Winter Heating, Air Quality, and Mortality in China

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Abstract

China's coal-fired central heating systems generate large amounts of hazardous emissions and significantly deteriorate air quality. In a regression discontinuity design based on the dates of winter heating, we estimate the acute health impacts of air pollution. We find that a 10-point increase in the weekly Air Quality Index will cause a 4% increase in mortality. Poor and vulnerable groups are particularly sensitive to this sudden air quality deterioration, suggesting that the health impacts of air pollution can be mitigated by better socio-economic conditions. Exploratory cost-benefit analysis suggests that replacing coal with natural gas for heating will improve social welfare.

Keywords: Winter Heating Policy, Air Pollution, Coal to Gas, Regression Discontinuity
JEL: I18, Q48, Q53

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1. Introduction

Over 70 percent of China's energy consumption comes from coal and emissions from coal combustion is the major anthropogenic contributor to air pollution in China (Chan and Yao, 2008). During the winter-heating seasons, large centralized coal-fired boilers provide low or zero-priced indoor heating to residential and commercial buildings in northern China. These boilers cause a significant deterioration in air quality when they are fired up (Xiao et al., 2015). The health impacts of such periodic, sudden and widespread environmental degradation have yet to be ascertained.

In this study, we estimate the causal impacts of air pollution on mortality by exploiting a regression discontinuity (RD) design based on the switching-on dates of the winter heating systems in northern Chinese cities. The identification strategy builds on the fact that turning on of the winter heating systems requires burning large amounts of coal and generates substantial emissions; this leads to an immediate deterioration in air quality and further diminishes health.

Using comprehensive weekly data on air quality, mortality, and weather conditions for 139 urban districts and rural counties in Northern China from 2014 to 2015, we find that turning-on of the winter heating systems increases the weekly air quality index (AQI) by 36 points and causes a 14% increase in all-cause mortality rate.[1] We estimate that a 10-point increase in weekly air quality index (AQI) leads to a 3.8 percent increase in weekly mortality. Heterogeneity analyses show that air pollution has a greater impact on males than females and affects the elderly more than the young. More importantly, the short-term impacts of air pollution on mortality are almost entirely attributable to extra deaths in rural and low-income areas. These results suggest that improving socio-economic conditions could significantly mitigate the health impacts of air pollution.

Our work contributes to the existing literature in several important ways. First, due to the expansion of the coverage of China's Disease Surveillance Point System, we are able to extend the health effect analysis of air pollution to rural areas in China and highlight the long-overlooked disparity in air pollution exposure between urban and rural areas.[2] Residents in low-income and rural areas can be particularly vulnerable to air pollution shocks because they are less aware of the

[1] Accidental deaths are excluded from our analysis throughout the paper.
[2] Facing data limitations in developing countries, previous studies have focused almost exclusively on large urban cities, while the majority of people living in the rural areas have been ignored. One exception is that Zhou et al. (2015) use data from five cities and two rural counties and find that smog episodes and fine particulates have greater impacts on rural residents compared with urban residents.

harmful effects of air pollution and are less likely to adopt avoidance behaviors against air pollution. They also have less access to medical treatments when they get sick. Existing literature largely neglects these economically disadvantaged groups because air pollution information was not available in rural areas. Our finding that air pollution mainly impacts rural and poor people suggests that existing evidence may significantly under-estimate the overall costs of air pollution.

The second contribution of our research is that it adds to a growing strand of economic research investigating the impact of air pollution in the developing countries (Chen et al., 2013; Ebenstein et al., 2017; Greenstone and Hanna, 2014; He et al., 2016). Our findings add new evidence to this literature and show that temporal changes in air quality can cause an immediate spike in death rates among vulnerable groups in China. Our estimates are relevant to the 4.5 billion people in developing countries who are currently exposed to high levels of air pollution, for example, the mean daily $PM_{2.5}$ concentrations is 85 $\mu g/m^3$ in our sample.

A third contribution of this study is that we show the bias in the estimates in public health and epidemiology studies that use associational approaches. The estimates from these observational studies are widely used by governments and international organizations and have generated profound policy implications. After comparing our estimates with these associational estimates, we find that the impact of air pollution estimated from our quasi-experimental design is several times greater than the impacts estimated in associational studies. This finding echoes the argument made in a *Science* article: conventional approaches relying on "adjusting" for confounding factors often provide unreliable estimates of air pollution effects (Dominici et al., 2014).

Fourth, based on our estimates, we conduct an exploratory benefit-cost analysis on China's coal replacement policy. To deal with the severe air pollution from the coal-fired winter heating system, the Chinese government initiated a clean energy plan that eventually will replace coal with natural gas or electricity for heating. Combining data from multiple sources, we find that the benefits of replacing coal with natural gas for winter heating are likely to be larger than the costs, despite the high cost of switching.

This paper complements two recent studies that also exploit China's winter heating policy: Chen et al. (2013) and Ebenstein et al. (2017). Both studies use regression discontinuity designs to estimate the long-term impacts of air pollution on health in China. The primary difference between this study and the aforementioned two is that we use variations in the timing of the start of the winter heating season, while they exploit variations in geographic distance from the Huai River line, which is the boundary between southern China and the colder northern region, where centralized winter heating systems are used. We focus on the acute effect of air pollution by comparing health outcomes before and after the winter heating period starts, while Chen et al. (2013) and Ebenstein et al. (2017) estimate the long-term impact by comparing health outcomes between southern and northern China. We find that our estimates are smaller than the long-term estimates, suggesting that long-term exposure to air pollution might cause people to develop chronic diseases and have an even larger impact on population health.

We conduct a set of robustness checks to strengthen the credibility of the research design. First, we show that weather conditions, which are typical confounding factors in estimating the short-term health effects of air pollution, have negligible effects on the RD estimates but can significantly affect associational estimates. Second, location-specific fixed effects change the estimated coefficients in associational approaches, but they do not affect the estimates using the RD design. Third, we construct placebo cut-offs by moving the switching-on date of winter heating before and after the actual dates, and find that the air pollution effect is only evident on the actual dates. Fourth, we assign a fake winter heating period to southern Chinese cities using the most common switching-on date (November 15th) and cannot find similar effects. Finally, we show that only cardiorespiratory mortality increases after the winter heating period starts suggesting that air pollution is the causal factor.

The remainder of this paper is structured as follows. Section 2 provides background on the winter heating system. Section 3 discusses the data. Section 4 presents the empirical strategies. Section 5 discusses main results and a battery of robustness checks. Section 6 explores the heterogeneous impacts of air pollution. Section 7 applies our estimates to an exploratory benefit-cost analysis of China's coal-to-gas policy, and Section 8 concludes.

2. Winter Heating System

China's winter heating system was initiated in the 1950s following the example of the Soviet Union and was gradually expanded during the planned economy period (1950s-1980s). The Chinese government limited the heating entitlement to areas located in the north because of energy and financial constraints (Chen et al., 2013). The dividing line between northern and southern China roughly follows the Huai River and Qinling Mountains along which the average temperature in January is around zero Celsius.

The heating system connects large centralized boilers with residential and commercial buildings. A network of the heating system consists of a boiler, water pipelines, and radiators that deliver hot water to homes and offices. In northern China, the centralized winter heating service is provided either at a zero price or a heavily subsidized one. In contrast, state-provided centralized winter heating does not exist in southern China because the government arbitrarily decided that it was not needed south of the Huai River line.

Most northern Chinese cities receive free or heavily-subsidized heating between November 15th and March 15th. For some northern cities regarded as very cold in winter (e.g., Harbin in Heilongjiang Province), the heating season is extended to over six months of the year, from October until April. City governments have discretion to determine whether winter heating starts early if the weather is unusually cold, on a year-to-year basis. For our identification strategy, it is critical to have accurate dates when the heating started for each Disease Surveillance Points (DSP) location. To guarantee accuracy, we collected and verified the winter heating starting dates through both government websites and online local community forums.

The winter heating system is mostly coal-based and technically inefficient. Researchers in chemical and environmental sciences have documented that incomplete combustion of coal increases air pollution by generating substantial particulate matter emissions, SO_2, and NOx (Almond et al., 2009; Muller et al., 2011). When the winter heating period starts, coal consumption jumps to a much higher level and leads to a rapid and substantial increase in air pollution. This provides a quasi-experimental setting for researchers to utilize the discontinuity in air pollution caused by turning on the coal-burning furnaces to estimate the impact of air pollution on health.

As the evidence of the negative impacts of air pollution on health accumulates in China, the public increasingly demands that governments to deal with poor air quality. As a result, governments have initiated various programs to control emissions from the winter heating systems. The most notable one is the replacement of coal with natural gas or electricity as primary fuels for heating. The switch was first proposed in Beijing, starting in 2013, then the pilot runs were gradually expanded to other northern cities, including Tianjin and cities in Hebei, Shanxi, Shandong, and Henan in 2015 and 2016. Under this policy, the coal-fired boilers are gradually replaced by gas or electric boilers in urban areas; households in rural areas receive subsidies to replace coal stoves with natural gas or electric stoves.[3]

3. Data

3.1. Mortality

The mortality data come from the Chinese Center for Disease Control and Prevention's (CDC) Disease Surveillance Points (DSP) System.[4] The DSP System is a remarkably high-quality nationally representative survey; it provides detailed cause-of-death data for a coverage population of around 324 million people (nearly a quarter of the total population in China) at 605 separate locations (322 city districts and 283 rural counties) for each year since 2013. The community or hospital doctors report the cause of death to the CDC.[5] This information is used to assign all deaths to either cardiorespiratory causes of death (i.e., heart, stroke, lung cancers, and respiratory illnesses) that are plausibly related to air pollution exposure or non-cardiorespiratory causes (i.e., cancers other than lung and all other causes). We exclude accidental deaths and suicides from our analysis. We use created weekly mortality datasets created for each DSP location in 2014 and 2015 for this project.

3.2. Air Pollution

We collected comprehensive air pollution data from the National Urban Air Quality Real-time Publishing Platform.[6] The platform is administrated by China's Ministry of Environmental Protection and publishes real-time AQI and concentrations of criteria air pollutants in all state-controlled monitoring sites.[7]

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[3] A summary of the policy to switch from coal to gas/electricity policy in northern provinces can be found on the website of the Association of Urban Natural Gas: http://www.chinagas.org.cn/hangye/news/2017-06-16/39267.html.

[4] See Appendix A1 for a detailed description of the sampling and development of the DSP System.

[5] All communities were subject to strict quality control procedures administered by the CDC network at county/district, prefecture, province and national levels, for accuracy and completeness of the death data.

[6] The system is the largest real-time air quality monitoring network ever built in China, implementing the full coverage of municipalities, provincial capitals, cities with independent planning, all prefecture-level cities, key environmental protection cities, and environmental protection model cities. The real-time data is published on the following website: http://106.37.208.233:20035.

[7] Appendix A2 explains how the AQI is constructed based on six major air pollutants: $PM_{2.5}$, PM_{10}, SO_2, NO_2, O_3 and CO.

The Chinese government has mandated detailed quality assurance and quality control programs at each monitoring station. According to the requirements of Ambient Air Quality Standard (GB3095-2012), this platform was put in operation beginning in January 2013, and cities were added to the platform in a staggered manner.[8] We collected data from 1,497 individual air monitoring stations during the sample period. Figure 1 shows DSP points and air monitoring sites. The stations cover all Chinese prefectural cities and encompass most of China's geography. We compute weekly air pollution data for each monitoring station by taking the mean of the hourly values. To assign these weekly values of pollution from the monitors to DSP locations, we: 1) calculate the centroid of each DSP location (either a city district or a county); 2) measure the distances between the monitoring sites and the center of the DSP location using the geographic coordinates of monitoring sites; and 3) use the weekly pollution level of the closest monitoring site within a 100KM radius of the DSP location. All DSP locations that did not have a monitoring site within a 100KM radius were excluded from the sample.

In the matching process, we used accurate readings of the AQI or individual pollutant for DSP locations. The AQI level can differ dramatically across monitoring sites on a weekly basis. The inaccurate assignment of air pollution to DSP locations potentially introduces substantial measurement error bias and the direction of the bias is uncertain (Sarnat et al., 2005). As such, we experiment with different tolerance distances between DSP locations and monitoring sites. As a robustness check, we also generate a weighted average of the weekly pollution level using all monitors within a 50KM radius of the DSP location, using the inverse of the distance to the monitor as the weight.

3.3. Weather

We obtained daily weather information from Global Summary of the Day (GSOD).[9] Our analysis uses 409 ground weather stations with nearly-complete weather data for 2014 and 2015. The weather information includes temperature, dew point, and precipitation. We adopt the same matching mechanism as we do for DSP locations and air pollution monitoring sites.

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[8] The reporting system covers 338 prefecture-level cities and 1,436 sites across the country by the end of 2015.

[9] The GSOD data are available for download from https://data.noaa.gov/dataset/global-surface-summary-of-the-day-gsod.

