The Winter Choke: Coal-Fired Heating, Air Pollution, and Mortality in China

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Abstract

China's coal-fired winter heating systems generate large amounts of hazardous emissions that significantly deteriorate air quality. Exploiting regression discontinuity designs based on the exact starting dates of winter heating across different cities, we estimate the contemporaneous impact of winter heating on air pollution and health. We find that turning on the winter heating system increased the weekly Air Quality Index by 36% and caused 14% increase in mortality rate. This implies that a 10-point increase in the weekly Air Quality Index causes a 2.2% increase in overall mortality. People in poor and rural areas are particularly affected by the rapid deterioration in air quality; this implies that the health impact of air pollution may be mitigated by improved socio-economic conditions. Exploratory cost-benefit analysis suggests that replacing coal with natural gas for heating can improve social welfare.

Keywords: Winter Heating Policy, Air Pollution, Mortality, Coal to Gas, Regression Discontinuity

JEL: Q53, I18, Q48

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I. Introduction

China's winter heating policy is one of the largest and most expensive energy welfare policies in the developing world. During the winter-heating seasons, large centralized coal-fired boilers provide free or heavily-subsidized indoor heating to residential and commercial buildings in northern China. As emissions from coal combustion are the major anthropogenic contributor to air pollution in China, these boilers cause a significant deterioration in air quality when they are in use (Xiao et al., 2015). The health impact of this sudden and widespread environmental degradation has not been thoroughly examined.

This paper assesses the impact of winter heating on air pollution and health utilizing regression discontinuity (RD) designs based on the turning-on dates of the heating systems in northern Chinese cities. We collected data on the exact dates when the winter heating systems were turned on for 114 northern Chinese cities from 2014 to 2015; we compare air pollution and mortality levels around the turning-on time. As the dates of turning-on the winter heating systems are pre-determined and arguably orthogonal to other health risk factors (such as weather conditions) that may affect population health, the Chinese winter heating program provides a compelling natural experiment to estimate the causal effects of air pollution on health.

We have three key findings. First, there is strong evidence that air quality deteriorated immediately with the onset of winter heating. On average, we observe the Air Quality Index (AQI) increased by 40 points (36%) at the onset of the winter heating. After further examining the meteorological data, we conclude that the changes in air quality were caused by winter heating, rather than by variations in weather conditions.

Second, we find that the sudden deterioration in air quality caused by winter heating immediately increased mortality. On average, the weekly mortality increased by 14% with the start of the winter heating. This effect is driven mostly by extra deaths from cardiorespiratory diseases, confirming air pollution as the causal factor. Heterogeneity analyses further show that the deterioration in air quality increased mortality rates for the elderly, but not for young people. We find that increased mortality is heavily concentrated among economically disadvantaged groups, i.e. residents in rural and low-income areas.

Third, combining these results, we can estimate the causal impact of air quality on mortality using a fuzzy RD (instrumental variable) framework. Our analysis shows that a 10-point increase in AQI will lead to a 2.2% increase in weekly mortality and that a 10-$\mu g/m^3$ increase in $PM_{2.5}$ concentrations will lead to a 2.5% increase in mortality. This size of the effect is substantially larger than the OLS estimates, suggesting the OLS estimates can be severely biased. In addition, unlike the OLS estimate which is sensitive to the inclusion of and different weather controls, our fuzzy RD estimates are remarkably robust to different specifications, suggesting that the air pollution variations caused by turning on the heating systems are indeed orthogonal to the factors that tend to confound the OLS estimates.

Our findings contribute to the existing literature in four major ways. First and foremost, we are among the first to extend the air pollution effect studies to rural areas and highlight the longoverlooked disparity in air pollution exposure between urban and rural areas. As air quality monitors are often placed in urban areas, the majority of the existing studies focus on outcomes of urban residents, who tend to be richer, more educated, take more avoidance behaviors, and have better access to medical services.[1] Arguably, these factors can reshape the pollution-health relationship, as richer and more educated people may be better informed about the potential harms of pollution and can also get faster access to urgent medical care when necessary. Indeed, when we separately investigate the urban and rural subsamples, we find the effects of air pollution for rural residents are more than 3 times larger than those for urban residents. This suggests that: 1) improving socioeconomic conditions could significantly mitigate the health impact of air pollution; and 2) policymakers should be more cautious about policies/regulations that may transfer pollution from rich urban to poor rural areas, as the health damages of the transfer may be significantly larger for the poor rural areas.

Second, we add to a growing strand of economic research investigating the impact of air pollution on mortality in developing countries. Much of the existing evidence on the air pollution effect comes from developed countries, where the level of air pollution is far below what is observed in some very polluted developing countries such as China and India (see Graff Zivin and Neidell (2013) for a review on the economics literature). [2] As the pollution-health relationship can depend on local socioeconomic conditions and may possibly be non-linear (e.g., Arceo et al., 2016; Lefohn et al., 2010; Smith and Peel, 2010), our estimates are thus more relevant to more than 4 billion people in developing countries who are currently exposed to similar levels of air pollution as in China (mean daily $PM_{2.5}$ concentration is

[1] To the best of our knowledge, the only exception is a concurrent paper from He et al. (2019). He et al. (2019) estimate the impact of air pollution and mortality using straw burning activities as the instrument. They find that straw burning has significant impact on air pollution and health in rural areas but not in urban areas.

[2] Econlit shows only less than 20% of air pollution and health studies focus on developing countries. Studies focus on air pollution and mortality in developing countries include, but not limited to, Jayachandran (2009), Chen et al. (2013), Greenstone and Hanna (2014), He et al. (2016), Arceo et al. (2016), and Ebenstein et al. (2017).

76 μg/m^3 in our data). Additionally, we also document that the fuzzy RD estimates (which reflect the causal relationship rather than an association between air pollution and mortality) are substantially larger than OLS estimates. This implies that there may exist a severe downward bias in associational estimates which are still widely used by both governments and international agencies to establish air quality standards. This echoes a key argument made in a *Science* article: approaches relying on controlling for confounding factors provide unreliable estimates of the air pollution effects and that there is a great need to re-assess the consequences of air pollution at a much larger scale (Dominici et al., 2014).

Third, in terms of the empirical setup, this paper exploits a new identification strategy embedded in China's winter heating policy and provides a different perspective to understanding the costs of coal-fired heating. Previously, both Chen et al., (2013) and Ebenstein et al. (2017), who also studied China's winter heating policy, focused on long-term health outcomes and compared the air pollution levels *across different cities* caused by the policy.[3] We bring the time dimension into this study and use changes in air pollution levels *within the same city* for identification. In doing so, we complement the previous two studies by (1) confirming that winter heating policy indeed degrades air quality in China (using a different source of variation), and (2) showing that the polluted air can bring about immediate disastrous health consequences. This approach can also be used to study other short-term economic and health outcomes, such as morbidity, avoidance behavior, and absenteeism.

