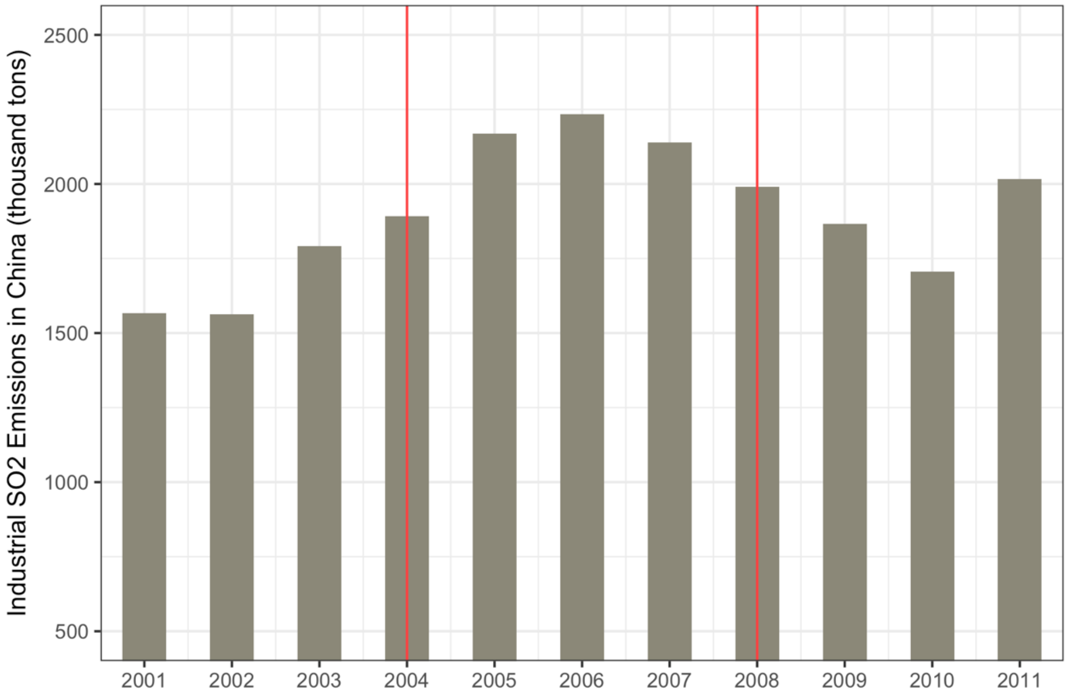
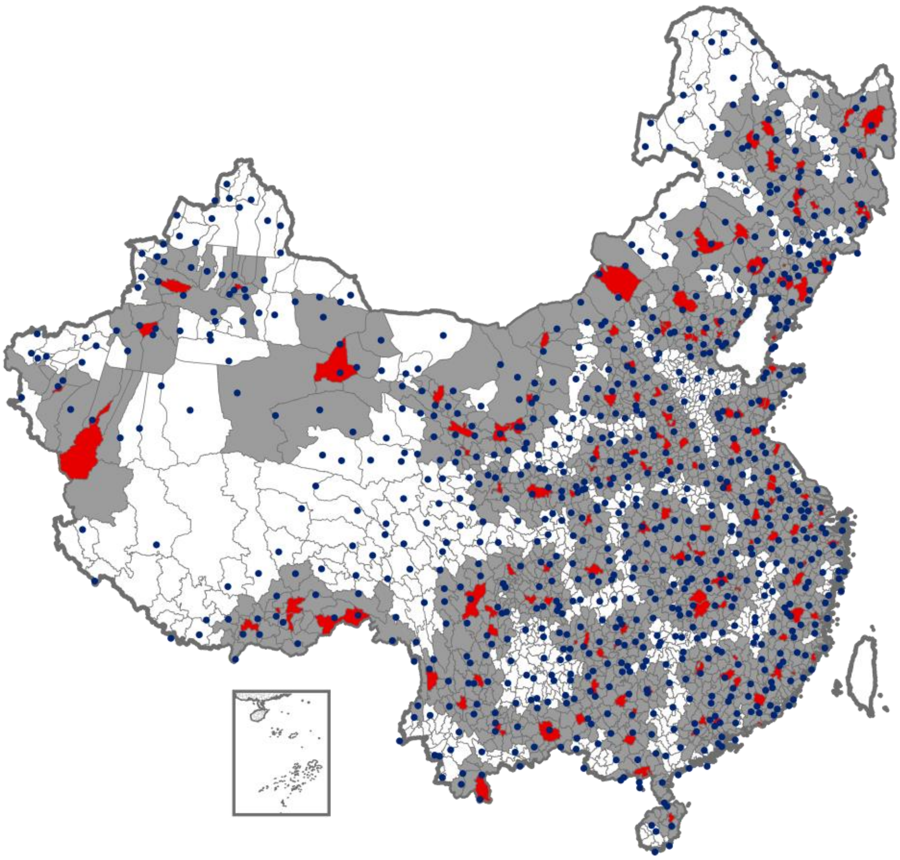
Figures

Figure 1: Industrial SO_2 Emissions in China (2011-2011)