4. Empirical Strategy

We begin with estimating the associations between air quality and health outcomes by fitting the following ordinary least square equation:

$$Y_{it} = \beta_0 + \beta_1 AQI_{it} + X_{it}\Pi + d_i + \varepsilon_{it} \tag{1}$$

where Y_{it} is age-adjusted mortality rates in DSP location i during week t. AQI_{it} is mean air quality index in DSP_i during week t. X_{it} is a vector of weekly weather conditions in DSP_i that might influence health outcomes, d_i are location fixed effects capturing time-invariant characteristics of DSP_i, and ε_{it} is a disturbance term.

The coefficient β_1 measures the effect of air quality on mortality, after controlling for the available covariates. Consistent estimation of β_1 requires that unobserved determinants of mortality do not covary with AQI_{it} after adjustment for weather conditions. Thus, the "conventional" approach rests on the assumption that controlling for the limited set of variables available (often weather conditions and seasonality indicators in multi-year analysis) removes all sources of confounding factors. Previous research has raised substantive concerns about the validity of this assumption (Chay et al., 2003; Dominici et al., 2014). Further, pollution concentrations are measured with error and it is well known that classical measurement error will attenuate the coefficient associated with the air pollution variable.

The second approach leverages the regression discontinuity (RD) design implicit in the winter heating policy to measure its impact on the AQI and mortality. We exploit the fact that the winter heating period starts on November 15th in most cities, and separately test whether turning on winter heating causes discontinuous changes in air quality and mortality in northern China. In practice, we estimate the following parametric equations to test for the impacts of winter heating:

$$AQI_{it} = \alpha HeatingOn_{it} + f(T_{it}) + HeatingOn_{it} f(T_{it}) + X_{it}\Phi + d_i + u_{it} \tag{2a}$$

$$Y_{it} = \delta HeatingOn_{it} + f(T_{it}) + HeatingOn_{it} f(T_{it}) + X_{it}\Psi + d_i + \varepsilon_{it} \tag{2b}$$

where $HeatingOn_{it}$ is an indicator variable equal to 1 for location i's winter heating period, and $f(T_{it})$ is a polynomial in weeks before and after the threshold. The week sequence is defined as follows: *t*=1 for the first week after heating starts and so on; and *t*=-1 indicates the last week before the heating starts, and so on. Our main sample includes 12 weeks before and after the winter heating start date for each city.[10] We choose the order of the polynomial in $f(T_{it})$ based on goodness of fit criteria. We also include interaction terms, $HeatingOn_{it}f(T_{it})$, to allow flexible functional forms from both sides of the threshold. The identifying assumptions are that any unobserved determinants of the AQI or mortality change smoothly around the dates when the winter heating period starts. If the relevant assumption is valid, adjustment for a sufficiently flexible polynomial in time before and after the heating start date will remove all potential sources of bias and allow for causal inference.

The parameters of interest are α and δ, which provide an estimate of whether there is a discontinuity in outcomes when the winter heating period starts, relative to no heating period. If the RD assumptions hold, estimates of δ will provide an unbiased estimate of the change in the mortality rate in the week immediately after the heating started. Note that this parameter is not a laboratory-style estimate of the consequences of exposure to air pollution where all other factors are held constant, since it reflects individuals' actions to protect themselves from the resulting health problems of pollution. While the laboratory-style estimate might be of interest for researchers interested in how air pollution affects the human body, its relevance for understanding the real-world consequences of air pollution is unclear. In fact, an appealing feature of the estimates of δ is that they reflect all the compensatory behavior that individuals undertake to protect themselves against air pollution, such as using air filters and wearing masks.

The results in Equation (2) can be used to develop estimates of the impact of air quality on mortality. Specifically, if winter heating only influences mortality only through its impact on air quality, it is valid to treat Equation (2a) as the first-stage in a two-stage least squares (2SLS) system of equations. An important appeal of the 2SLS approach is that it produces estimates of the impact of units of the AQI (or other individual pollutant) on mortality, so the results are applicable to other settings (e.g., other developing countries with comparable air pollution levels). The second stage equation becomes:

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[10] The winter heating period of most cities in our sample is from November 15th to March 15th, which is about 17 weeks long. As shown in the appendix, we conduct robustness checks with different numbers of weeks in the appendix and find consistent results.

$$Y_{it} = \gamma \widehat{AQI}_{it} + f(T_{it}) + HeatingOn_{it} f(T_{it}) + X_{it}\Theta + d_i + \varepsilon_{it} \tag{2c}$$

where $\widehat{AQI}_i$ represents the fitted values from estimating (2a) and the other variables are as described above. The 2SLS approach offers the prospect of solving the confounding or omitted variables problem associated with the estimation of the impacts of air pollution, and is a solution to the attenuation bias associated with the mismeasurement of air pollution.

Although the polynomial RD approach in Equations (2a), (2b) and (2c) has been commonly used in the literature, a recent development in RD methodology shows that estimates based on high-order polynomials can be sensitive to the order of polynomials and have several other undesirable statistical properties (Gelman and Imbens, forthcoming). As a result, estimators based on local linear regression or other smooth functions are often preferred because they can assign larger weights to observations closer to the threshold and produce more accurate estimates. Because we have a panel data with a large number of DSP locations, we can estimate the RD parameters with sufficient statistical power, even if the bandwidth shrinks to a very small time horizon around the threshold. In light of this, we also estimate local linear RD using the most restrictive sample around the threshold: two weeks before and after the winter heating start date.

5. Empirical Results

5.1. Summary Statistics

Table 1 reports the summary statistics for mortality, the AQI, temperature, dew point, and precipitation for 139 DSP locations. The sample period includes 24 weeks: 12 before and 12 after the starting date of winter heating. There are 3,336 DSP-week observations in the full sample. Column (1) reports the means along with the standard deviations for the full sample period. Columns (2) and (3) report the means along with the standard deviations before and after heating starts.

A comparison of columns (2) and (3) shows substantial differences in the mortality rate and the AQI. Both the mortality rate and the AQI are higher during the heating season. For example, the AQI is 119 overall, 139 during the heating season, otherwise 99. Comparing urban with rural areas reveals that rural residents are exposed to higher AQI and also suffer a higher mortality rate than their urban counterparts.

5.2. Estimates of the Effect of the Winter Heating Policy on the AQI and Mortality Rates

We begin the analysis graphically with an assessment of the Winter Heating Policy's impact on air pollution and mortality. Figure 2 plots mean AQI at DSP locations, along with the 90 percent confidence interval, against weeks before and after the cutoff. Each square represents the average AQI across locations in a particular week. The plotted line is generated by using a polynomial function on either side of the cutoff. The figure shows a discontinuous change in the AQI when the heating period starts. Figure 3 shows the RD plot for mortality rate against time. We also observe that the mortality rate jumps upward discretely after the winter heating period starts.

Table 2 presents the estimated discontinuity of the AQI and mortality rates (and standard errors). DSP fixed effects are included for all specifications to control for location-specific socio-economic characteristics (e.g., health facilities, medical professionals, and income) that do not vary in a short period of time. Columns (1) and (2) report the RD estimates from Equations (2a) and (2b), using the full sample and third order of the polynomial function of the running variable. The order of the polynomial is chosen based on the Akaike Information Criteria (AIC) of goodness of fit. Columns (3) and (4) report local linear RD estimates with and without weather controls. In all specifications, the function of the week is interacted with the heating period dummy, so that time is allowed to affect outcomes differently before and after the cutoff.

Panel A summarizes the estimates for the AQI. In the polynomial RD specifications, the AQI increases by 71 units after winter heating is turned on. The estimates are slightly reduced to 56 units after weather conditions are controlled. In the local linear case, the AQI rises by 35 units at the threshold and the increase is very robust to the inclusion of weather controls.[11] In Panel B, we find that mortality also increases at the threshold. Polynomial RD results show a discontinuity in mortality rates by 7-8 percent; and the local linear regression results show an increase of 14 percent.

Note that the RD estimates using the local sample ($|T| \leq 2$) are more robust than the global polynomial RD estimates. In Appendix Table A1, we report results from different orders of global polynomial RD approach and find that the results tend to be sensitive to the choices of polynomial functions, an undesirable feature discussed in Gelman and Imbens (2017). We therefore focus primarily on the local linear RD results for the rest of the discussion, and present the polynomial

[11] The average AQI for northern cities during the week before turning on the winter heating is 117.

RD results mainly for comparison and as a way of checking the robustness of the results.

5.3. Estimates of the Effect of Air Pollution on Mortality Rates

Table 3 reports the estimated effects of a 10-point change in the AQI on mortality rates using OLS and 2SLS approaches. Panel A shows 2SLS estimates from the RD design. Panel B reports OLS estimates. Columns (1) and (2) include a third-order polynomial of the running variable and its interactions with the heating-on dummy. Columns (3) and (4) estimate linear regressions with a local sample around the threshold.

We find that OLS produces substantially smaller estimates and that weather controls decrease OLS estimates considerably. In contrast, the 2SLS approach produces stable estimates across different specifications. When weather conditions are controlled, the 2SLS approach produces substantially greater estimates of the health effects of the AQI than OLS. Specifically, the column (4) estimate from OLS suggests that a 10-point increase in the AQI is associated with a statistically significant increase in mortality rate of 0.55 percent when we use the full sample and control for weather conditions. The column (4) estimate from the 2SLS approach indicates that a 10-point increase in the AQI increases mortality by 3.8 percent. The greater magnitude of these 2SLS estimates suggests that some combination of omitted variables and measurement error reduces the magnitude of the OLS estimates relative to the true effect of the AQI on mortality rates.

5.4. Evaluating the Validity of the Research Design

To assess the validity of the RD research design, we conduct two placebo tests showing that the impacts are only evident using the actual winter heating switching-on time, and only for northern China. Panel A of Table 4 reports the 2SLS estimates of the impact of the AQI on mortality rates at one-week intervals before and after the actual switching-on date, as well as at the actual date. The results show that the only statistically significant effects occur at the actual threshold. In all other instances, estimates are either statistically indifferent from zero or have the wrong sign. A second placebo test uses southern cities and a fake switching-on date (we use the most common date of November 15th). Estimates for southern cities should be small and insignificant because winter heating does not exist in the south. We find that the 2SLS estimates in Panel B of Table 4 are consistent with our prediction. These results provide further evidence that the effects in Table

3 are due to winter heating, rather than an artifact of this application of the 2SLS approach.

For an instrumental variable to be valid, it must only affect mortality only through its impact on air pollution. We check the validity of the instrumental variable in two ways. First, we check whether the results are robust to the inclusion of DSP fixed effects. If controlling for location fixed effects changes the estimates substantially, this would indicate that location-specific missing variables affecting mortality are correlated with the instrumental variable. In this case, the validity of the "heating-on" as the instrumental variable would be questionable and the estimates might not be reliable. Panel A of Table 5 shows that the OLS estimates change substantially when DSP fixed effects are included in the regressions. In contrast, for the 2SLS estimates, including DSP fixed effects has little impact. This suggests that the instrumental variable is not correlated with DSP-specific characteristics. Second, it is well documented that weather conditions are important confounders in estimating the health effects of air pollution because they change air pollution levels and also affect human health. Panel B of Table 5 shows estimates with different weather controls. OLS estimates change substantially when the weather controls are included. 2SLS estimates stay stable for different weather controls. In conclusion, these results show little evidence that the winter heating variable is correlated with unobserved potential confounding factors.

Finally, as has been documented in the literature (Ebenstein et al., 2017; He et al., 2016), air pollution affects only cardiorespiratory diseases. We conduct a similar analysis by estimating the impacts of winter heating on cardiorespiratory and non-cardiorespiratory mortality separately. The division of cardiorespiratory and non-cardiorespiratory mortality is based on the ICD10 code. Cardiorespiratory mortality includes deaths caused by respiratory diseases (J30-J98), respiratory infections (J00-J06, J10-J18, J20-J22, H65-H66), lung cancers (C33-C34), and cardiovascular diseases (I00-I99). Non-cardiorespiratory mortality includes all other causes except injuries (V01-Y89). Table 6 presents the estimation results. The empirical results bear out such predictions: in all specifications, a statistically significant increase in cardiorespiratory mortality rates is found at the onset of the winter heating period. In contrast, the change in mortality rates of non-cardiorespiratory illnesses is much more modest and statistically insignificant. These findings confirm that air pollution is the causal factor that leads to a sharp increase in mortality after winter heating is turned on.

5.5. Robustness Checks

In this section, we check the robustness of our results and investigate whether our results were affected qualitatively by the decisions made in our study along several dimensions.

First, we experiment with different numbers of weeks before and after the threshold because RD estimates might be sensitive to different samples. Table A2 in the Appendix shows the results of different numbers of weeks because RD estimates might be sensitive to different samples. We use the preferred polynomial model in Table 2. All results are qualitatively similar to the main estimates.

Second, we chose the nearest monitoring station within a 100KM tolerance distance, though we acknowledge that other choices could have been made. Table A3 examines the sensitivity of the results to other choices of acceptable distance from a DSP location to its nearest monitoring stations. In addition to using the closest monitoring station, we also use a distance-weighted set of monitoring stations. Results show that our main findings are not affected by our choice of acceptable distance or matching rules. Table A4 presents analogous results for local linear regressions. We find that the local linear estimates are also rather stable to different sets of DSP locations selected by the tolerance distance.