Finally, based on the estimates from our study we conducted an exploratory benefit-cost analysis on China's coal replacement policy. In 2014 to deal with the severe air pollution, the Chinese government declared a "war against pollution." Among the various initiatives that attempted to reduce air pollution, the government launched an ambitious plan that planned for phasing out coal-fired boilers, with cleaner energy substuting for coal during the winter in northern China. Following these mandates, in 2017 many places were required to replace coal with natural gas or electricity for heating. As the costs of these substitutes are higher than coal, many people in the areas affected by these substitutions were skeptical about the efficacy of the policy. Combining results of our study and estimates from multiple other sources, we show that while the *long-run* benefits of replacing coal with

[3] The two previous studies estimate the air pollution discontinuity across China's Huai River line, which is the boundary between southern China and the northern region where centralized winter heating systems are provided. The identification strategy in both papers is a cross-sectional RD design based on the geographical discontinuity caused by the Huai River line. This paper provides an alternative design to study the impact of the winter heating policy: turning on the winter heating systems (coal-fired boiler systems) causes an immediate increase in air pollution and damage to health.

natural gas for winter heating are likely to be greater than the costs, the *short-run* benefits are lower than the costs. This suggests that the government policies should be "gradual" and "incremental" in substituting gas/electricity for coal, rather than implementing a "one-fit-all" policy that might engender greater resistance. Ideally, the government should start from regions that have a higher willingness to pay (frequently associated with higher incomes and development) for clean air, and then gradually extend the policy to less developed areas.

The remainder of this paper is structured as follows. Section II provides background on the winter heating system. Section III discusses the data. Section IV presents the empirical strategies. Section V summarizes the main results, conducts a battery of robustness checks, and compare our estimates with other studies. Section VI explores the heterogeneous impacts of air pollution. Section V applies our estimates to the exploratory benefit-cost analysis of China's coal-to-gas policy and discuss potential biases in the calculations. Section VIII concludes.

II. China's Winter Heating System

Following the example of the former Soviet Union's system, China's winter heating system was initiated in the 1950s 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, from October until April. Once the city governments determine when to turn on the winter heating system (it may be one to two months ahead of time), they will announce it to the public. Unless weather conditions change dramatically, the exact date of the winter heating season will not be altered. During our sample period, we did not observe any city changed the dates of winter heating during our sample period.

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 rises substantially, resulting in rapid and substantial increases 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 boilers to estimate the impact of air pollution on health.

As the evidence of the negative impact of air pollution on Chinese health accumulates, there is an increasing demand that governments alleviate air quality. Consequently, the Chinese government initiated various programs to control emissions caused by 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 and initiated there 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 to be gradually replaced by gas or electric boilers in urban areas; households in rural areas will receive subsidies to replace coal stoves with natural gas or electric stoves.[4]

III. Data and Summary Statistics

A. Winter Heating and Air Pollution Data

For our identification strategy, it is crucial to have accurate information about when the winter heating system was started for each city. We collected data for the winter heating period of all the cities in China from city governments' websites. We then verified the winter heating starting dates through local online forums.

[4] 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

To understand how winter heating affects air pollution we collected comprehensive air quality information from the National Urban Air Quality Real-time Publishing Platform.[5] The platform is administrated by China's Ministry of Environmental Protection and publishes real-time Air Quality Index (AQI) and concentrations of criteria air pollutants for all state-controlled monitoring sites.[6]

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 (GB30952012), this platform was put in operation beginning in January 2013, and cities were added to the platform in a staggered manner.[7] We collected data from 1,497 individual air monitoring stations during the sample period (Appendix Figure A1 shows the distribution of air monitoring sites). These stations cover all Chinese prefectural cities and encompass most of China's geography. We computed weekly air pollution data for each monitoring station by taking the mean of the hourly values.

Because local governments in China are given strong incentives to reduce air pollution in China and air quality readings are used by the central government to assess local governments' environmental performance, there is a concern that local governments may manipulate the data. Previously, several studies investigated the air pollution data in China and found suspicious patterns in the distribution of the reported data (e.g. Chen et al., 2012; Ghanem and Zhang, 2014). However, we do not find such evidence in our data, likely due to the new air quality monitoring system (established in 2013) automated the sampling and reporting process of air quality. The new system is able to collect air pollution information in real time and send data to the central government without local interference. Greenstone et al. (2019) find that the automated air quality monitoring system significantly improved the reliability of the air quality data, as evidenced by the levels, variance, and seasonality of reported air pollution measures, as well as the correlation between particulate matter concentration and satellite data.

[5] 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.

[6] Appendix Table 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.

[7] The reporting system covers 338 prefecture-level cities and 1,436 sites across the country by the end of 2015. [8] See Appendix A1 for a detailed description of the sampling and development of the DSP System.

B. Mortality Data

The mortality data come from the Chinese Center for Disease Control and Prevention's (CCDC) Disease Surveillance Points (DSP) system.[8] The DSP system is a remarkably high-quality nationally representative survey and provides detailed cause-of-death data for a coverage population of around 324 million people (nearly a quarter of the total population) 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 CCDC.[8] 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). Following the literature on air pollution and mortality (e.g. Dockery and Pope, 1994; Peng et al., 2006; Schwartz, 1993), we exclude deaths from external causes in our subsequence analysis.[9] We use weekly mortality datasets created for each DSP location in 2014 and 2015 for this project.

C. Weather Data

We obtained daily weather information from the Global Summary of the Day (GSOD).[10] 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.

D. Matching

We matched mortality data with air pollution data and weather data at the DSP location level, following the process of Ebenstein et al. (2017). To assign weekly values of pollution from the monitors to DSP locations, we first identified the centroid of each DSP location (either a city district or a county) and the geographic coordinates of air monitoring stations. Then, we calculated the distance between the monitoring stations and each DSP locations and created a distance matrix. Our measure of air pollution for a DSP location in a week was calculated as follows. If a DSP location was within 50 kilometers of a valid station reading, the nearest station's reading was used. If a DSP location was not

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[8] 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.
[9] The external causes of mortality include ICD 10 codes from V01 through Y99. For example, traffic accidents and other causes of accidental injury.
[10] The GSOD data are available for download from NOAA's website

within 150 kilometers of any of the stations, the DSP location was excluded from the sample. If a DSP location was within 150 kilometers of a station but not within 50 kilometers, the pollution was calculated as the weighted average of air pollution at each monitor with a valid reading within 150 kilometers, with the weights determined by the inverse of the distance between the two points.

We focus on DSP locations in 13 provinces in northern China for our main analysis. Five provinces in northwestern China, namely Gansu, Ningxia, Qinghai, Xinjiang, and Xizang, are excluded because these regions have low population densities and encompass vast swaths of desert, semi-desert, and mountain terrain. The winter heating systems in these regions, while they do exist, are small in scale and do not generate large amounts of emissions that could induce significant changes in air quality.[11]

Appendix Table A3 lists the starting dates of winter heating in all DSP locations in the sample. The majority of the cities started winter heating between mid-October and mid-November. While southern Chinese cities do not have winter heating systems, we used them to conduct a placebo test.

The AQI level can differ substantially across monitoring sites on a weekly basis. The inaccurate assignment of air pollution to DSP locations can potentially introduce measurement error and thus bias the estimates (Sarnat et al., 2005). As such, we checked the robustness of the results by experimenting with different tolerance distances between DSP locations and monitoring sites.

E. Summary Statistics

Table 1 reports the summary statistics for mortality, AQI, temperature, dew point, and precipitation for 114 DSP locations in northern and northeastern China. For each DSP location, we created timeseries data that cover sixteen weeks before and after the starting date of winter heating.[12] In total, we have 3,647 DSP-week observations entering the analysis. The mortality rate was higher in rural areas than in urban areas. The mean AQI during our sample period was 109, with rural air quality slightly worse than urban air quality. The average $PM_{2.5}$ concentration was 76 $\mu g/m^3$, which is more than 7 times higher than the WHO annual standard.