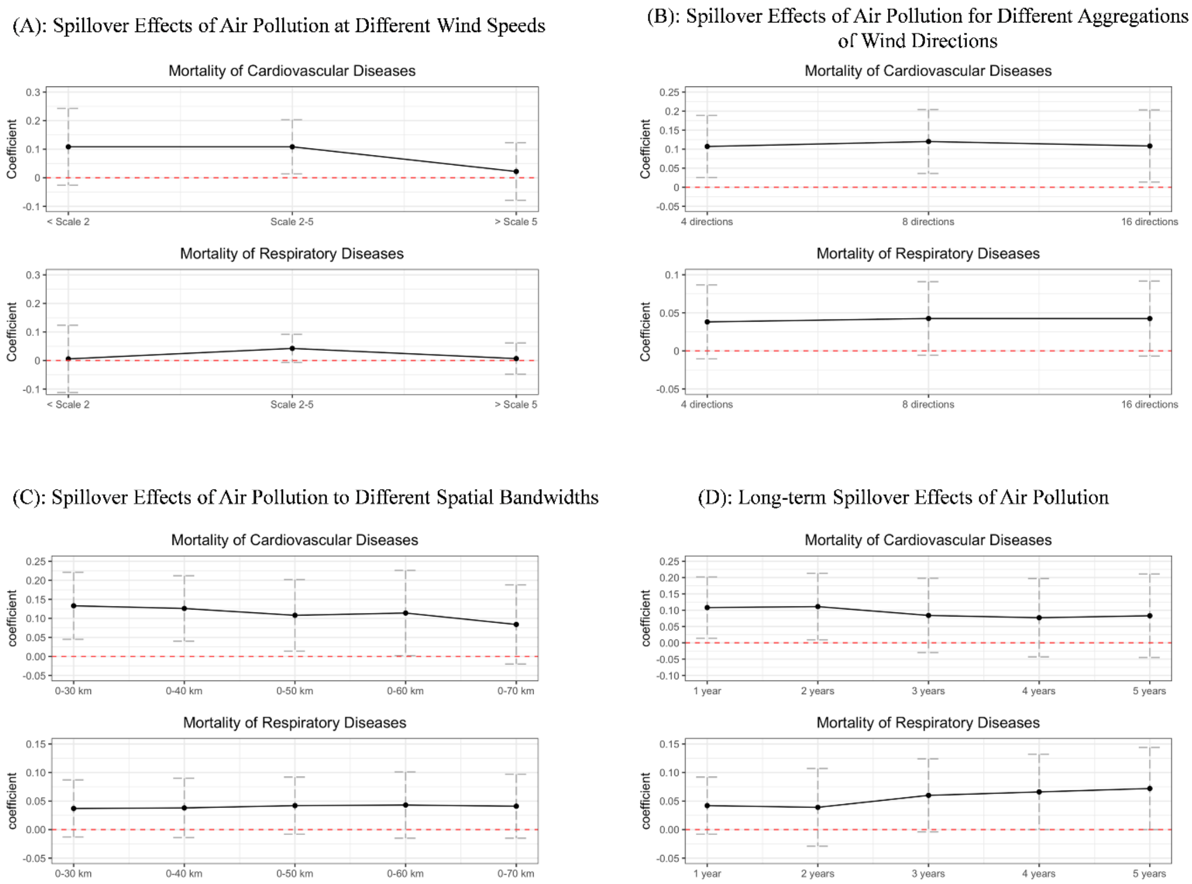
Source: China Statistical Yearbook on Environment and China Environment Yearbook.

Figure 2: Spatial Distribution of Sample



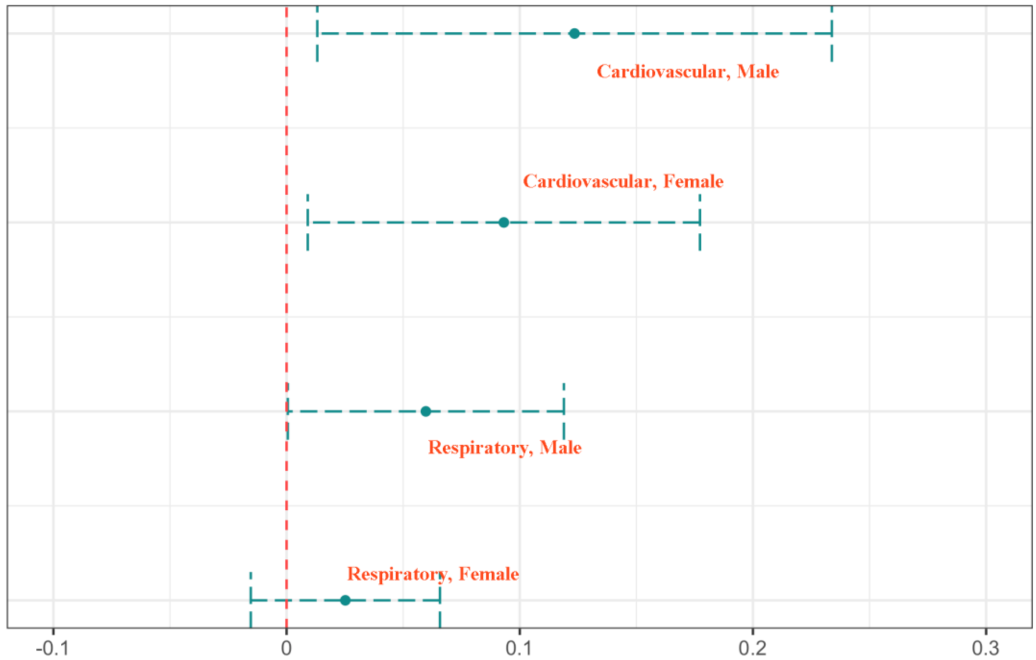
Note: The red parts indicate DSP counties, the grey parts indicate neighboring counties within 50 kilometers, and the blue dots indicate weather stations.