Third, Beijing is the first city that started the switch from coal to gas for its traditional coal boilers in order to battle air pollution in 2013. According to a city government report, by the end of 2014, Beijing had retired forty-four thousand coal boilers and finished a coal to clean energy transfer for another seventeen thousand coal boilers.[12] Therefore, Beijing can be treated as a "contaminated" city in our natural experimental design and might cause downward bias to our estimates. We thus re-estimate the equations after excluding all 9 DSP locations that belong to the Beijing area. Appendix Table A5 presents the estimates without DSP locations in Beijing. We find that the estimates are similar to the main results in Tables 2 and 3.

6. Heterogeneity

We explore the heterogeneous impacts of winter heating on mortality in Table 7.[13] In Panel A, we compare urban with rural areas. The results show that winter heating has no significant impact on

[12] The coal to clean energy transfer statistics are reported on Beijing's city government website at http://zhengwu.beijing.gov.cn/gzdt/bmdt/t1373103.htm.
[13] For rural and urban areas, and for regions with different income levels, we estimate the impacts of turning on winter heating on AQI and present the results in Table A6.

mortality rates in urban areas. In sharp comparison, we find a 21 percent increase in mortality rates when the heating period starts in rural areas. The results are robust to the inclusion of the weather conditions in the model and across different specifications.

The differences between rural and urban areas are striking, as they suggest a form of a largely ignored environmental inequality that has been largely ignored: the free winter heating, as a welfare system that mainly serves urban populations, results in sudden deterioration in air pollution beyond urban areas. This sudden deterioration of air pollution kills people – mainly rural people living nearby the urban cities.

Many factors may contribute to this difference, including information, avoidance behavior, medical conditions, and air pollution exposure. First, air pollution information is more available for urban populations because the city governments publish real-time air quality data online and issue haze alerts when air pollution levels are high. In contrast, air pollution information is largely absent in rural areas. Second, because urban residents are more aware of the harmful effects of air pollution, they are more likely to adopt avoidance behaviors. Urban residents often wear face masks, use air filters, and reduce outdoor activities when air quality deteriorates, while most rural residents are not aware of the risks or cannot afford such expenditures. Third, rural residents lack immediate access to emergency medical care. When the sudden spike in air pollution triggers strokes, heart attacks, or acute respiratory diseases, rural residents are more likely to die due to lack of immediate medical treatment. Finally, the total exposure to air pollution of rural residents may be several times higher than that of urban residents, because rural residents spending more time working outdoors and may also suffer from severe indoor air pollution caused by biomass and coal combustion.

We also collect GDP per capita data for DSP locations in the sample. We divide the sample into three groups as high, medium, and low GDP per capita. Panel B of Table 7 shows similar differences between poor and rich areas. For the low-income areas, we estimate that the increase in mortality at the threshold is 28 percent in our preferred specification. For the medium-income areas, the magnitude of the estimate decreases significantly and it becomes statistically insignificant. For high-income areas, the estimates are close to zero and statistically insignificant. The results indicate that wealth mitigates the health impact of air pollution in China. The possible channels of this wealth effect could be similar to those discussed in connection with the rural and urban differences. In some related studies, Ito and Zhang (2017) find that high-income families are willing to spend significantly more on air filters than low-income families; Sun et al. (2017) find richer people spend more money on protection against air pollution especially when air pollution levels are higher.

To account for the gender difference, we analyze males and females separately. Panel C presents the gender-specific estimates. The winter heating has positive and significant impacts on mortality rates for men, but the effect is statistically insignificant for women. For example, in our preferred specification (column (4)), we estimate that the increase in mortality at the threshold is 16 percent for men. For women, the estimate is 11 percent but statistically insignificant. In summary, men are more likely than women to die if the air quality suddenly deteriorates. In Appendix Table A7, we further stratify the sample by both gender and location. We find that in urban areas, the estimates are insignificant for both sexes. We find a consistent positive and significant impact only for males in the rural area. Therefore, the significant results for males in Table 7 are driven by more deaths in rural areas. One explanation to this gender heterogeneity is that the actual pollution exposure between males and females can be very different. In rural areas, men are more likely to work outdoors in the fields and thus men are exposed to a higher dose of air pollution. Another possible explanation is that males in general have poorer cardiorespiratory functions than females due to smoking and drinking.[14] When air quality deteriorates, men are more likely to die because more of them have pre-existing cardiorespiratory diseases. However, these explanations are highly conjectural, and future research is warranted to further investigate the causes of this gender difference.

Finally, we investigate the impact of winter heating on mortality for different age groups. As reported in Panel D of Table 7, our results reveal a significant difference between young and old people. The results indicate that the winter heating has no impacts for people younger than 60. In contrast, winter heating increases mortality rates by 9 percent for people older than 60 in our preferred specification. This difference is reasonable because younger people have a stronger immune systems and fewer pre-existing health problems. Sudden pollution spikes thus have smaller impacts on young people than on old people. This finding is consistent with a previous study which estimates the monthly effect of air pollution on mortality using the 2008 Beijing

[14] For example, the Chinese CDC reports that more than 50% of Chinese men smoke, but only 2.7% of women smoke in 2015. The report can be accessed at: http://www.tcrc.org.cn/UploadFiles/2016-03/318/201603231215175500.pdf.

Olympic Games as a natural experiment (He et al., 2016). We also stratify the sample by age and location and find the results are driven by old people in rural areas.

Table 8 present the heterogeneity analysis for IV estimates. Panel A shows that a 10-point AQI increase leads to a 5.86 percent increase in morality in rural areas, while no significant effect is found in urban areas. Panel B indicates a similar mitigating effect of wealth on air pollution impact: consistent positive impact is only found only in the low-income group, based on GDP per capita. Panel C still shows that only males' mortality rate increases as the AQI suddenly rises. Panel D shows that only people older than 60 are affected by short-term air pollution change: a 10-point AQI increase leads to a 2.61 percent increase in mortality rate.

7. Comparison with Related Studies in the Literature

Existing epidemiological estimates largely focus on individual air pollutants such as $PM_{2.5}$ instead of an index like the AQI. As discussed in Appendix A2, the AQI is calculated based on the maximum pollutant concentration among six criteria air pollutants. In calculating the AQI, the primary pollutant is defined as the one with the maximum concentration. During our sample period, $PM_{2.5}$ is the primary pollutant over 90 percent of the time. Within two weeks before and after the threshold, $PM_{2.5}$ is also the primary pollutant for over 90 percent of the time. Presumably, the health impacts of the AQI are driven by the primary pollutant (i.e., $PM_{2.5}$). Therefore, we replace the main explanatory variable, the AQI, by $PM_{2.5}$ concentrations and generate results that can be used for comparison.

Table 9 presents the 2SLS results for $PM_{2.5}$ concentrations. Columns (1) and (2) present results using 2SLS, where the heating-on dummy is an excludable instrument for PM (after controlling for other factors, including the polynomial function in weeks). Columns (3) and (4) present local linear results. The local linear estimate of column (4) suggests that an additional 10 $\mu g/m^3$ of exposure is associated with a 3.9 percent increase in mortality rate. We also estimate the impacts of $PM_{2.5}$ on cardiorespiratory and non-cardiorespiratory mortality separately and compare the results. We find that the estimates on cardiorespiratory mortality are substantially greater than those on non-cardiorespiratory mortality. A 10-$\mu g/m^3$ increase in $PM_{2.5}$ is associated with a 4 percent increase in mortality from cardiorespiratory diseases. However, we fail to find a significant impact on mortality from non-cardiorespiratory diseases at the 5 percent level.

Many epidemiological studies assess the short-term association between fine particulates and health outcomes. We compare our results with several studies in China, the United States, and other counties. The goal is not to conduct a comprehensive literature review on the estimates, so we primarily focus on time-series estimates published in recent years. Table 10 lists those studies. Zhou et al. (2015) examine the association between smog episodes and mortality in five cities and two rural counties in China in 2013. They find that a 10-$\mu g/m^3$ increase in two-day average $PM_{2.5}$ is associated with a 0.6-0.9 percent increase in all-cause mortality. Shang et al. (2013) review seven $PM_{2.5}$ studies that focus on one to three cities in China including Beijing, Shanghai, Guangzhou, Xi'an, Shenyang, and Chongqing. Their meta-analysis shows that a 10-$\mu g/m^3$ increase in $PM_{2.5}$ concentrations is associated with a 0.5 percent increase in respiratory mortality, and a 0.4 percent increase in cardiovascular mortality. Franklin et al. (2008) examine 27 U.S. communities between 1997 and 2002 and show that a 1.21 percent increase in all-cause mortality was associated with a 10-$\mu g/m^3$ increase in the previous day's $PM_{2.5}$ concentrations. Kloog et al. (2013) study the short-term effects of $PM_{2.5}$ exposures on population mortality in Massachusetts in the United States, for the years 2000–2008. The results show that, for every 10-$\mu g/m^3$ increase in $PM_{2.5}$ exposure, PM-related mortality increases by 2.8 percent. Atkinson et al. (2014) conduct a review of global time series studies of $PM_{2.5}$ and mortality. Based upon 23 estimates for all-cause mortality, they show that a 10-$\mu g/m^3$ increment in $PM_{2.5}$ was associated with a 1.04 percent increase in the risk of death.

Compared with past epidemiological studies, our estimates are substantially larger. Our results show that a 10-$\mu g/m^3$ change in weekly average $PM_{2.5}$ concentrations would lead to a 3.9 percent change in all-cause mortality, and a 4 percent change in cardiorespiratory mortality. The difference suggests that estimates derived from associational approaches may under-estimate the health impacts of air pollution.

However, compared with long-term cohort studies of the effect of $PM_{2.5}$ on mortality (Pope et al., 2002; Pope et al., 2004), our estimates are smaller. In particular, Ebenstein et al. (2017) investigate the long-term effect of the Winter Heating Policy in China and estimate that a 10-$\mu g/m^3$ increase in long-term exposure to particulate matter (i.e., PM_{10}) increases cardiorespiratory mortality by 8 percent, which is greater than the estimate in this study ($PM_{2.5}$ accounts for roughly 70% of PM_{10} in our data). The comparison suggests long-term exposure to air pollution imposes a greater risk to people's health than short-term exposure does.

8. Benefits and Costs of Replacing Coal with Natural Gas for Winter Heating

To deal with the severe air pollution during the winter heating season and its negative health consequences, Chinese governments have initiated ambitious clean energy programs that are meant to gradually replace coal with natural gas as the main fuel for winter heating. The Chinese government also prioritizes household-use natural gas and imposes restrictions for industrial and other usages of natural gas.[15] The strictest restrictions on the use of coal were implemented in the winter of 2017; Beijing and many neighboring cities banned coal heating and switch to gas. These policies were immediately effective in reducing air pollution. For example, compared to the air pollution levels in 2014, the mean $PM_{2.5}$ concentrations in December 2017 was 50% less in Beijing.

The coal replacement plan is controversial. China has abundant resources of coal, but lacks a large supply of natural gas. China imports almost 40% of its natural gas and is expected to import an even larger share in the future (IEA, 2017). Critics argue that a wholesale substitution of coal with natural gas ("shock therapy") would cause natural gas shortages in China or possibly internationally. They argue that "shock therapy" would threaten China's energy security.[16] Concerns are also raised because the higher prices of natural gas will impose hardships on the poor. Critics argue that governments provided subsidies for natural gas are inadequate, and that Beijing's blue skies were at the cost of poor.

Despite these controversies the Chinese governments are working to increase replacement of coal with cleaner energy. According to the "Clean Energy Plan for Winter Heating in Northern China, 2017-2021" from the Ministry of Environmental Protection of China, by 2021 more than 150 million tons of winter-heating coal will be replaced and more than 90% of heating boilers will use cleaner energy such as natural gas or electricity.[17] Beijing, Tianjin and twenty-six other major northern Chinese cities are required to implement the Clean Energy Plan. The substitution of cleaner energy for coal may bring about significant health benefits, but the change can also be

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[15] Natural Gas Utilization Policy (NDRC, 2012) can be accessed from the government website: http://www.gov.cn/gongbao/content/2013/content_2313190.htm.

[16] In the winter of 2017, China faced a serious gas shortage as the governments banned the use of coal as the winter heating fuel. The gas shortage implies that the ambitious energy swap plan was ill-prepared. Many people had to suffer from cold because of the shortage. The MEP then directed local governments to allow households to burn coals if the supply of natural gas was not sufficient. See for example: https://www.ft.com/content/6fbc6dac-db13-11e7-a039-c64b1c09b482.

[17] The plan can be accessed from: http://www.ndrc.gov.cn/zcfb/zcfbtz/201712/W020171220351385133215.pdf.

costly. Here, we provide back-of-the-envelope estimates on the benefits and costs of the policy. While not precise, our estimates give some ideas over the range and magnitude of the costs and benefits of replacing coal with natural gas.