[11] Given that the population density is low in those provinces and the winter-heating system in those provinces only covers a very small portion of the population, the emissions generated from the winter heating system can be quickly dispersed. Empirically, we also find that there is no discontinuity in air quality in these provinces when the winter heating system is turned on.

[12] Most DSP locations start to provide winter heating in November. The sample period covers approximately 8 months from July 2014 to March 2015.

IV. Empirical Strategy

A. The Impact of Winter Heating on AQI and Mortality

We first estimate the impact of winter heating on AQI and mortality using a regression discontinuity design, in which the date serves as the running variable. We examine whether there exist discontinuous changes in air quality and mortality when the winter heating system is turned on using the following specification:

$$PP_{ii,tt} = \beta\beta_1 IItt \geq WWWW_{ii,tt} + \beta\beta_2 \mathrm{f}tt - WWWW_{ii,tt} + \beta\beta_3 \mathrm{I} * \mathrm{f}tt - WWWW_{ii,tt} + \gamma\gamma WW_{iitt} + \theta\theta_{ii} + uu_{ii,tt} \quad (1)$$

$$YY_{ii,tt} = \alpha\alpha_1 IItt \geq WWWW_{ii,tt} + \alpha\alpha_2 \mathrm{f}tt - WWWW_{ii,tt} + \alpha\alpha_3 \mathrm{I} * \mathrm{f}tt - WWWW_{ii,tt} + \theta\theta WW_{iitt} + \theta\theta_{ii} + \epsilon\epsilon_{ii,tt} \quad (2)$$

where $PP_{ii,tt}$ and $YY_{ii,tt}$ respectively indicate the air pollution and mortality in location *i* at time *t*. $II(tt \geq WWWW_{iitt})$ is an indicator variable that equals one if the winter heating system is turned on in location *i* at week *t*. $tt - WWWW_{ii,tt}$ represents the number of weeks from the turning-on date and is our running variable. The specification includes a function $\mathrm{f}tt - WWWW_{ii,tt}$ and allows its effect to differ before and after the turn-on date, which is the basis of the "control function" style approach of the RD design. WW_{iitt} are weather controls correlated with air pollution, including temperature, precipitation, and dew point. $\theta\theta_{ii}$ indicates DSP location-specific fixed effect, and $uu_{ii,tt}$ and $\epsilon\epsilon_{ii,tt}$ are the error terms.

We can assess the sensitivity of the results to several functional forms for f, using both nonparametric and parametric methods. In this paper, we emphasize the results from the non-parametric approach, as the parametric RD approach is found to have several undesirable statistical properties (Gelman and Imbens (2019). In practice, the choice of bandwidth in the non-parametric estimation involves balancing the conflicting goals of focusing on comparisons near the turning-on dates of winter heating, where the identification assumption is strongest, and providing a large enough sample for reliable estimation. We choose the optimal bandwidth and correct the bias caused by small bandwidth following Calonico et al. (2014) and Calonico et al. (2019). Robust standard errors are clustered at the DSP level. To control for DSP fixed effects and weather conditions in the nonparametric estimation, we adopt a two-stage approach following Lee and Lemieux (2010). First, we residualize the outcome variable by absorbing DSP fixed effects and weather variables through OLS regressions. Then, we apply the local linear RD to the residualized outcome.

The parameters of interest are β_1 and α_1, which provides an estimate of whether there exist discontinuities in air pollution and mortality levels immediately after winter heating starts, after flexible adjustment for the week before/after the turn-on dates and the covariates. If unobserved determinants of $P_{i,t}$ and $Y_{i,t}$ are uncorrelated with the exact dates when the heating system is turned on, the estimated β_1 and α_1 reveals the causal effect of winter heating on $P_{i,t}$ and $Y_{i,t}$.

One may be concerned that winter heating itself may affect mortality. For example, the increased indoor temperature (due to heating) will be beneficial to human health and should lower mortality rates. If this were the case, what we capture in the RD design would be a lower bound of the air pollution effect. In other words, if the potential health gain from warmer indoor temperature can be properly controlled, we should observe an even greater impact of air pollution on mortality. [13] However, we will show evidence that the air pollution effect is unlikely to be confounded by potential indoor temperature change.

B. The Impact of AQI on Mortality

We use a fuzzy RD approach to estimate the impact of air quality on mortality. In the simplest form, the fuzzy RD approach assesses the impact of a binary treatment where the probability of treatment rises at some threshold, but being above or below the threshold does not fully determine treatment status. In our context, exposure to air pollution increases significantly when winter heating starts, but pollution exists before the winter heating starts, making our context naturally analogous to a fuzzy RD.[15] The fuzzy RD approach produces estimates of the impact of units of the AQI on mortality, so the results can be applicable to other settings (e.g., other developing countries with comparable air pollution levels).

Note that the estimated effect is not a laboratory-style estimate of the consequences of exposure to air pollution where all other factors are held constant. Instead, it already reflects individuals' actions to protect themselves from the resulting health problems of pollution. While the laboratory-style

[13] The mean temperature when the winter heating system was turned on in our sample was about 49 degrees Fahrenheit (9.4 degrees Celsius). In a separate project, we estimated the temperature-mortality relationship in major Chinese cities and find that low temperature does not lead to excess deaths until it goes below 32 degrees Fahrenheit (or 0 degrees Celsius). These results are available upon request. [15] See Calonico et al. (2014) for more details.

estimate might be of interest to pure scientists who want to know the pathology of air pollution effect, its relevance for understanding the real-world consequences is less clear.

V. Main Results

A. Visualizing the Data using RD Plots

Before turning to the estimation results, we visualize the patterns of air pollution and mortality in the data. In Figure 1, we plot the AQI changes over time. The Y-axis indicates the weekly AQI and the X-axis indicates the number of weeks before and after the threshold. We plot the polynomial fit of AQI, along with the 95% confidence interval, against weeks around the threshold. It is apparent that there is a large increase in AQI immediately after the heating period starts.

In Figure 2, we fit the mortality data. We also observe that the mortality rate jumps upward to a higher level when the heating system is on. Compared with the AQI data, the mortality data are less volatile. Nevertheless, the shapes of the two fitted curves are similar, suggesting that air quality may be an important determinant of mortality on a weekly basis.

In Figure 3, we separately look at the cardiorespiratory (Panel A) and non-cardiorespiratory mortality (Panel B).[14] As air pollution affects primarily cardiorespiratory diseases (Ebenstein et al., 2017; He et al., 2016), we expect to observe a significant discontinuity in cardiorespiratory mortality, but not in non-cardiorespiratory mortality. Figure 3 confirms this conjecture: we observe that only cardiorespiratory mortality significantly increased after the heating system is turned on.

In Figure 4, we plot the RD graphs for the weather variables which are important confounders in estimating the short-term health effects of air pollution as they can affect both air pollution and human health. We cannot visually detect major changes in these variables, suggesting that our findings in Figures 1 to 3 are unlikely to be driven by temporary weather changes.