Figure 3: Spillover Effects of Air Pollution



Note: The grey dashed lines indicate the 95% confidence intervals. In Panel A, the horizontal axis measures the wind speed, and the vertical axis indicates coefficients from separate regressions, using different wind speeds as the independent variable. "< Scale 2" represents wind speed lower than 1.6 m/s, "Scale 2-5" represents wind speed between 1.6-10.7 m/s and "> Scale 5" represents wind speed larger than 10.7 m/s. In Panel B, the horizontal axis measures numbers of directions, and the vertical axis indicates coefficients from separate regressions, using different aggregation of wind directions as the independent variable. In Panel C, the horizontal axis measures the distance to DSP counties, and the vertical axis indicates coefficients from separate regressions, using various distances to DSP counties as the independent variable. In Panel D, the horizontal axis represents the number of years since the sample year of 2004 and 2008. The vertical axis represents the estimated coefficients of 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.

Figure 4: Spillover Effects of Air Pollution by Gender



Note: The horizontal axis indicates coefficients from separate regressions, using different genders as subsamples. The dashed lines indicate the 95% confidence intervals.

Tables

Table 1: Statistical Description

Variable	Obs	Mean	S.D.	Min	Max
Dependent Variables					
Mortality of cardiovascular diseases per 1,000 population [A]	3,864	4.165	8.637	0	46.904
Mortality of respiratory diseases per 1,000 population [A]	3,864	1.669	4.096	0	37.686
Mortality of transport accidents [B]	3,864	33.58	62.64	0	647.400
Independent Variables					
Output (ln) of coal-fired power plants [C]	3,864	7.914	5.185	0	14.608
Output (ln) of Hydraulic power plants [C]	3,864	5.191	4.213	0	15.303
Asset (ln) of coal-fired power plants [C]	3,864	8.565	5.525	0	14.865
Income (ln) of coal-fired power plants [C]	3,864	7.895	5.182	0	14.629
The number of employees (ln) of coal-fired power plants [C]	3,864	3.159	2.388	-1.789	7.560
Economic control variables					
Population density (ln) [D]	3,360	-3.553	1.642	-8.579	1.191
GDP per capita (ln) [D]	3,336	0.120	0.884	-2.234	2.460
Revenue per capita (ln) [D]	3,240	-3.182	1.048	-5.579	0.125
Weather control variables					
Average air pressure (0.1hPa) [E]	3,864	9562	823.2	6236	10168
Average temperature (0.1°C) [E]	3,864	138.719	49.593	5.421	247.544
Rainfall from 20 pm to 20 pm(0.1°C) [E]	3,864	24.272	13.240	0.512	74.546
Average sunlight (0.1h) [E]	3,864	57.591	15.003	24.180	94.350
Average humidity (100%) [E]	3,864	0.658	0.101	0.359	0.840
Poverty County [F]	3,864	0.118	0.323	0	1
Two Control Zone [G]	3,864	0.469	0.499	0	1

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)
F: The State Council Leading Group Office of Poverty Alleviation and Development (http://www.cpad.gov.cn/)
G: Official Reply to the State Council Concerning Acid Rain Control Areas and Sulfur Dioxide Pollution Control Areas, published by the State Council in 1998.

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
Number of Clusters	143	143	143	143	143	143
Observations	3,228	3,228	3,228	3,228	3,228	3,228

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 3: 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
Number of Clusters	143	143	143
Observations	3,228	3,228	3,228

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 4: Spillover Effects of Air Pollution Concerning Migration

	Mortality of Cardiovascular Diseases		Mortality of Respiratory Diseases	
	65+ years old	Divergent wind directions	65+ years old	Divergent wind directions
	(1)	(2)	(3)	(4)
Output (ln)	0.566^{**}	0.162^{***}	0.242^{*}	0.085^{**}

	(0.255)	(0.046)	(0.138)	(0.035)
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
Number of Clusters	143	111	143	111
Observations	538	2,076	538	2,076

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 5: 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	Yes	Yes	Yes	Yes	Yes	Yes

variables						
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
Number of Clusters	143	143	143	143	143	143
Observations	3,228	3,228	3,228	3,228	3,228	3,228

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 6: 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
Number of Clusters	143	143	143	143	143	143
Observations	3,228	1,614	1,614	3,228	1,614	1,614

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).