8.1. Averted Deaths from Cleaner Air and Their Values

First we estimate the number of premature deaths that could be averted if air pollution in northern China is reduced by the substitution of natural gas for coal. We compare the AQI values between northern and southern DSP locations during the winter. Using the period from November 15th, 2014 to March 15th, 2015, we find that the average AQI in northern China was 37.6 units higher than that of southern China. We estimate that a 10-point increase in the AQI results in 3.8 percent increase in weekly all-cause mortality rate. Given that the age-adjusted mortality rate per 100,000 is 10.64 in our sample and there are 594 million residents living to the north of the winter heating line according to the 2010 Census, a crude calculation indicates that over 144,000 premature deaths per winter could be avoided if northern residents were not exposed to the extra air pollution caused by burning coal.[18]

Using the value of a statistical life (VSL), expressed as the amount of money that people are willing to pay to reduce their risk of dying, we provide estimates on the monetary value of the averted deaths. Qin et al. (2013) is the only study that estimates the VSL for the Chinese at the national scale and, separately, for urban and rural residents. Using China's 2005 Census data, Qin et al. (2013) estimates that the VSL using the national sample is about 1.81 million RMB. The VSL of urban workers is 3.84 million RMB, which is 4.3 times that of rural workers (0.89 million RMB). Note that these values were derived from 2005 data. As incomes rise, the VSL of the Chinese should, in all likelihood, also rise. We follow the guidelines of OECD (2012) and use an income elasticity of 0.9 for mid-income countries to adjust the VSL. From 2005 to 2016, China' per capita GDP has increased from 1,750 USD to 8,120 USD, a 364% rise in relative scale. That implies that the average VSL of a typical Chinese would be around 5.86 (=1.81*3.64*0.9) million RMB or 0.87 million USD in 2016. An urban Chinese would have a VSL of 12.58 (=3.84*3.64*0.9) million RMB or 1.88 million USD, while a rural resident's VSL would be 2.92 (=0.89*3.64*0.9)

[18] We calculate the averted deaths as follows: mortality rate×northern population×pollution effect on mortality×south-north difference in AQI×weeks in the heating season. We use 16 weeks (from November 15th to March 15th) as the heating season.

million RMB or 0.44 million USD in 2016.[19] In comparison, the VSL of an average American is between 6 million and 10 million USD (Doucouliagos et al., 2014), which is seven to eleven times higher than our calculation. We consider the calculations of the VSL as reasonable and note that the U.S. VSL was a multiple of our Chinese estimate, the multiple of per capita GDP income in the United States was seven times as much as in China in 2016;[20] this approximates the multiple of the American VSL over the Chinese.

Table 11 summarizes our benefit calculations. We first monetarize the benefit of averted premature deaths. Recall that there are an estimated 144,000 more deaths per year as a result of heating with coal; the majority of the deaths are of older people in rural areas. If we use 2.92 million RMB as the VSL for a rural resident, the total monetary value of 144,000 averted rural deaths will be converted to about 420 billion RMB or 62.7 billion USD. We further discount the benefits based on the empirical results that only old people suffered from higher mortality rates upon the start of the heating season. In the literature researchers show that the VSL can be discounted by age (see Aldy and Viscusi (2007) for more details). Therefore, we calculate the monetary value of averted deaths using a discount rate of 70%,[21] which gives us an annual benefit estimate of 126 billion RMB or 18.8 billion USD. This estimate reflects both the rural-urban difference and the young-old gap in the VSL.

Aside from averted premature deaths, improved air quality will also reduce morbidity and defensive expenditures. However, these benefits are generally smaller. We utilize estimates from the literature to quantify the benefits of reduced morbidity and defensive expenditures. Jia Barwick et al. (2017) estimate that a reduction of 10 μg/m^3 in $PM_{2.5}$ would lead to total annual savings of 11.7 billion USD in health spending in China, implying that 4.2 billion USD can be saved in medical spending if northern China's air quality becomes similar to southern China's during the

[19] Throughout the paper, we use the annual average exchange rate between dollar and RMB: 1 dollar for 6.7 RMB.
[20] Per capita GDP in each county is from World Bank national accounts data and OECD National Accounts data which are available at https://data.worldbank.org/indicator/NY.GDP.PCAP.CD.
[21] Discounting VSL by age is controversial in the literature and our estimates should be interpreted with caution. In a 2000 analysis for the Canadian government (Hara and Associates Inc., 2000), the VSL used for the over-65 population was 25% lower than the VSL for the under-65 population. When the US Environmental Protection Agency (EPA, 2003) prepared an illustrative analysis of the Clear Skies Initiative in which it used a VSL estimate for those aged 65 and older that was 37% lower than for those aged 18–64. More generally, European Commission (2001) recommended that its member countries value benefits using VSL levels that decline steadily with age.

winter season. Ito and Zhang (2016) use air filter sales data to estimate the Willingness to Pay (WTP) for clean air, and find that in northern China a household is willing to pay about 43 USD per year for clean air. Aggregating over the relevant population, this amounts to approximately 2.65 billion USD per winter. These estimates aggregate to a total benefit for the reduction in air pollution of at least 26.85 billion USD per winter.

Note that the estimates of benefits above are based on short-term impacts of air pollution. In the long run, exposure to air pollution leads to development of chronic diseases and decreases the life expectancy of northern residents. Ebenstein et al. (2017) estimates that air pollution from the heating systems reduces life expectancy by 3.1 years for northern residents. The life expectancy in China is 76 years. That implies that each year a northern resident loses 3.1/76 years of life expectancy due to air pollution from the heating boilers. The gain in life expectancy would be approximately 24.2 million life years for northern residents if coal is replaced by natural gas. We value each life year as the VSL divided by life expectancy, i.e., 5.86million/76 years = 77.1 thousand yuan (11.5 thousand USD). Therefore, we estimate that the monetary benefit in terms of gains in life expectancy is 1,866 billion RMB (278 billion USD) per year. In other words, the benefits in the long run are substantially higher than in the short run.

8.2. Cost of Replacing Coal with Natural Gas

The cost of replacing coal with natural gas include two main components: 1) expenditures on new stoves and pipelines, and 2) operational expenditures (fuel and maintenance).[22] To the best of our knowledge, the Chinese government did not provide a total cost estimation for the clean energy plans. This presents challenges for our analysis, as we do not have accurate numbers for some important cost components. In the following we make several simplifying assumptions. First, we assume that the change in operational and maintenance costs from coal-fired to gas-fired stoves is negligible.[23] Under the assumption of equal maintenance costs, then the increased fuel cost and infrastructure investments are major costs involved in switching to gas. Second, the estimates for fuel costs are derived from data of survey conducted by Renmin University; we applied them to

[22] Pipeline constructions and new stove installations are heavily subsidized by Chinese governments. Households only pay a negligible amount for replacing their coal-fired stoves. In contrast, households are responsible for covering most of the fuel cost despite subsidies.
[23] There is some evidence that this is not correct; gas-fired stoves are technically more complicated and may have a higher maintenance cost.

all of northern China. Third, we use Beijing's "Coal to Gas" project approved by the Asian Infrastructure Investment Bank (AIIB) to estimate the total cost of the required infrastructure and assume a life expectancy of 20 years.

Xie et al. (2018) conducted a comprehensive survey in a community (660 households) in Beijing and collected detailed information about the costs of replacing coal with natural gas. The community replaced coal-based heating systems with gas-based ones in 2017. According to the survey, the average annual fuel cost for natural gas is around 7,000 RMB for each household for the winter; that is approximately 3,000 RMB more than costs of using coal. Public media also reported fuel cost estimations through interviewing the households who experienced the coal to gas switch. According to the news articles, an average household with a 100 square meters house will spend 2,000 to 4,000 RMB more on fuel cost during the 2017 winter.[24] Northern China has approximately 200 million households. If all of them substitute natural gas for coal, then the total increased fuel cost will be approximately 600 billion (=3000×200 million) RMB or 89.6 billion USD every year.

The Beijing municipal government has submitted a project proposal to the Asian Infrastructure Investment Bank (AIIB) to request a loan for implementing Beijing's 2017-2020 Rural "Coal-to-Gas" Program in 2017.[25] According to the project implementation plan, Beijing will install natural gas infrastructure for 216,751 user households in 510 villages during 2017-2020. The project will cover pipelines, regulator boxes and meters. The total investment proposed for the whole project is 3,318.48 million RMB. We assume that the equipment lasts for 20 year and a 6% interest rate; the annual fixed cost is 285.24 million RMB for 216,751 households. Based on the cost estimation of the pipeline construction in Beijing, installing natural gas infrastructure for 200 million northern households will cost approximately 263 billion RMB or 39 billion USD every year.

Replacing a new gas stove for a household costs from 5,000 to 10,000 RMB. We assume

[24] Many news media report the cost of natural gas: http://www.qdaily.com/articles/48092.html; and http://news.dichan.sina.com.cn/2017/09/07/1248573.html.

[25] The detailed project description can be found on the AIIB's website: https://www.aiib.org/en/projects/approved/2017/air-quality-improvement-coal-replacement.html. The estimates of the total cost are described in the Environmental and Social Management Plan: https://www.aiib.org/en/projects/approved/2017/_download/beijing/environment-social-management-plan.pdf.

the same life expectancy for gas stove and the same interest rate; the annual cost is from 430 to 860 RMB. In total, new stove expenditures will amount to 86 billion to 172 billion RMB or 13 billion to 26 billion USD per year.

In sum, adding up the cost estimates gives us a rough estimate of the total annual cost of replacing coal with natural gas; that is between 949 billion to 1,035 billion RMB or 142 billion to 154 billion USD.

8.3. Discussions

The unsystematic and preliminary benefit-cost analysis presented here suggests that the short-run costs of replacing coal with natural gas are greater than its benefits; but the long-run health benefits seem to substantially outweigh the costs. Nevertheless, one should interpret the cost and benefit estimates with caution because the data available are incomplete and we rely on a number of assumptions that may overly simplify the real-world situations.

Mortality displacement, economic growth, and other factors relating to benefit analyses affect our estimates of the economic impact of air pollution. In the literature, mortality displacement (also referred to as harvesting effect) denotes a temporal or temporary increase in the mortality rate (number of deaths) that is attributable to a sudden deterioration of air quality. After some periods with excess mortality, the overall mortality may decline during the subsequent days or weeks, because the most vulnerable groups have been died. The concern is that the VSL of a healthy individual should be very different from that of a close-to-death individual. Because we are unable to identify the close-to-death individuals and do not discount their VSL of them, our calculation of the short-term health benefits may be overstated. However, the rate of economic growth will positively impact the VSL, somewhat mitigating the effects of the close-to-death individuals. As people become richer the VSL and willingness to pay for clean air of will steadily increase. Air pollution also affects agricultural yields, labor productivity, and tourism; these factors would further increase the benefits of clean air. World Bank (2016) estimates that exposure to ambient and household air pollution causes enormous welfare losses amounting to as much as 7.5 percent of GDP in East Asia; consequently, using these estimate yields greater benefits.

On the cost side, estimates are sensitive to the price of natural gas. The Chinese natural gas market is still embryonic, changing from a regime of regulated prices to a market-based price system during the 12th Five-Year Plan period (2011-2015). Market mechanisms are new to both governments and natural gas suppliers; currently expansion of natural gas consumption still faces significant economic and institutional barriers. The natural gas shortage of the winter of 2017 shows that the market mechanism is far from mature. If in the future the greater demand for natural gas drives up the price, the cost of replacing coal with natural gas will be higher still. In that case, poor households and rural households may become unable to afford cleaner energy. Appropriate governmental policies may be able to alleviate these possible problems and resources should be used to explore ways to ameliorate the problems faced by the poor in the switch to natural gas.

9. Conclusion

This paper estimates the acute effect of air pollution on mortality in a regression discontinuity design based on China's coal-fired winter heating policy. We compare air pollution and mortality rates immediately before and after the winter heating is started, and find that the increased air pollution caused by switching on winter heating results in a higher mortality rate in northern China. Heterogeneity analyses reveal that elevated air pollution has greater impacts on rural residents than on their urban counterparts, affects the old more than the young, and are more detrimental to males than females. We believe the estimates using a sample from the rural areas are closer to the true effects of air pollution because rural residents are less aware of the air pollution impacts and do not adopt avoidance measures.

More than half of the world's population lives in rural areas where accurate air quality information is largely non-existent. Our findings suggest air pollution can impose significant health risks on those people, and failure to take the rural population into account when making environmental policies may result in significant welfare loss.

The sharp comparison between urban and rural areas as well as between poor and rich areas suggests that income inequality has affected Chinese people's quality of life through its impact on individual pollution exposure. Poor people and rural residents are *de facto* disproportionally affected by high levels of air pollution. In addition to short- and long-term health impacts, air pollution exposure could also affect cognitive performance, labor productivity, and human capital accumulation (Chang et al., 2016; Currie et al., 2014; Lavy et al., 2014). Given the differential impacts of air pollution on different socioeconomic groups, future research is warranted to understand causal factors resulting in such drastic differences and to provide policy implications for designing policies that bridge the rich/poor and urban/rural gap.

These results also imply that policies that aim to transfer pollution from urban to rural (or rich to poor) areas should be reconsidered with tighter scrutiny. Presumably, moving polluting firms or industries from urban areas to rural areas can be welfare-improving (in terms of saving more lives) because urban areas have higher population density. However, as shown in our analysis, if the impacts of air pollution are larger in rural areas, then shifting polluting industries from urban to rural areas (or from rich to poor areas), may lead to more deaths. To date, much of the effort to address air pollution in China has focused primarily on urban areas, and our findings highlight the urgency of making a change in the scope of policy coverage.