B. The Impacts of Winter Heating on AQI and Mortality

Table 2 presents the estimated discontinuities of the AQI and mortality rates at the threshold. Columns (1)-(3) summarize the bias-corrected RD estimates and the robust standard errors following Calonico

[14] 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, H65H66), lung cancers (C33-C34), and cardiovascular diseases (I00-I99). Non-cardiorespiratory mortality includes all other causes except injuries (V01-Y89).

et al. (2014). All estimations use the Epanechnikov kernel.[15] The DSP location fixed effects are included in column (2), and both the DSP location fixed effects and weather controls are included in column (3). The DSP fixed effects control for location-specific socio-economic (e.g. the number of health facilities, availability of medical services, and income) conditions that do not vary in the short run. Weather conditions are important confounding factors that may affect the mortality rate. For comparison, column (4) presents the conventional RD estimates with traditional standard errors. Each RD estimate also has the optimal bandwidth for both sides of the threshold.

We emphasize the estimates from the most comprehensive specification with the most conservative standard errors (column (3)). In Panel A, we find that winter heating increases the AQI by 40 units; this translates into a 36% increase at the threshold (the mean AQI in the week before winter heating is 110). Panel B estimates the impact of winter heating on overall mortality and finds that turning on winter heating increases overall mortality by 14%. Panels C and D report the results separately for cardiorespiratory and non-cardiorespiratory mortality. 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 more modest and statistically insignificant. These results echo the graphical analyses that winter heating can cause a significant deteriorate in the air quality in northern Chinese cities and cause an increase in mortality due to cardiorespiratory diseases.

Note that the estimated coefficients are remarkably robust to alternative specifications. In particular, including the DSP location-fixed effects and weather controls has negligible impact on the estimated coefficients. This suggests that time-invariant risk factors and weather conditions are not correlated with the heating indicator around the threshold. Appendix Table A4 provides the RD estimates for each weather variable; there is no statistically significant discontinuity in any of the weather variables, providing additional support for our RD approach.

D. The Impact of Air Pollution on Mortality

Table 3 reports the estimated effects of a 10-point change in the AQI on mortality rates. We present the result in column (3), where both DSP fixed effects and weather conditions are controlled. Panel A shows that for each 10-point increase in the AQI, there is a 2.2% increase in overall mortality. For

[15] Triangle kernel yields quantitatively similar baseline results, but sometimes we cannot obtain convergence in the subsample analyses using triangle kernel.

the cardiorespiratory mortality rate, a 10-point increase in AQI increases mortality by 2.7% (Panel B). In contrast, for the non-cardiorespiratory mortality rate, we fail to observe a statistically significant result (Panel C). Such a difference is consistent with the results in the previous section and indicates that winter heating affects mortality through its impact on air pollution. Again, these findings are remarkably stable and are not affected by the inclusion of different controls and alternative ways to estimate the RD coefficient and standard errors.

For comparison Table 4 presents the OLS estimates. The dependent variable in Panel A is overall mortality. In column (1), we run a single variable regression in which AQI is the only explanatory variable. The estimate 0.016 in column (1) implies that a 10-point increase in AQI is associated with a 1.6% increase in overall mortality. In columns (2), we include DSP location fixed effects in the regressions. In column (3), we add weather controls on top of DSP fixed effects. The addition of weather control significantly reduces the estimate to a much lower level: 0.06. The instability repeats in Panel B and Panel C where the dependent variables are respectively CVR mortality and non-CVR mortality. The fuzzy RD estimates, however, are more stable and considerably larger in magnitude than OLS estimates, suggesting OLS estimates are biased downward possibly due to omitted variable bias and/or measurement error.

E. Robustness Checks

In this section we investigate whether our main results are affected qualitatively by the decisions made in our study along several dimensions; these are available in the Appendix. First, we use the level of AQI and mortality rate as dependent variables and re-estimate the models. We take the log of mortality rates in the main tables because log transformation could reduce the influence of outliers which are not uncommon in weekly mortality rates. Appendix Table A5 has the results using the level instead of the logarithm of mortality rate as the dependent variable. In general, we find that results are similar in sign and magnitude to those in Tables 2 and 3.

Second, we experiment with alternative ways to match between DSP locations and air pollution monitor sites. Appendix Table A6 examines the sensitivity of the results to other choices of acceptable distance from a DSP location to its nearest monitoring stations. Results show that the main findings are stable and not affected by our choice of tolerance distance of matching rules.

Third, we use southern cities to conduct a placebo test.[16] Cities located to the south side of the Huai River do not provide free winter heating. We randomly assign fake winter heating starting dates (used by the northern cities) to southern cities and estimate the impact of the fake winter heating on both AQI and mortality rates. The results are in Appendix Table A7. None of the estimates is statistically significant at the conventional level. This provides supportive evidence for our overall empirical strategy.

Finally, weather conditions are important confounding factors in our study because they may have a direct impact on health (Deschênes and Greenstone, 2011; Deschenes and Moretti, 2009). We want to make sure weather conditions are properly controlled and the functional form of weather variables is carefully considered in our analysis. The main specification controls for weather variables using the linear form. To make sure that the main results are not sensitive to different functional forms of weather controls, we experiment with high-order (up to 4th polynomial) weather controls and present the results in Appendix Table A8. We find the RD estimates with high-order weather controls are consistent with the main results.

F. 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. The AQI is calculated based on the maximum pollutant concentrations among the six criteria air pollutants (Appendix Table A2). In calculating the AQI, the primary pollutant is defined as the one with the maximum concentrations. During our sample period, $PM_{2.5}$ is the primary pollutant over 90% of the time. Presumably, the health impact of the AQI are mostly driven by the primary pollutant (i.e., $PM_{2.5}$). Therefore, we replace the main explanatory variable, the AQI, by $PM_{2.5}$ concentrations to generate results that are comparable to other relevant studies.[17]

Table 5 presents the fuzzy RD results using $PM_{2.5}$ concentrations as the explanatory variable. The sign and magnitude of the estimates are consistent with those using the AQI. We focus on the

[16] We also conducted a difference-in-differences (DiD) analysis using southern cities as the control. However, we find that southern cities are very different from northern cities and neither the air pollution level nor the mortality rate is parallel before the winter heating period. This finding violates the identifying assumption of the DiD approach, so we did not include these results in the paper.

[17] Here we wish to caution readers that the $PM_{2.5}$ results are only used for comparison purposes. Since burning coal produces multiple air pollutants including SO_2, NO_x, and particulates, only looking at $PM_{2.5}$ may lead to biased estimates. For example, when $PM_{2.5}$ is correlated with one or multiple other pollutants, focusing on $PM_{2.5}$ only may result in bias. The direction of the bias depends on the sign of the correlation between the pollutants. [20] We list these studies in the Appendix Table A9.

biascorrected robust estimates in columns (2) and (4). We find that an additional 10 μg/m^3 increase in $PM_{2.5}$ concentration leads to a 2.5% increase in overall mortality rate and a 2.9% increase in cardiorespiratory mortality. However, we fail to find a significant impact on mortality from noncardiorespiratory diseases at conventional levels.