Together with Chen et al. (2013) and Ebenstein et al. (2017), our findings show that the coal-fired winter heating system significantly affects people’s health, in both the short and long run. Replacing the coal-fired winter heating system is likely to bring about significant health benefits. Our exploratory benefit-cost analysis of China’s coal replacement policy shows that long-term health benefits resulting from using cleaner energy are likely to outweigh the costs.

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Table 1. Summary Statistics

	Overall	Before Winter Heating Starts	After Winter Heating Starts
	(1)	(2)	(3)
Mortality (per 100,000, log)	2.39	2.31	2.47
	(0.33)	(0.30)	(0.34)
Urban	2.32	2.25	2.39
	(0.29)	(0.26)	(0.29)
Rural	2.45	2.37	2.54
	(0.35)	(0.32)	(0.35)
AQI	119.11	99.00	139.22
	(52.19)	(43.29)	(52.60)
Urban	112.71	92.93	132.48
	(47.16)	(39.82)	(45.64)
Rural	124.27	103.88	144.66
	-55.39	(45.33)	(57.04)
Temperature	47.05	61.98	32.12
	(17.65)	(9.39)	(9.43)
Dew Point	31.41	49.12	13.71
	(21.35)	(12.42)	(11.40)
Precipitation	0.05	0.09	0.01
	(0.11)	(0.15)	(0.04)
$PM_{2.5}$ (μg/m^3)	83.97	66.73	101.21
	(46.96)	(38.25)	(48.52)
Observations	3,336	1,668	1,668

Notes: Mortality is age-adjusted mortality per 100K. Temperature and dew point are in Fahrenheit. Precipitation is in inches. The sample period includes 12 weeks before and after winter heating starts in 139 northern Chinese cities/counties. The first column is mean and standard deviation for all 24 weeks. The second column is for 12 weeks before the heating starts. The third column is for 12 weeks after the heating starts. The number of observations for urban and rural areas are 1,488 and 1,848 respectively.

Table 2. RD Estimates of the Impacts of Winter Heating

	Global Polynomial		Local Linear	
	(1)	(2)	(3)	(4)
Panel A: RD Estimates of Winter Heating on AQI				
Heating On	71.29***	55.90***	34.82***	35.97***
	(8.04)	(6.46)	(5.88)	(5.89)
R-Squared	0.55	0.61	0.59	0.63
Panel B: RD Estimates of Winter Heating on Mortality (log)				
Heating On	0.07**	0.08***	0.14***	0.14***
	(0.03)	(0.03)	(0.04)	(0.04)
R-Squared	0.45	0.45	0.70	0.70
Weather Controls	N	Y	N	Y
DSP Fixed Effects	Y	Y	Y	Y
Polynomial Function	Cubic	Cubic	-	-
Observations	3,336	3,336	556	556
Sample	± 12 weeks	± 12 weeks	± 2 weeks	± 2 weeks

Notes: Each cell in the table represents a separate regression. We report OLS estimates of the coefficient on a "heating-on" dummy after controlling for polynomial functions in weeks before/after the cutoff interacted with a "heating-on" dummy in columns (1)-(2). In columns (3)-(4), we include only 2 weeks before and after the heating starts and use a linear interaction term. Standard errors clustered at the DSP location level are reported below the coefficients. * significant at 10% ** significant at 5% *** significant at 1%.

Table 3. The Impacts of the AQI on Weekly Mortality (Log)

	(1)	(2)	(3)	(4)
Panel A. IV Estimates				
AQI (per 10 points)	0.92**	1.49***	3.94***	3.80***
	(0.42)	(0.55)	(1.17)	(1.06)
Panel B. OLS Estimates				
AQI (per 10 points)	1.35***	0.53***	0.21	0.55**
	(0.13)	(0.11)	(0.21)	(0.27)
Weather Controls	N	Y	N	Y
DSP Fixed Effects	Y	Y	Y	Y
Polynomial Function	Cubic	Cubic	Linear	Linear
Observations	3,336	3,336	556	556
Sample	± 12 weeks	± 12 weeks	± 2 weeks	± 2 weeks

Notes: Each cell in the table represents a separate regression. In Panel A, we report the 2SLS IV estimates using "heating-on" as the instrumental variable. In Panel B, we report OLS estimates of the association between the AQI and weekly mortality. The results in columns (1)-(2) include a cubic polynomial in weeks before/after the cutoff interacted with the "heating-on" dummy. The results in columns (3)-(4) include an interaction between weeks before/after the cutoff and the "heating-on" dummy. Standard errors clustered at the DSP location level are reported below the coefficients. * significant at 10% ** significant at 5% *** significant at 1%.

Table 4. The Impacts of the AQI on Mortality: Placebo Results

	IV Estimates per 10 points change in AQI			
	(1)	(2)	(3)	(4)
Panel A. Placebo Tests using Fake Winter Heating				
IV: 3 Weeks before Actual Cutoff	0.98	1.33	0.76	4.93
	(2.17)	(2.53)	(1.04)	(3.29)
IV: 2 Weeks before Actual Cutoff	-0.98	-0.91	-1.69*	-4.47
	(0.68)	(0.87)	(1.02)	(9.21)
IV: 1 Week before Actual Cutoff	-5.26	13.17	-	-
	(4.88)	(32.87)		
IV: Actual Cutoff	0.92**	1.49***	3.94***	3.80***
	(0.42)	(0.55)	(1.17)	(1.06)
IV: 1 Week after Actual Cutoff	0.34	0.57	-	-
	(0.80)	(1.02)		
IV: 2 Weeks after Actual Cutoff	-3.01*	-3.91	-7.12**	-11.68
	(1.72)	(2.73)	(2.92)	(7.12)
IV: 3 Weeks after Actual Cutoff	1.33	1.82	5.93**	31.15
	(0.95)	(1.21)	(2.56)	(36.35)
Panel B. A Placebo Test using Southern Cities				
Fake Cutoff	0.97	0.82	0.83	2.52
(Nov. 15 for all Southern Cities)	(0.69)	(0.55)	(1.02)	(1.78)
Weather Controls	N	Y	N	Y
DSP Fixed Effects	Y	Y	Y	Y
Polynomial Function	Cubic	Cubic	Linear	Linear
Sample	± 12 weeks	± 12 weeks	± 2 weeks	± 2 weeks

Notes: The table presents two placebo tests of IV estimates of AQI effect on mortality. Panel A reports the 2SLS IV estimates using "heating-on" as the instrumental variable at discontinuities at one week shifts from the actual "Heating-on" week. Panel B reports the 2SLS IV estimates using 137 southern cities and counties where no winter heating is provided. The fake "Heating-on" date is set on Nov. 15th. Standard errors clustered at the monitoring DSP level are reported below the coefficients. * significant at 10% ** significant at 5% *** significant at 1%.

Table 5. Assessing the Validity of the Identification: The Impacts of the AQI on Weekly Mortality (Log)

	OLS Estimates				IV Estimates			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A. Estimates with/without DSP Fixed Effects								
AQI (per 10 points)	1.23***	0.53***	1.04***	0.55**	1.12**	1.49***	4.32***	3.80***
	(0.27)	(0.11)	(0.39)	(0.27)	(0.56)	(0.55)	(1.28)	(1.06)
Weather Controls	Y	Y	Y	Y	Y	Y	Y	Y
DSP Fixed Effects	N	Y	N	Y	N	Y	N	Y
Observations	3,336	3,336	556	556	3,336	3,336	556	556
Sample	± 12 weeks	± 12 weeks	± 2 weeks	± 2 weeks	± 12 weeks	± 12 weeks	± 2 weeks	± 2 weeks
Panel B. Estimates with Different Weather Controls								
AQI (per 10 points)	0.21	0.55**	0.51*	0.54**	3.94***	3.80***	3.79***	4.01***
	(0.21)	(0.27)	(0.27)	(0.27)	(1.17)	(1.06)	(1.20)	(1.25)
Weather Controls	None	Linear	Quadratic	Cubic	None	Linear	Quadratic	Cubic
DSP Fixed Effects	Y	Y	Y	Y	Y	Y	Y	Y
Observations	556	556	556	556	556	556	556	556
Sample	± 2 weeks	± 2 weeks	± 2 weeks	± 2 weeks	± 2 weeks	± 2 weeks	± 2 weeks	± 2 weeks

Notes: Each cell in the table represents a separate regression. In Panel A, we show results with and without DSP location fixed effects. In Panel B, we show results with different orders of weather controls. In columns (1)-(4), we report OLS estimates of the association between the AQI and weekly mortality. In columns (5)-(8), we report the 2SLS IV estimates using "heating-on" as the instrumental variable. * significant at 10% ** significant at 5% *** significant at 1%.

Table 6. RD and 2SLS Estimates by Cause of Death

	Global Polynomial		Local Linear	
	(1)	(2)	(3)	(4)
Panel A: RD Estimates of Winter Heating on Mortality				
Cardiorespiratory (per 100,000, log)	0.08**	0.09***	0.14***	0.14***
	(0.03)	(0.03)	(0.04)	(0.04)
Non-Cardiorespiratory (per 100,000, log)	0.03	0.04	0.09*	0.09*
	(0.04)	(0.04)	(0.05)	(0.05)
Panel B: 2SLS Estimates of AQI (10-point) on Mortality				
Cardiorespiratory (per 100,000, log)	1.06**	1.68***	4.05***	3.89***
	(0.46)	(0.60)	(1.28)	(1.15)
Non-Cardiorespiratory (per 100,000, log)	0.41	0.72	2.55*	2.48*
	(0.56)	(0.74)	(1.52)	(1.45)
Weather Controls	N	Y	N	Y
DSP Fixed Effects	Y	Y	Y	Y
Polynomial Function	Cubic	Cubic	Linear	Linear
Observations	3,336	3,336	556	556
Sample	± 12 weeks	± 12 weeks	± 2 weeks	± 2 weeks

Notes: Each cell in the table represents a separate regression. In Panel A, we report OLS estimates of the coefficient on a "heating-on" dummy after controlling for polynomial functions in weeks before/after the cutoff interacted with a "heating-on" dummy. In Panel B, we report the 2SLS estimates of the AQI on mortality using "heating-on" as the instrumental variable. In columns (1) and (2), we include 12 weeks before and after the heating starts. In columns (3) and (4), only 2 weeks before and after the heating starts are included in the sample. Standard errors clustered at the DSP location level are reported below the coefficients. * significant at 10% ** significant at 5% *** significant at 1%.

Table 7. Heterogeneous Impacts of Winter Heating on Mortality

	Global Polynomial		Local Linear	
	(1)	(2)	(3)	(4)
Panel A: By Region				
Urban areas	0.01	0.02	0.05	0.05
	(0.03)	(0.04)	(0.05)	(0.05)
Rural areas	0.11**	0.14***	0.21***	0.21***
	(0.04)	(0.04)	(0.05)	(0.05)
Panel B. By GDP per capita				
0-33.3%	0.13**	0.17***	0.28***	0.28***
(<35,000 CNY)	(0.06)	(0.06)	(0.06)	(0.06)
33.3-66.7%	0.09	0.11**	0.12	0.11
(35,000–67,000 CNY)	(0.06)	(0.05)	(0.08)	(0.09)
66.7-100%	-0.01	-0.00	0.04	0.05
(>67,000 CNY)	(0.03)	(0.03)	(0.04)	(0.04)
Panel C: By Gender				
Male	0.08**	0.09**	0.16***	0.16***
	(0.04)	(0.04)	(0.05)	(0.05)
Female	0.05	0.07	0.11	0.10
	(0.05)	(0.05)	(0.07)	(0.07)
Panel D: By Age Group				
Young People (<60)	0.01	0.02	0.01	0.01
	(0.02)	(0.02)	(0.03)	(0.03)
Old People (>=60)	0.07***	0.09***	0.10***	0.09***
	(0.02)	(0.02)	(0.03)	(0.03)
Weather Controls	N	Y	N	Y
DSP Fixed Effects	Y	Y	Y	Y
Polynomial Function	Cubic	Cubic	Linear	Linear
Sample	± 12 weeks	± 12 weeks	± 2 weeks	± 2 weeks

Notes: Each cell in the table represents a separate regression. We report OLS estimates of the coefficient on a "heating-on" dummy after controlling for polynomial functions in weeks before/after the cutoff interacted with a "heating-on" dummy. Standard errors clustered at the monitoring DSP level are reported below the coefficients. Panel A compares rural with urban areas. Panel B examines locations with different income levels. Panel C estimates the impacts for males and females separately. Panel D explores heterogeneous impacts across age groups. * significant at 10% ** significant at 5% *** significant at 1%.

Table 8. Heterogeneous Impacts of AQI (10 points) on Weekly Mortality

	Models			
	(1)	(2)	(3)	(4)
Panel A: By Region				
Urban areas	0.17	0.40	1.36	1.30
	(0.60)	(0.79)	(1.47)	(1.47)
Rural areas	1.35**	2.18***	6.05***	5.86***
	(0.57)	(0.72)	(1.88)	(1.51)
Panel B. by GDP per capita				
0-33.3%	1.53*	2.59***	7.37***	5.31***
(<35,000 CNY)	(0.78)	(0.98)	(2.52)	(1.38)
33.3-66.7%	1.19	2.28**	3.53	4.50
(35,000–67,000 CNY)	(0.78)	(1.15)	(2.46)	(3.50)
66.7-100%	-0.21	-0.09	1.18	1.17
(>67,000 CNY)	(0.59)	(0.65)	(1.16)	(0.96)
Panel C: By Gender				
Male	1.11*	1.68**	4.63***	4.54***
	(0.58)	(0.77)	(1.55)	(1.46)
Female	0.72	1.29	3.05	2.82
	(0.70)	(0.92)	(1.98)	(1.87)
Panel D: By Age Group				
Young People (<60)	-0.03	0.07	1.36	1.29
	(0.52)	(0.61)	(1.16)	(0.97)
Old People (>=60)	1.38***	1.85***	3.23***	2.61***
	(0.44)	(0.51)	(0.98)	(0.82)
Weather Controls	N	Y	N	Y
DSP Fixed Effects	Y	Y	Y	Y
Polynomial Function	Cubic	Cubic	Linear	Linear
Sample	± 12 weeks	± 12 weeks	± 2 weeks	± 2 weeks

Notes: Each cell in the table represents a separate regression. We report the 2SLS IV estimates using "heating-on" as the instrumental variable. Panel A compares rural with urban areas. Panel B examines locations with different income levels. Panel C estimates the impacts for males and females separately. Panel D explores heterogeneous impacts across age groups. Standard errors clustered at the DSP location level are reported below the coefficients. * significant at 10% ** significant at 5% *** significant at 1%.

Table 9. The Impacts of PM2.5 on Mortality

	2SLS IV Estimates			
	(1)	(2)	(3)	(4)
	Weekly Mortality (% Change)			
$PM_{2.5}$ (per 10 μg/m^3)	0.94**	1.56***	4.09***	3.90***
	(0.43)	(0.57)	(1.24)	(1.10)
	Cardiorespiratory Mortality (% Change)			
$PM_{2.5}$ (per 10 μg/m^3)	1.08**	1.76***	4.21***	3.99***
	(0.47)	(0.62)	(1.34)	(1.18)
	Non-Cardiorespiratory Mortality (% Change)			
$PM_{2.5}$ (per 10 μg/m^3)	0.42	0.75	2.65*	2.55*
	(0.57)	(0.77)	(1.59)	(1.50)
Weather Controls	N	Y	N	Y
DSP Fixed Effects	Y	Y	Y	Y
Polynomial Function	Cubic	Cubic	Linear	Linear
Observations	3,336	3,336	556	556
Sample	± 12 weeks	± 12 weeks	± 2 weeks	± 2 weeks

Notes: Each cell in the table is a 2SLS IV estimates using "heating-on" as the instrumental variable. In columns (1) and (2), we report global polynomial RD estimates. In columns (3) and (4), we report the local linear RD estimates. Standard errors clustered at the monitoring DSP level are reported below the coefficients. * significant at 10% ** significant at 5% *** significant at 1%.

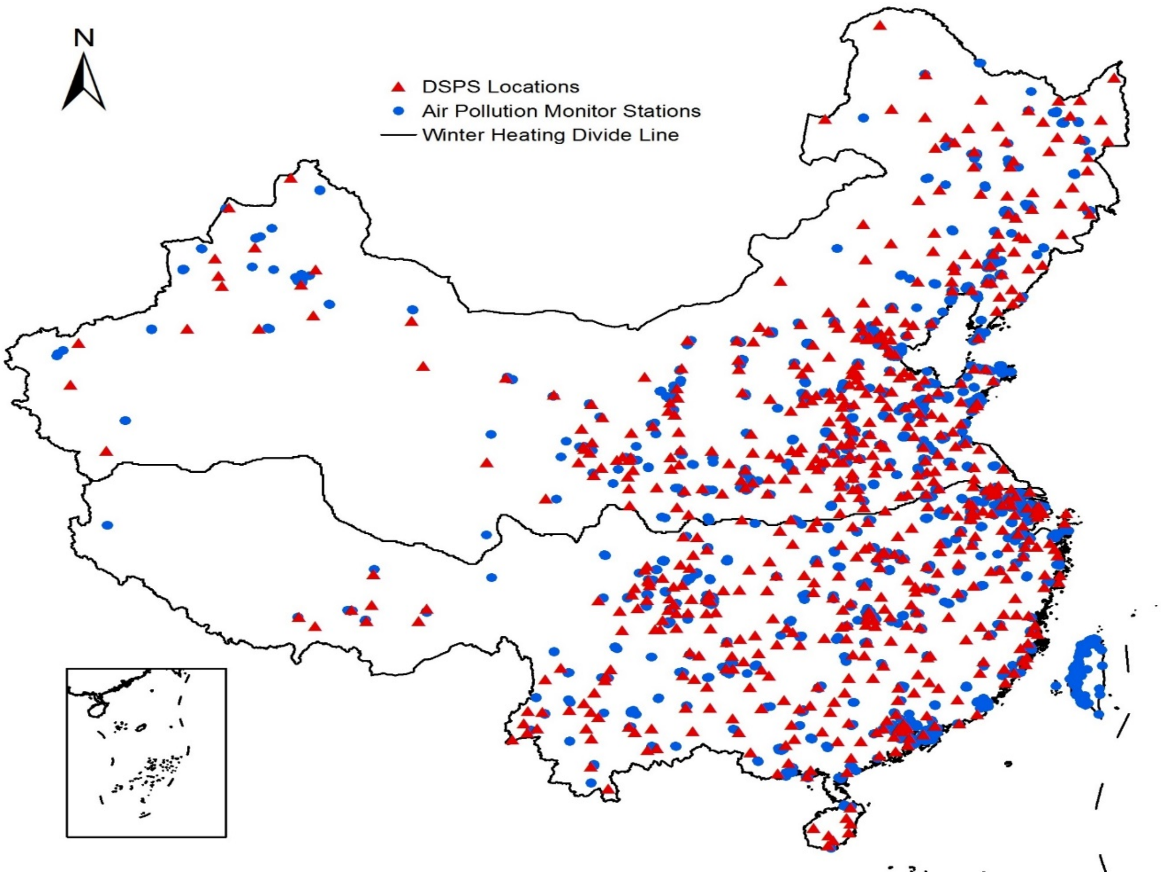
Table 10. Comparisons with Selected Studies of Short-term Effects of PM2.5 on Mortality

Study	Country	Period	Method	Effects
Shang et al. (2013)	China	2004-08	Meta Analysis	A 10-μg/m3 increase in PM2.5 concentrations associated with a 0.5% increase in respiratory mortality and a 0.4% increase in cardiovascular mortality.
Zhou et al. (2015)	China	2013	Multi-City Time-Series	A 10-μg/m3 increase in two-day average PM2.5 concentrations associated with a 0.6-0.9% increase in all-cause mortality in rural China.
Franklin et al. (2008)	USA	2000-05	Hierarchical Model	A 1.21% increase in all-cause mortality associated with a 10-μg/m3 increase in previous day's PM2.5 concentrations. Composition of PM2.5 helps explain the association.
Kloog et a. (2015)	USA	2000-08	Time-Series	For every 10-μg/m3 increase in PM2.5 exposure, PM-related mortality increases by 2.8%.
Atkinson et al. (2014)	World	-	Meta Analysis	A 10-μg/m^3 increment in PM2.5 associated a 1.04% increase in the risk of death. Substantial regional variation observed around the globe.

Table 11. Estimated Benefit of Replacing Coal with Natural Gas For Winter Heating

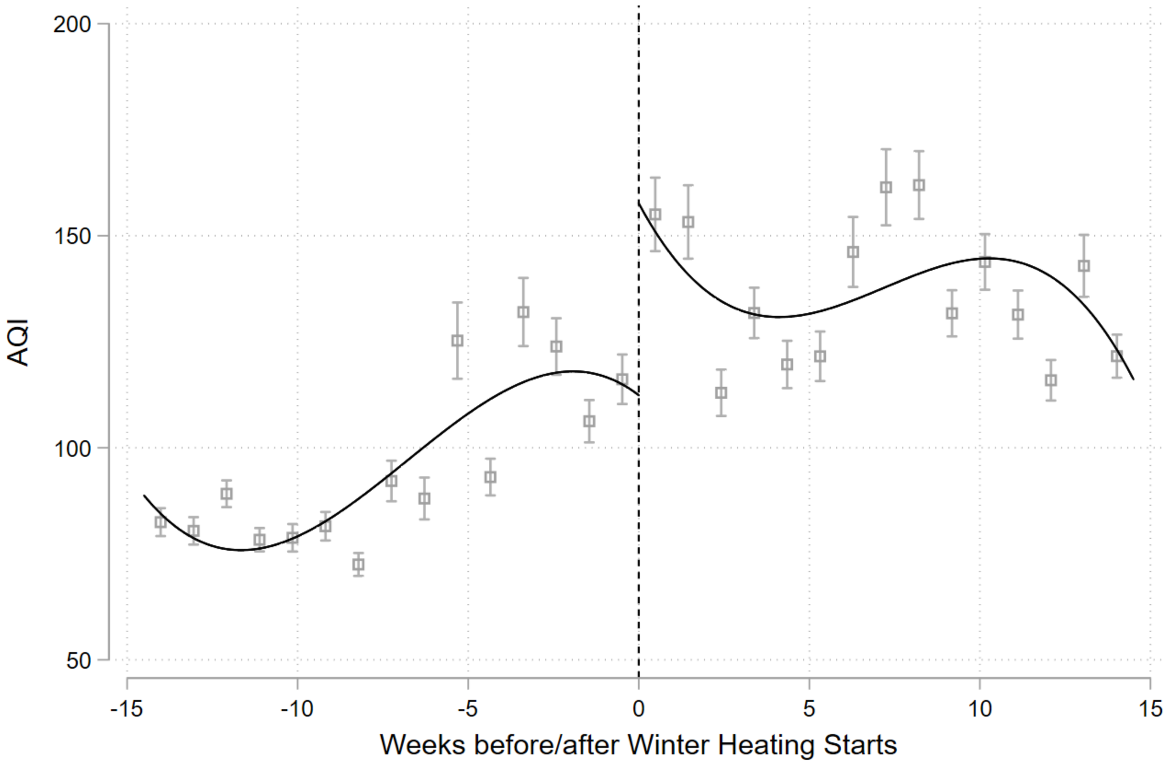
	Effect Size	Source	Calculation	Value
Pane A. Short-term benefit				
Pre-mature Deaths	A 10-point increase in the AQI would cause a 3.8% increase in weekly mortality.	Self-calculation	VSL (2.92 million yuan) * 30% (discounting the VSL of the elderly) *144,000 premature deaths = 126 billion yuan	20 billion USD
Defensive Expenditure	A northern household is willing to pay about 43 USD per year to clean the air.	Ito and Zhang, 2016	43 USD per year * 1/4 (for winter season) * northern Chinese population = 2.65 billion USD	2.65 billion USD
Medical Expenditure	A reduction of 10 μg/m3 in PM2.5 would lead to total annual savings of 11.7 billion USD.	Jia et al. 2017	11.7 billion USD * 1/4 (winter season) * PM2.5 difference between northern and southern China during the winther = 4.2 billion USD	4.2 billion USD
Total				26.85 billion USD
Panel B. Long-Term Benefit				
Life Expectancy	Winter heating casues a 3.1 years losss in life expectancy for Nothern Chinese people	Ebenstein et al. 2017	Life years will be saved each year: 3.1 Years/76 Years * northern population = 24.2 million years; Each life year worth: 5.27 million yuan/76 years = 69.3 thousand yuan/year; Total benefit: 24.2 million * 69.3 thousand = 1,696 billion yuan/year	266 billion USD

Figure 1
Distribution of DSP Locations and Air Pollution Monitor Stations



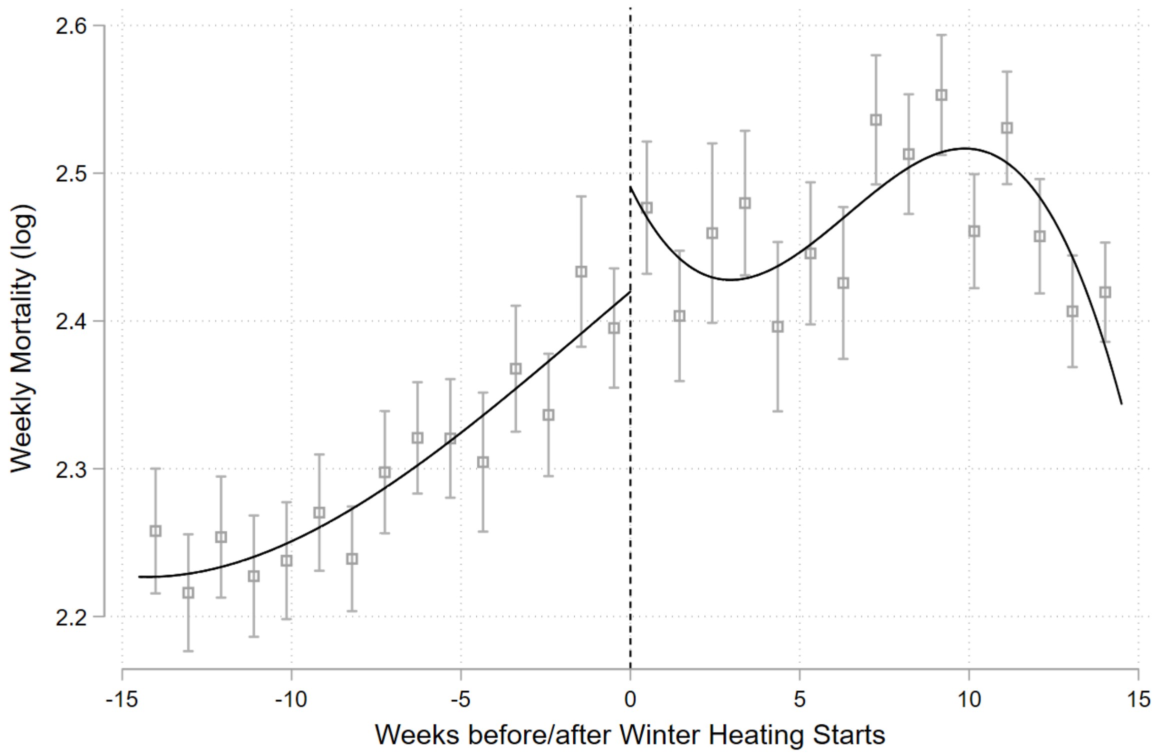
Notes: The red triangles are the DSP locations. Cities north of the solid line are covered by the winter heating policy. The blue dots are the locations of the air pollution monitor stations.