Many epidemiological studies have assessed 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. Since the goal is not to conduct a comprehensive literature review on the estimates, we focus on time-series estimates published in recent years. [20] 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 μg/m^3 increase in two-day average $PM_{2.5}$ is associated with a 0.6-0.9% increase in all-cause mortality. Shang et al. (2013) review seven $PM_{2.5}$ studies that focus on cities in China including Beijing, Shanghai, Guangzhou, Xi'an, Shenyang, and Chongqing. Their meta-analysis shows that a 10 μg/m^3 increase in $PM_{2.5}$ concentrations is associated with a 0.5% increase in respiratory mortality and a 0.4% increase in cardiovascular mortality. Franklin et al. (2008) examine 27 U.S. communities between 1997 and 2002 and show that a 1.21% increase in all-cause mortality was associated with a 10 μg/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 μg/m^3 increase in $PM_{2.5}$ exposure, PM-related mortality increases by 2.8%. 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 μg/m^3 increment in $PM_{2.5}$ was associated with a 1.04% increase in the risk of death. The only economic study that we are aware of and that focuses on $PM_{2.5}$ and mortality is Deryugina et al. (forthcoming). Using changes in wind directions as the instruments, they estimate that a 10 μg/m^3 increase in $PM_{2.5}$ is associated with 1.8% increase in three-day mortality rate per million people aged 65+.

Compared with past epidemiological studies in China, our estimates are substantially larger. Our results show that a 10 μg/m^3 change in weekly average $PM_{2.5}$ concentrations would lead to a 2.5% change in all-cause mortality. However, our estimate is similar in magnitude to Deryugina et al. (forthcoming). The finding that the causal estimate of the air pollution effect is larger than the associational estimate is consistent with several other quasi-experimental studies (e.g. Deryugina et al., forthcoming; He et al., 2016; Schlenker and Walker, 2016). This difference suggests that estimates derived from associational approaches can significantly under-estimate the health impact of air pollution. This 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%, 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.

VI. Heterogeneity

A. Rural-Urban Difference

We first examine how the air pollution effect differs between rural and urban populations. There are several reasons why this heterogeneity is important. First, rural residents in China are substantially poorer than urban residents. As income levels play an important role in determining people's avoidance behaviors and thus the actual air pollution exposure (Ito and Zhang, forthcoming; Sun et al., 2017), rural residents may be disproportionally affected by air pollution. Second, air pollution information is readily available in urban areas, but the same information is difficult to obtain in rural areas.[18] As air pollution information is a key determinant of pollution avoidance and associated health impact (Barwick et al. (2019), we expect the air pollution effect to be larger in rural areas. Third, rural and poor residents often lack immediate access to emergency medical care. When the sudden spike in air pollution triggers strokes, heart attacks, or acute respiratory diseases, they can be more likely to die due to lack of immediate medical treatment.[19] Finally, due to the nature of the work, people working in rural areas have to spend more time outdoors (e.g. work on the field). The total exposure to air pollution of rural residents may be significantly higher than that of urban residents.

[18] For remote rural counties, there is simply no air quality monitoring station. For rural counties close to major cities, the residents can theoretically obtain such information from their nearest urban cities, but doing so requires them to have internet/mobile phone connection, which again is costly with their low income levels.

[19] Cheung et al. (2019) study Hong Kong and find that the air pollution effect has dramatically decreased due to the improvement in the quality of medical services and the availability of emergency service is important.

Table 6 summarizes our findings.[20] We start with the urban population in Panel A; columns (1) and (2) report the RD estimates for AQI; columns (3) and (4) report the RD estimates for mortality; and finally columns (5) and (6) summarize the estimates of the impact of AQI on mortality. We find that winter heating increases both AQI and mortality; this is consistent with our baseline results. A 10-point increase in AQI increases urban mortality by 2.3% for the urban population. In Panel B, we report the results for rural populations. Here there are two findings. First, air quality immediately deteriorated after the heating season began in rural areas, but the change is less dramatic than that in urban areas. This pattern is consistent with air quality changes in rural areas being driven by transboundary pollution from the urban winter heating system, and the air pollutants can be dispersed as they travel. Second element of Panel B is that air pollution has a much greater impact on people's health in rural areas than in urban areas. A 10-point increase in AQI will lead to a 9.3% increase in weekly mortality in rural areas, which is more than three times larger than its impact on urban areas.

The rural-urban heterogeneity suggests an important inequality that is largely overlooked in the literature; the winter heating subsidy is a welfare system that mainly serves urban populations, but in rural areas it causes a sudden increase in air pollution that inflicts a very substantial deterioration in the physical well-being of the adjacent rural population.

One may be concerned that the urban-rural heterogeneity is driven by the winter heating system itself, rather than by income or other channels. As urban people could enjoy the warmer indoor temperature brought by the heating system, this "protective" effect of heating may be large enough to offset the air pollution effect, resulting in a much smaller estimated coefficient using the urban sample. To test this hypothesis, we further divide the urban sample into two equal-size sub-samples based on their GDP per capita in 2014 and estimate the winter heating impact separately for rich and poor urban populations. As reported in Panel C of Table 6, we find that people living in low-income urban areas, who should enjoy the same level of "protection" against cold from the heating system as the richer urban people do, suffer from a greater increase in mortality rate at the onset of winter heating. This comparison exclude the conjecture that the protective effect of winter heating drives the differences

[20] We use the urban/rural definition by the Chinses CDC to create urban and rural subsamples for Table 6. However, some counties are similar to urban areas because the majority of its population live in the county capital. To address this concern, we categorize some CDC designated rural areas as an urban area because they have a large share of urban population (e.g., the share of urban Hukou holders is higher than 0.5) in a robustness check. In other words, all rural counties with more urban Hukou holders are treated as urban areas. We re-estimated the model and the results are similar to those in Table 6. Results are available upon request.

between urban and rural areas and supports the argument that better socio-economic conditions could mitigate the effects of air pollution..

B. Effects by Gender and Age Group

We examine the gender difference in Panel A of Table 7. Columns (1)-(3) summarize the RD estimates of winter heating on mortality, and column (4)-(6) summarize the fuzzy RD estimates of AQI on mortality. We find that the winter heating has a positive and statistically significant impact on mortality rates for both men and women and the effect size is also similar. We estimate that the increase in mortality at the threshold is around 14% and 13% (statistically significant) for females and males respectively. A 10-unit increase in AQI will increase the mortality rate for males and females by 2.9 and 2.4% respectively. The results indicate that men and women are equally likely to die when they suffer from a sudden increase in air pollution.

Second, in Panel B of Table 7, we investigate the impact of winter heating on mortality for different age groups. Our results show that the elderly suffer from air pollution resulting from winter heating. The results indicate that winter heating increases mortality rates by 16% for people older than 60 (column (3)). In contrast, the magnitude of the estimates is much smaller and statistically insignificant for the young group. It is not unreasonable for us to find no impact on young people because we are evaluating the impact of air pollution in a short period of time and young adults are more resilient to short-term air pollution. Based on fuzzy RD results, a 10-unit increase in AQI will increase the mortality rate by 2.5% for the elderly.

VII. 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, the Chinese government has initiated ambitious clean energy programs that are meant to gradually replace coal with natural gas (or electricity in some regions) for winter heating. The coal replacement policy was first piloted in Beijing from 2014 and was later extended to multiple provinces in northern China. In the winter of 2017, Beijing and many cities nearby completely banned coal use for heating and are required to use natural gas instead. It turns out that the coal replacement policy was 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 reduced by 50% in Beijing.

Yet, the coal replacement policy is controversial. China is abundant in coal but lacks a large supply of natural gas. Almost 40% of China's natural gas is imported and it is expected that China will import an even larger share in the future (IEA, 2017). Critics argue that a wholesale substitution of coal with natural gas would cause natural gas shortages in China (or possibly internationally), threatening China's energy security. People are also worried that the unstable supply of natural gas may expose themselves to extreme cold, despite that the Chinese government has prioritized household-use natural gas over industrial and other uses.[21] Concerns are further 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 the poor.

Despite these concerns, Chinese governments are working to increase the 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. [22] 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 has costs. Here, we aim to provide some back-of-the-envelope calculations on the benefits and costs of the policy, using our air pollution effect estimates. While a number of critical assumptions have to be made for such calculations, this exploratory analysis sheds light on the range and magnitude of the costs and benefits of replacing coal with natural gas.

A. Averted Deaths from Cleaner Air and Its Values

For the benefit estimate, we need to estimate the number of averted premature deaths by the substitution of natural gas for coal and assign a value to life. We compare the AQI values between northern and southern DSP locations during the winter. Using the most common winter heating period from November 15th, 2014 to March 15th, 2015, we find that the average AQI in northern China

[21] In the winter of 2017, China faced a serious gas shortage because of the coal ban. People in several cities claimed that they had to suffer from cold due to lack of stable supply of natural gas. The MEP then directed local governments to lift the coal ban and allow households to use coals if the supply of natural gas was not sufficient.
See for example: https://www.ft.com/content/6fbc6dac-db13-11e7-a039-c64b1c09b482.

[22] The plan is described here: http://www.gov.cn/xinwen/2017-12/20/content_5248855.htm.

was 37.6 units higher than that of southern China.[23] We estimate that a 10-point increase in the AQI results in a 2.2% increase in the weekly all-cause mortality rate using the full sample. Given that the age-adjusted mortality rate per 100,000 is 10.98 in our sample and there are 617 million residents living to in the 13 provinces in our study, a crude calculation indicates that 89,664 premature deaths per winter could be avoided if northern residents were not exposed to the extra air pollution caused by burning coal.[24]

There are three critical assumptions in this calculation. First, the RD estimates of the air pollution effects can be applied to the whole winter heating season. Second, differences between northern China and southern China's air pollution levels during the heating season are entirely driven by the winter heating system. Third, natural gas and coal provide the same level of warmth to households, so the averted deaths can be exclusively attributed to reduced air pollution. We acknowledge that all three assumptions can be overly strong, but the advantage is that they make the benefit estimation straightforward.

We explicitly differentiate between "deaths caused by higher levels of air pollution" and "deaths caused by winter heating." The associated counterfactual question we ask is: "what would happen if the level of air pollution caused by the heating system goes down by using cleaner fuel?" not "what would happen if winter heating system does not exist at all?" This differentiation is important because the "protective" effect of winter heating, which is not quite relevant just before and after the turningon dates, can become crucial when the temperatures become very low. What is captured by our RD estimate is the air pollution effect caused by the winter heating system when the temperature is held constant. We reason that replacing coal with natural gas will only affect the pollution: we assume that coal and gas can provide the same level of warmth during winters.

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) estimate

[23] In table 2, we show that winter heating increase the AQI level by 40 units. This suggest that winter heating is a major contributor of the north-south difference in air quality.

[24] We use 2010 China Census to calculate the population and households in 13 provinces in the sample. Those provinces include Anhui, Beijing, Hebei, Heilongjiang, Henan, Inner Mogolia, Jiangsu, Jilin, Liaoning, Shaanxi, Shandong, Shanxi, and Tianjin. We calculate the averted deaths as follows: mortality rate×population in 13 northern provinces×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.

that the VSL using the national sample is about 1.81 million Chinese Yuan (CNY). Note that these values were derived from 2005 data. As incomes rise, the VSL in Chian rises. 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 2015, China's per capita GDP has increased from 1,753 USD to 8,033 USD, a 358% rise in relative scale. That implies that the average VSL of a typical Chinese would be around 7.46 million CNY or 1.15 million USD in 2015.[25] In comparison, the VSL of an average American is between 6 million and 10 million USD (Doucouliagos et al., 2014), which is five to nine times higher than our calculation. We consider the calculations of the VSL as reasonable as per capita GDP in the United States was approximately seven times as large as China in 2015.[29] This approximates the multiple of the American VSL over the Chinese.

Table 8 summarizes our benefit calculations. We first monetarize the benefit of averted premature deaths. Recall that there are an estimated 89,664 more deaths per year as a result of heating with coal; If we use 7.46 million CNY as the VSL for an average Chinese, the total monetary value of 89,664 averted deaths will be converted to about 669 billion CNY or 103 billion USD. We further discount the benefits based on the empirical results that only old people suffered from higher mortality rates. In the literature, discounting VSL is controversial as it assigns different monetary values to different age groups (see Aldy and Viscusi (2007) for more discussions). Leaving aside this controversy, here we discount the VSL of the elderly at 30%; this provides a lower and more conservative estimate fo the benefits.[26] This gives us an annual benefit estimate of 469 billion CNY or 72 billion USD.

Aside from averted premature deaths, improved air quality will also reduces morbidity and defensive expenditures, however, these benefits are genrally smaller. We utilize estimates from the literature to quantify the benefits of reduced morbidity and defensive expenditures. Barwick et al. (2018) estimate that a reduction of 10 $\mu g/m^3$ in $PM_{2.5}$ leads to total annual savings of 9 billion USD in health spending in China, implying that 3.6 billion USD can be saved in medical spending if northern China's air quality becomes similar to southern China's during the winter season. Ito and Zhang (forthcoming) use air filter sales data to estimate the Willingness to Pay (WTP) for clean air and find

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[25] Throughout the paper, we use the annual average exchange rate between dollar and CNY in 2015: 1 dollar for 6.5 CNY. The average Chinese VSL in 2015 is calculated as:1.81*0.9*8033/1753=7.46 million CNY (1.15 million dollars). [29] 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.

[26] 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)

that in northern China a household is willing to pay about 32.7 USD per year for clean air. Aggregating over the relevant population and average household size, this amounts to approximately 1.75 billion USD per winter. These estimates aggregate to a total benefit for the reduction in air pollution of at least 5.35 billion USD per winter.

Note that the estimates of benefits above are based on the short-term impact of air pollution. In the long run, exposure to air pollution leads to the development of chronic diseases and decreases the life expectancy of northern residents. Ebenstein et al. (2017) estimate 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 25.5 million life-years for northern residents if coal is replaced by natural gas. Using the same VSL, we can calculate the value of per life-year: 5.83million/76 years = 76.7 thousand CNY. We estimate that the monetary benefit in terms of gains in life expectancy is 1,956 billion CNY (301 billion USD) per year. In conclusion, the long-run benefits of improving air quality is substantially higher than the short-run benefits.

B. Cost of Replacing Coal with Natural Gas

The cost of replacing coal with natural gas includes two main components: 1) expenditures on new stoves and pipelines, and 2) operational expenditures (higher fuel cost and maintenance).[31] To the best of our knowledge, the Chinese government did not provide a total cost estimate for the clean

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.

[31] 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.

energy plans. This presents some challenges for our analysis, as we do not have accurate numbers for some important cost components. In the following analysis, we make several assumptions to simplify the calculation. First, we assume that the change in operational and maintenance costs from coal-fired to gas-fired stoves is negligible. [27] Under the assumption of equal maintenance costs, then the

[27] In practice, the cost to maintain gas-fired stoves can be slightly higher because they are technically more complicated.