Figure 2
The AQI Before and After Winter Heating Starts



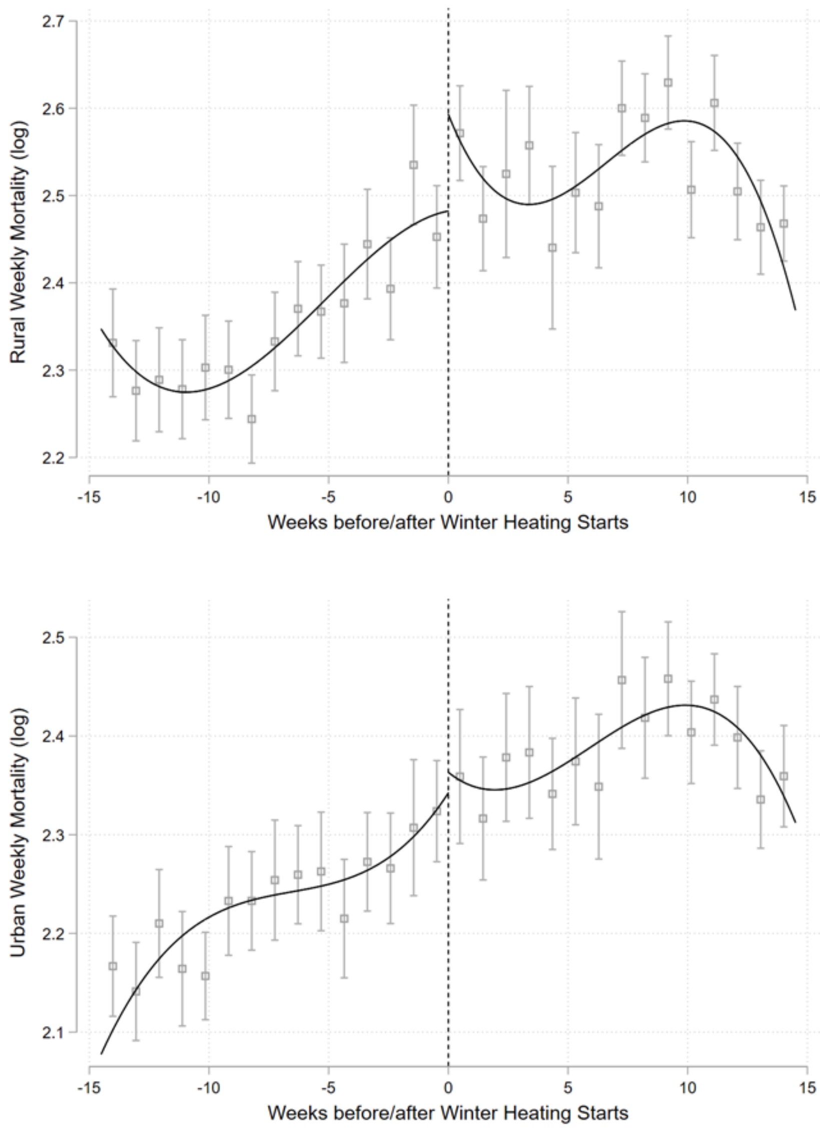
Notes: Each observation (square) is generated by averaging AQI across the DSP locations within a week. The plotted line reports a third order polynomial estimated separately on each side of the cutoff.

Figure 3
Adjusted Mortality Rate (log) Before and After Winter Heating Starts



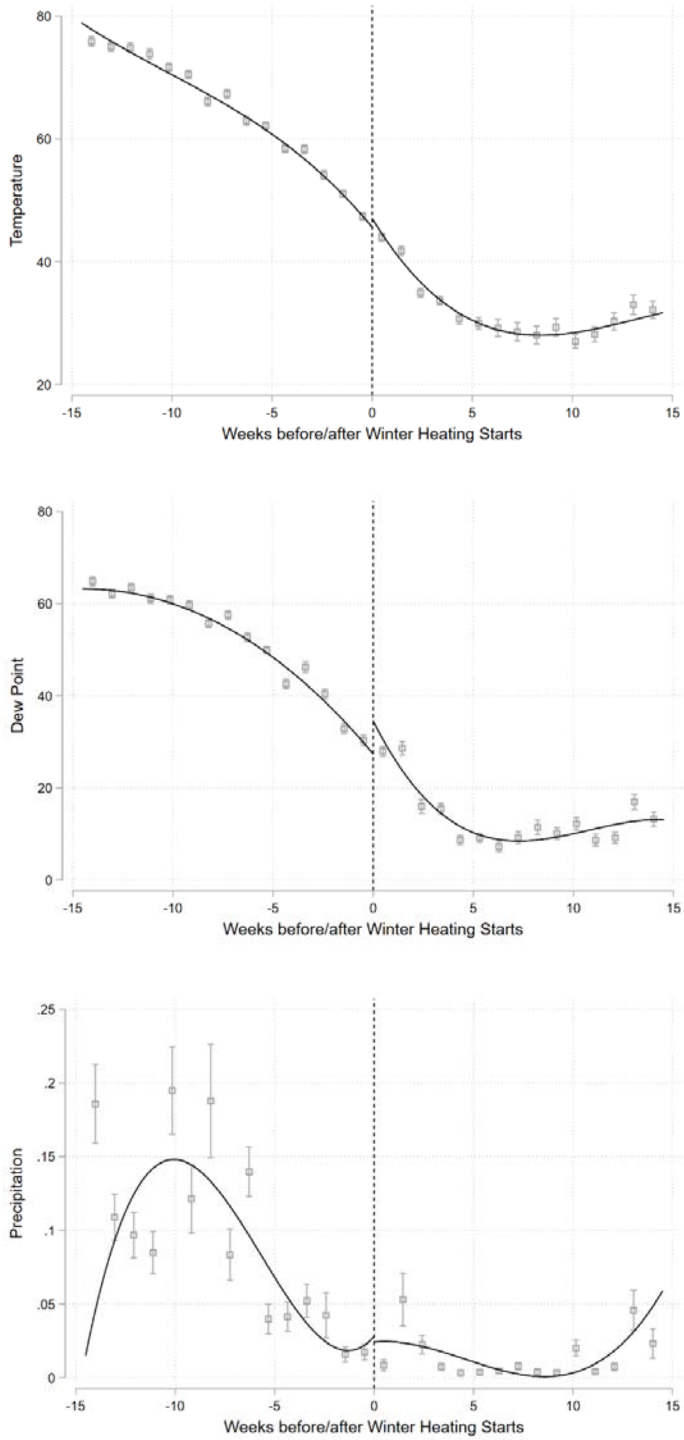
Notes: Each observation (square) is generated by averaging weekly mortality rate across the DSP locations. The plotted line reports a third order polynomial estimated separately on each side of the cutoff.

Figure 4
Rural vs Urban Comparison



Notes: Each observation (square) is generated by averaging weekly mortality rate across the DSP locations. The plotted line reports a third order polynomial estimated separately on each side of the cutoff.

Figure 5
Weather Controls Before and After Winter Heating Starts



Notes: Each observation (square) is generated by averaging weekly mortality rate across the DSP locations. The plotted line reports a third order polynomial estimated separately on each side of the cutoff.

Online Appendix
Winter Heating, Air Quality, and Mortality in China

A1. Disease Surveillance Point System

Our sample of mortality in China is taken from the Disease Surveillance Points System (DSPS) administered by the Chinese Center for Disease Control and Prevention (China CDC). The system started in the late 1970s and was designed to monitor the health status of Chinese people in selected cities and counties because a mortality registration system for all 1.3 billion people was infeasible. In 1990, the system was expanded to 145 DSPs in 31 provinces, based on random sampling to represent the whole population of China. In the early 2000s, the DSPS was overhauled and a new set of 161 DSPs were included in the system starting in 2003. The data quality since 2003 represents a significant improvement in data quality relative to earlier data collected by the DSP during the 1980s and 1990s. In 2013, the Chinese government decided to increase the DSP locations from 161 to 605 to cover a population of 324 million people.

Information on all deaths in the designated DSP locations is collected and reported to the DSPS. If the patient died in a health facility, there is a standard protocol for death registration and reporting. If the patient died at home, the attending doctor (e.g. a community doctor) will follow a standard procedure to fill out a death certificate and report the information to the DSPS. All reported death information is subject to strict quality control procedures for accuracy and completeness. We use 2014-2015 data made available to the research team for this project.

A2. Air Quality Index

Air quality index (AQI) is a quantitative description of the air quality. It tells the public how polluted their air is, and what associated health effects might be a concern for them. The major pollutants involved in the analysis includes fine particulate matter ($PM_{2.5}$), inhalable particles (PM_{10}), sulfur dioxide (SO_2), nitrogen dioxide (NO_2), ozone (O_3), carbon monoxide (CO). All pollutants are measured in micrograms per cubic meter (μg/m^3).

Appendix A2 - Table I. The Thresholds of Individual Air Quality Index

IAQI	Thresholds of Individual Pollutant									
	SO_2 24-hour Average (μg/m^3)	SO_2 1-hour Average (μg/m^3)	NO_2 24-hour Average (μg/m^3)	NO_2 1-hour Average (μg/m^3)	PM_{10} 24-hour Average (μg/m^3)	CO 24-hour Average (μg/m^3)	CO 1-hour Average (μg/m^3)	O_3 1-hour Average (μg/m^3)	O_3 8-hour Average (μg/m^3)	$PM_{2.5}$ 24-hour Average (μg/m^3)
0	0	0	0	0	0	0	0	0	0	0
50	50	150	40	100	50	2	5	160	100	35
100	150	500	80	200	150	4	10	200	160	75
150	475	650	180	700	250	14	35	300	215	115
200	800	800	280	1 200	350	24	60	400	265	150
300	1600	-	565	2 340	420	36	90	800	800	250
400	2100	-	750	3 090	500	48	120	1 000	-	350
500	2620	-	940	3 840	600	60	150	1 200	-	5ool

The scale of AQI for an individual air pollutant is from 0 to 500. The goal is to convert the pollution concentrations into a number between 0 and 500. There are eight thresholds, 0, 20, 100, 150, 200, 300, 400, and 500. Each threshold corresponds to a defined pollution concentration. The pollution concentration between the thresholds is linearly interpolated using the following equation:

$$IAQI_P = \frac{IAQI_{Hi} - IAQI_{Lo}}{BP_{Hi} - BP_{Lo}}(C_P - BP_{Lo}) + IAQI_{Lo}$$

where
$IAQI_P$: individual air quality index for pollutant P.
C_P: the rounded concentration of pollutant P
BP_{Hi}: the threshold greater than or equal to C_P
BP_{Lo}: the threshold less than or equal to C_P
$IAQI_{Hi}$: the AQI corresponding to BP_{Hi}
$IAQI_{Lo}$: the AQI corresponding to BP_{Lo}

The index $IAQI_P$ has a linear relationship with the concentration C_p, with $\frac{IAQI_{Hi}-IAQI_{Lo}}{BP_{Hi}-BP_{Lo}}$ as the slope.

The AQI is determined by the pollutant with the highest index. The pollutant with the maximum individual air quality index (IAQI) is primary pollutant when AQI is greater than 50.

$$AQI = max\{IAQI_1, IAQI_2, IAQI_3, \dots, IAQI_n\}$$

For example, if the PM2.5 AQI is 125, the PM10 AQI is 50, SO2 is 30, NOx is 50, and all other pollutants are less than 125, then the AQI is 125–determined ONLY by the concentration of PM2.5.

The AQI focuses on health effects one may experience within a few hours or days after breathing polluted air. The AQI is divided into six levels in total, with Level one being the best and Level six being the worst.