[33] Local governments often provide subsidies to households to help them reduce the burden of higher fuel cost. The

increased fuel cost and infrastructure investments are major costs involved in switching to natural gas. Second, we borrow estimates for fuel costs from survey data collected by a research team from Renmin University and apply them to all of northern China (Xie et al., 2018). 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 of the facility.

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 CNY for each household for the winter (including government subsidy), which is approximately 3,000 CNY more than the costs of using coal.[33] We also collect data from multiple news article reports in which households were interviewed. Based on the news reports, an average household with a 100 square meters house would spend 2,000 to 4,000 CNY more using natural gas during the 2017 winter.[28] The 13 northern provinces have approximately 214 million households. If all of them substitute natural gas for coal, then the total increased fuel cost will be approximately 642 billion (=3000×214 million) CNY or 98.8 billion USD every year.

For infrastructure cost, the Beijing municipal government 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.[29] According to this plan, to install natural gas infrastructure for 216,751 user households in 510 villages during 2017-2020, Beijing will require a total of 3,318.48 million CNY to cover pipelines and meters. We assume that the equipment lasts for 20 years with a 6% interest rate; then the annual fixed cost is 285.24 million CNY for 216,751 households. Based on the cost estimation of the pipeline construction in Beijing, installing natural gas infrastructure for 214 million northern households will cost approximately 282 billion CNY or 43 billion USD every year.

Installing a new gas stove for each household costs an additional from 5,000 to 10,000 CNY. If we assume the same life expectancy for gas stove and the same interest rate, the annual costs range from 430 to 860 CNY. In total, new stove expenditures will amount to 92 billion to 184 billion CNY

amount of the subsidy varies across different cities, with the average being about 1,000–1,200 CNY per season per household.

[28] For example: http://www.qdaily.com/articles/48092.html and http://news.dichan.sina.com.cn/2017/09/07/1248573.html.

[29] 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

or 14 billion to 28 billion USD per year. Adding these cost estimates gives us a rough estimate of the total cost of replacing coal with natural gas; the cost estimates range from 1,016 billion to 1,108 billion CNY (or 156 billion to 170 billion USD) each year to use natural gas for winter heating.

Comparing cost estimates with the benefit estimates, we see that the costs of replacing coal with natural gas (156 billion to 170 billion USD) are greater than the benefits (77.35 billion USD) in the short term; but the long-run health benefits (301 billion USD) still significantly outweigh the costs. In conclusion, policymakers should anticipate potential backlash in implementing these changes because the costs of the switch are quite substantial and it takes a long period to reap the total benefits of lowering air pollution.

C. Potential Biases

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 real-world situations. In particular, mortality displacement, economic growth, and other factors relating to benefit analyses may affect our estimates of the impact of air pollution.

First, mortality displacement (also referred to as harvesting effect) denotes a 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 died. However, existing evidence in the literature does not support this argument. In the environmental epidemiology literature, a large number of studies have examined the dynamic pattern of mortality response to air pollution and the general finding is that air pollution-induced deaths cannot be attributed to temporal mortality replacement (Zanobetti and Schwartz, 2008; Zanobetti et al., 2002; Zanobetti et al., 2000). Notably, when one includes the lagged pollution measure in the time-series regressions or when one uses more aggregated outcome measures (from daily to weekly, monthly, or yearly), the estimated effect of air pollution actually becomes stronger rather than weaker. In other words, the short-term estimates tend to underestimate, instead of overestimating the health effect of air pollution.

Second, the rate of economic growth will positively affect the VSL. As people become richer, the willingness to pay for clean air and their VSL will 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 estimates 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, the 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 its 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.

VIII. Conclusion

This paper utilizes China's winter heating policy as an RD design to evaluate the contemporaneous effect of air pollution on mortality. We examined the changes in air quality and mortality at the onset of winter heating and find that the increased air pollution caused by turning on winter heating results in higher mortality rates in northern China. Heterogeneity analyses show that elevated air pollution has greater impact on poor and rural residents than on their richer and urban counterparts and is more harmful to old people.

The results provide the first evidence of the impact of the periodic increases in air pollution caused by winter heating. We show that air pollution imposes more significant health risks on poor/rural people relative to rich/urban people. Failure to take the disparities in pollution effects into account when making environmental policies may result in significant welfare losses. More than half of the world's population lives in rural areas where accurate air quality information is largely nonexistent. More broadly, this suggests that policies that move polluting firms or industries from urban areas to rural areas need to be re-assessed, as the impact of air pollution can be greater in rural areas.

Chinese governments have planned to convert coal to gas for winter heating to reduce air pollution in northern China by 2021. Even though the energy transition in Beijing effectively reduced air pollution, the policy is still controversial and the public questions whether the benefits are worth the costs. Combining findings from this study and several other studies, we provide back-of-the envelope calculations on the benefits and costs of the policy. Our exploratory analyses show that while the long-term health benefits still outweigh the costs, the short-term benefits are lower than the costs. We thus recommend the government adopt a "gradual" reform, prioritizing regions with higher income and willingness to pay for clean air when making the transition.

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Table 1. Summary Statistics

		Mean	Std. Dev.	Min	Max
	Obs.	(1)	(2)	(3)	(4)
Mortality	3,647	10.98	3.82	1.20	54.56
Urban	1,344	10.43	3.40	3.14	44.70
Rural	2,303	11.30	4.02	1.20	54.56
CVR	3,647	7.92	3.07	0.61	37.38
Non-CVR	3,647	3.05	1.43	0.00	19.47
AQI	3,647	109.24	45.44	7.04	301.51
Urban	1,344	104.24	44.24	18.20	301.51
Rural	2,303	112.16	45.89	7.04	300.40
$PM_{2.5}$ ($\mu g/m_3$)	3,645	75.95	39.85	5.04	279.23
Temperature	3,647	49.31	19.84	-6.11	87.41
Dew Point	3,647	34.80	23.15	-17.56	76.73
Precipitation	3,647	0.06	0.13	0.00	1.49

Notes: Variables are observed at the county (city district) and week level. Mortality data are from China's Disease Surveillance Points (DSP) System. Air quality data are from the National RealTime Air Quality Platform. Weather information is from Global Summary of the Day. Mortality is age-adjusted mortality per 100K. Temperature and dew point are in Fahrenheit. Precipitation is in inches. The full sample includes 114 northern Chinese cities/counties.

Panel A: Winter Heating and AQI

	AQI			
Heating On	30.4**	20.5**	40.0**	43.3**
	(7.3)	(6.5)	(6.8)	(5.7)
Bandwidth (Left)	2.67	2.35	1.96	1.96
Bandwidth (Right)	1.63	1.69	3.95	3.95

Panel B: Winter Heating and Mortality

	Overall Mortality (log)			
Heating On	0.124**	0.134**	0.138**	0.127**
	(0.041)	(0.036)	(0.035)	(0.031)
Bandwidth (Left)	2.81	2.59	2.89	2.89
Bandwidth (Right)	6.00	5.40	5.32	5.32

Panel C: Winter Heating and CVR Mortality

	CVR Mortality (log)			
Heating On	0.135**	0.157**	0.154**	0.141**
	(0.045)	(0.040)	(0.038)	(0.032)

Bandwidth (Left)	2.72	2.44	2.79	2.79
Bandwidth (Right)	5.20	4.66	4.81	4.81

Panel D: Winter Heating and Non-CVR Mortality

		Non-CVR Mortality (log)		
Heating On	0.086	0.079	0.076	0.070
	(0.050)	(0.045)	(0.046)	(0.039)
Bandwidth (Left)	3.57	3.38	3.41	3.41
Bandwidth (Right)	4.94	4.47	4.14	4.14

Table 2. RD Estimates of the Impacts of Winter Heating on AQI and Mortality

		RD Estimates		
	(1)	(2)	(3)	(4)

Notes: Each cell in the table represents a separate RD estimate. The discontinuities are estimated using local linear regressions and MSE-optimal bandwidth selectors proposed by Calonico et al. (2014) and Calonico (2019). Weather controls include temperature, relative humidity, and precipitation. Standard errors clustered at the (DSP) county level are reported below the coefficients. * significant at 5% ** significant at 1%.