Appendix A2 - Table II. AQI and Health Implications

AQI	Air Quality	Health Implications
0–50	Excellent	No air pollution.
51–100	Good	Few hypersensitive individuals should reduce the time for outdoor activities.
101–150	Lightly Polluted	Slight irritations may occur, children, and those who with breathing or heart problems should reduce outdoor exercise.
151–200	Moderately Polluted	Irritations may occur, and it may have an impact on healthy people's heart and / or respiratory system, so all people should reduce the time for outdoor exercise.
201–300	Heavily Polluted	Healthy people will be noticeably affected. People with breathing or heart problems will lack exercise tolerance. Those patients, children and elders should remain indoors.
300+	Severely Polluted	Even healthy people will lack endurance during activities. There may be strong irritations and symptoms. So all people should avoid outdoor activities.

Table A1. RD Estimates on AQI with Different Orders of Polynomial

	Models							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Heating On	11.17***	25.37***	21.38***	15.31***	71.29***	55.90***	73.94***	68.00***
	(2.43)	(2.54)	(3.96)	(3.42)	(8.04)	(6.46)	(9.53)	(7.77)
Weather Controls	N	Y	N	Y	N	Y	N	Y
DSP Fixed Effects	Y	Y	Y	Y	Y	Y	Y	Y
Polynomial Function	Linear	Linear	Quadratic	Quadratic	Cubic	Cubic	Quartic	Quartic
R-Squared	0.55	0.61	0.55	0.61	0.59	0.63	0.59	0.63
AIC	33177	32749	33167	32729	32931	32566	32932	32549
BIC	33195	32786	33198	32778	32974	32627	32987	32623
Obs.	3,336	3,336	3,336	3,336	3,336	3,336	3,336	3,336
Sample	± 12 weeks	± 12 weeks	± 12 weeks	± 12 weeks	± 12 weeks	± 12 weeks	± 12 weeks	± 12 weeks

Notes: Each cell in the table represents a separate regression. We report OLS estimates of the coefficient on a "heating-on" dummy after controlling for polynomial functions in weeks before/after the cutoff date interacted with a "heating-on" dummy. We include 12 weeks before and after the heating starts in the sample. Standard errors clustered at the DSP location level are reported below the coefficients. * significant at 10% ** significant at 5% *** significant at 1%.

Table A2. Global Polynomial RD Estimates and IV Estimates for Different Length of Weeks

	Different Samples						
	± 10 weeks	± 11 weeks	± 12 weeks	± 13 weeks	± 14 weeks	± 15 weeks	± 16 weeks
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A: RD Estimates of Winter Heating on AQI							
Heating On	68.36***	63.01***	55.90***	52.27***	39.09***	34.65***	31.56***
	(7.16)	(6.85)	(6.46)	(6.06)	(5.15)	(5.07)	(5.16)
R-Squared	0.65	0.63	0.63	0.62	0.61	0.61	0.60
Panel B: RD Estimates of Winter Heating on Mortality (log)							
Heating On	0.06**	0.09***	0.08***	0.10***	0.09***	0.08***	0.05**
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
R-Squared	0.47	0.46	0.45	0.45	0.45	0.44	0.44
Panel C: IV Estimates of AQI on Mortality (log)							
AQI (per 10 points)	0.91**	1.44***	1.49***	1.85***	2.28***	2.30***	1.69*
	(0.41)	(0.45)	(0.55)	(0.59)	(0.74)	(0.81)	(0.88)
Weather Controls	Y	Y	Y	Y	Y	Y	Y
DSP Fixed Effects	Y	Y	Y	Y	Y	Y	Y
Polynomial Function	Cubic	Cubic	Cubic	Cubic	Cubic	Cubic	Cubic
Observations	2,780	3,058	3,336	3,614	3,892	4,170	4,446

Notes: The table reports OLS estimates of the coefficient on the "heating-on" dummy and the 2SLS IV estimates for different sample periods after controlling for polynomial functions in weeks before/after the cutoff interacted with a "heating-on" dummy. The sample size increases gradually from left to right. Column (3) is corresponding to column (2) in Table 2. Standard errors clustered at the DSP location level are reported below the coefficients. * significant at 10% ** significant at 5% *** significant at 1%.

Table A3. Global Polynomial RD Estimates and IV Estimates for Different Tolerance Distances

	Different Tolerance Distances							
	50KM	75KM	100KM	125KM	150KM	175KM	200KM	Weighted Distance
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: RD Estimates of Winter Heating on AQI								
Heating On	64.29***	60.55***	55.90***	52.10***	48.02***	47.00***	44.99***	47.67***
	(8.12)	(7.60)	(6.46)	(6.09)	(5.56)	(5.34)	(5.24)	(5.76)
R-Squared	0.62	0.63	0.63	0.63	0.63	0.62	0.62	0.63
Polynomial Function	Cubic	Cubic	Cubic	Cubic	Cubic	Cubic	Cubic	Cubic
Panel B: RD Estimates of Winter Heating on Mortality (log)								
Heating On	0.08**	0.07**	0.08***	0.07***	0.07***	0.07***	0.06**	0.08***
	(0.03)	(0.03)	(0.03)	(0.03)	(0.02)	(0.02)	(0.02)	(0.03)
R-Squared	0.50	0.49	0.45	0.44	0.42	0.43	0.41	0.44
Polynomial Function	Cubic	Cubic	Cubic	Cubic	Cubic	Cubic	Cubic	Cubic
Panel C: IV Estimates of AQI on Mortality (log)								
AQI (per 10 points)	1.23**	1.23**	1.49***	1.38***	1.55***	1.39***	1.27**	1.67***
	(0.55)	(0.54)	(0.55)	(0.52)	(0.53)	(0.50)	(0.50)	(0.56)
Weather Controls	Y	Y	Y	Y	Y	Y	Y	Y
DSP Fixed Effects	Y	Y	Y	Y	Y	Y	Y	Y
Observations	1,824	2,640	3,336	4,008	4,728	5,184	5,424	4,344

Notes: In the table we keep DSP locations sufficiently close to a monitoring station and drop others from the sample. For example, in column (1), any DSP location within 50 kilometers of a station is assigned the value at the closest station. We report OLS estimates of the coefficient on a "heating-on" dummy and the 2SLS IV estimates after controlling for polynomial functions in weeks before/after the cutoff interacted with a "heating-on" dummy. Standard errors clustered at the monitoring DSP level are reported below the coefficients. * significant at 10% ** significant at 5% *** significant at 1%.

Table A4. Local Linear RD Estimates and IV Estimates for Different Tolerance Distances

	Different Tolerance Distances							
	50KM	75KM	100KM	125KM	150KM	175KM	200KM	Weighted Distance
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: RD Estimates of Winter Heating on AQI								
Heating On	47.75***	39.46***	35.97***	32.45***	28.96***	28.67***	26.74***	29.66***
	(7.28)	(6.67)	(5.89)	(5.68)	(5.19)	(5.01)	(4.92)	(5.38)
R-Squared	0.77	0.77	0.76	0.75	0.74	0.72	0.73	0.74
Panel B: RD Estimates of Winter Heating on Mortality (log)								
Heating On	0.11***	0.12***	0.14***	0.14***	0.13***	0.11***	0.11***	0.13***
	(0.04)	(0.04)	(0.04)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
R-Squared	0.77	0.74	0.70	0.68	0.68	0.67	0.68	0.68
Panel C: IV Estimates of AQI on Mortality (log)								
AQI (per 10 points)	2.37***	3.05***	3.80***	4.28***	4.51***	3.74***	4.29***	4.48***
	(0.88)	(0.99)	(1.06)	(1.11)	(1.20)	(1.13)	(1.25)	(1.21)
Weather Controls	Y	Y	Y	Y	Y	Y	Y	Y
DSP Fixed Effects	Y	Y	Y	Y	Y	Y	Y	Y
Observations	304	440	556	668	788	864	904	724

Notes: In the table we keep DSP locations sufficiently close to a monitoring station and drop others from the sample. For example, in column (1), any DSP location within 50 kilometers of a station is assigned the value at the closest station. We report OLS estimates of the coefficient on a "heating-on" dummy after controlling for polynomial functions in weeks before/after the cutoff date interacted with a "heating-on" dummy. Standard errors clustered at the monitoring DSP level are reported below the coefficients. * significant at 10% ** significant at 5% *** significant at 1%.

Table A5. RD Estimates of the Impacts of Winter Heating Excluding Beijing

	Global Polynomial		Local Linear	
	(1)	(2)	(3)	(4)
Panel A: RD Estimates of Winter Heating on AQI				
Heating On	65.29***	52.16***	30.53***	33.52***
	(8.12)	(6.66)	(5.89)	(6.09)
R-Squared	0.60	0.64	0.61	0.76
Panel B: RD Estimates of Winter Heating on Mortality (log)				
Heating On	0.07**	0.09***	0.15***	0.14***
	(0.03)	(0.03)	(0.04)	(0.04)
R-Squared	0.44	0.44	0.69	0.70
Panel C: IV Estimates of AQI on Mortality (log)				
AQI (per 10 points)	1.08**	1.65***	4.78***	4.32***
	(0.49)	(0.61)	(1.45)	(1.23)
Weather Controls	N	Y	N	Y
DSP Fixed Effects	Y	Y	Y	Y
Polynomial Function	Cubic	Cubic	-	-
Observations	3,168	3,168	528	528
Sample	± 12 weeks	± 12 weeks	± 2 weeks	± 2 weeks

Notes: Each cell in the table represents a separate regression. We report OLS estimates of the coefficient on a "heating-on" dummy after controlling for polynomial functions in weeks before/after the cutoff date interacted with a "heating-on" dummy in columns (1)-(2). In columns (3)-(4), we include 2 weeks before and after the heating starts and use a linear interaction term. Standard errors clustered at the DSP location level are reported below the coefficients. * significant at 10% ** significant at 5% *** significant at 1%.

Table A6. Heterogeneous Impacts of Winter Heating on AQI

	Models			
	(1)	(2)	(3)	(4)
Panel A: By Region				
Urban areas	57.54***	45.45***	35.17***	35.67***
	(11.81)	(9.82)	(9.09)	(9.57)
Rural areas	82.36***	63.59***	34.54***	35.86***
	(10.90)	(8.48)	(7.77)	(7.32)
Panel B. By GDP per capita				
0-33.3%	87.52***	65.84***	37.88***	53.06***
(<35,000 CNY)	(15.71)	(11.81)	(10.09)	(8.80)
33.3-66.7%	75.53***	48.99***	34.80***	24.62**
(35,000–67,000 CNY)	(14.74)	(11.13)	(10.91)	(11.57)
66.7-100%	54.63***	50.86***	33.50***	42.71***
(>67,000 CNY)	(13.36)	(11.53)	(11.62)	(12.31)
Weather Controls	N	Y	N	Y
DSP Fixed Effects	Y	Y	Y	Y
Polynomial Function	Cubic	Cubic	Linear	Linear
Sample	± 12 weeks	± 12 weeks	± 2 weeks	± 2 weeks

Notes: Each cell in the table represents a separate regression. We report OLS estimates of the coefficient on a "heating-on" dummy after controlling for polynomial functions in weeks before/after the cutoff date interacted with a "heating-on" dummy. Standard errors clustered at the monitoring DSP level are reported below the coefficients. Panel A compares rural with urban areas. Panel B examines locations with different income levels. * significant at 10% ** significant at 5% *** significant at 1%.

Table A7. Urban vs. Rural

	RD				2SLS			
	Global Polynomial		Local Linear		Global Polynomial		Local Linear	
	Urban	Rural	Urban	Rural	Urban	Rural	Urban	Rural
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	By Sex				By Sex			
Male	0.01	0.16**	0.07	0.24***	0.26	2.53**	2.08	6.63***
	(0.05)	(0.06)	(0.07)	(0.06)	(0.99)	(1.09)	(2.06)	(2.09)
Female	0.04	0.11	0.02	0.16	0.82	1.67	0.64	4.51*
	(0.07)	(0.08)	(0.10)	(0.10)	(1.47)	(1.16)	(2.67)	(2.64)
	By Age				By Age			
Young	-0.00	0.02	0.02	0.08*	-0.02	0.47	0.39	2.25
	(0.03)	(0.04)	(0.05)	(0.05)	(0.80)	(0.79)	(1.23)	(1.38)
Old	0.04	0.12***	0.04	0.13***	1.09	2.38***	1.06	3.85***
	(0.03)	(0.03)	(0.04)	(0.04)	(0.68)	(0.67)	(1.14)	(1.09)
Weather Controls	Y	Y	Y	Y	Y	Y	Y	Y
DSP Fixed Effects	Y	Y	Y	Y	Y	Y	Y	Y
Polynomial Function	Cubic	Cubic	Linear	Linear	Cubic	Cubic	Linear	Linear
Sample	± 12 weeks	± 12 weeks	± 2 weeks	± 2 weeks	± 12 weeks	± 12 weeks	± 2 weeks	± 2 weeks

Notes: Each cell in the table represents a separate regression. We report OLS estimates of the coefficient on a "heating-on" dummy after controlling for polynomial functions in weeks before/after the cutoff week interacted with a "heating-on" dummy. Standard errors clustered at the monitoring DSP level are reported below the coefficients. * significant at 10% ** significant at 5% *** significant at 1%.