Table 3. Fuzzy RD Estimates on the Impacts of the AQI on Mortality

RD Estimates	Bias-Cor. Robust	Bias-Cor. Robust	Bias-Cor. Robust	Conventional
Weather Controls	N	N	Y	Y
DSP Fixed Effects	N	Y	Y	Y
Kernel	Epanech.	Epanech.	Epanech.	Epanech.
Observations	3,647	3,647	3,647	3,647

		Mortality (log)		
	(1)	(2)	(3)	(4)
Panel A: Impact of the AQI on Mortality				
AQI (per 10 points)	0.026**	0.034**	0.022**	0.020**
	(0.008)	(0.010)	(0.007)	(0.006)
Bandwidth (Left)	2.69	2.08	3.03	3.03
Bandwidth (Right)	4.40	3.84	3.53	3.53
Panel B: Impact of the AQI on CVR Mortality				
AQI (per 10 points)	0.037**	0.040**	0.027**	0.024**

	(0.011)	(0.011)	(0.008)	(0.007)
Bandwidth (Left)	2.52	1.90	2.89	2.89
Bandwidth (Right)	4.42	3.76	3.45	3.45
Panel C: Impact of the AQI on Non CVR Mortality				
AQI (per 10 points)	0.012	0.015	0.010	0.010
	(0.010)	(0.013)	(0.009)	(0.007)
Bandwidth (Left)	2.99	2.52	3.06	3.06
Bandwidth (Right)	4.17	3.51	3.56	3.56
RD Estimates	Bias-Cor. Robust	Bias-Cor. Robust	Bias-Cor. Robust	Conventional
Weather Controls	N	N	Y	Y
DSP Fixed Effects	N	Y	Y	Y
Kernel	Epanech.	Epanech.	Epanech.	Epanech.
Observations	3,647	3,647	3,647	3,647

Notes: Each cell in the table represents a separate fuzzy RD estimate. The discontinuities are estimated using local linear regressions and MSE-optimal bandwidth selectors proposed by Calonico et al. (2014) and Calonico (2019). Weather controls include temperature, relative humidity, and precipitation. Standard errors clustered at the (DSP) county level are reported below the coefficients. * significant at 5% ** significant at 1%.

Table 4. OLS Estimates on the Association between the AQI and Mortality

	Overall Mortality (log)		
	(1)	(2)	(3)
Panel A. Overall Mortality			
AQI (per 10 points)	0.016**	0.018**	0.006**
	(0.002)	(0.002)	(0.001)
R -Squared	0.062	0.307	0.390
Panel B. CVR Mortality			
AQI (per 10 points)	0.020**	0.022**	0.008**
	(0.002)	(0.002)	(0.001)
R -Squared	0.082	0.327	0.431
Panel C. Non-CVR Mortality			
AQI (per 10 points)	0.003	0.004**	0.000
	(0.002)	(0.001)	(0.002)
R -Squared	0.002	0.335	0.341
Weather Controls	N	N	Y
DSP Fixed Effects	N	Y	Y
Observations	3,647	3,647	3,647

Notes: Each cell in the table represents a separate OLS regression. Weather controls include temperature, relative humidity, and precipitation. Standard errors clustered at the (DSP) county level are reported below the coefficients. * significant at 5% ** significant at 1%.

Table 5. The Impacts of PM2.5 on Mortality (Log)

	Mortality (log)		CVR Mortality (log)		Non-CVR Mortality (log)	
	(1)	(2)	(3)	(4)	(5)	(6)
$PM_{2.5}$ (per 10 μg/m3)	0.023**	0.025**	0.027**	0.029**	0.012	0.013
	(0.006)	(0.007)	(0.007)	(0.008)	(0.007)	(0.009)
Bandwidth (Left)	2.60	3.04	2.48	2.89	3.54	3.10
Bandwidth (Right)	4.31	3.81	4.55	3.88	4.15	4.13
RD Estimates	Conv.	Bias-Cor. Robust	Conv.	Bias-Cor. Robust	Conv.	Bias-Cor. Robust
Kernel	Epanech.	Epanech.	Epanech.	Epanech.	Epanech.	Epanech.
Weather Controls	Y	Y	Y	Y	Y	Y
DSP Fixed Effects	Y	Y	Y	Y	Y	Y
Kernel	Epanech.	Epanech.	Epanech.	Epanech.	Epanech.	Epanech.
Observations	3,645	3,645	3,645	3,645	3,645	3,645

Notes: Each cell in the table represents a separate RD estimate. All regressions control for weather conditions (temperature, relative humidity, and precipitation) and DSP fixed effects. The discontinuities are estimated using local linear regressions and two different MSE-optimal bandwidth selectors proposed by Calonico et al. (2014) and Calonico (2019). Standard errors clustered at the (DSP) county level are reported below the coefficients. * significant at 5% ** significant at 1%.

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Table 6. Heterogeneous Impacts of Winter Heating and AQI: Urban vs. Rural and Across Income Groups

	RD: AQI		RD: Mortality (log)		Impact of AQI on Mortality	
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Urban Areas						
All Urban	49.7**	51.2**	0.125*	0.139*	0.022*	0.023*
	(10.2)	(12.0)	(0.049)	(0.058)	(0.009)	(0.011)
Panel B: Rural Areas						
All Rural	37.0**	24.4**	0.166**	0.168**	0.068*	0.093**
	(6.5)	(7.6)	(0.043)	(0.051)	(0.028)	(0.032)
Panel C: Decomposing the Urban Results						
High-Income Urban	37.4*	42.2*	0.050	0.047	0.014	0.010
	(16.6)	(19.6)	(0.057)	(0.066)	(0.017)	(0.021)
Low-Income Urban	61.6**	59.1**	0.184*	0.217*	0.024*	0.027*
	(11.9)	(14.5)	(0.081)	(0.099)	(0.010)	(0.012)
	Conv.		Conv.		Conv.	Bias-Cor. Robust

RD Estimates		Bias-Cor. Robust		Bias-Cor. Robust		
Weather Controls	Y	Y	Y	Y	Y	Y
DSP Fixed Effects	Y	Y	Y	Y	Y	Y
Kernel	Epanech.	Epanech.	Epanech.	Epanech.	Epanech.	Epanech.

Notes: Each cell in the table represents a separate RD estimate. All regressions control for weather conditions (temperature, relative humidity, and precipitation) and DSP fixed effects. The discontinuities are estimated using local linear regressions and MSE-optimal bandwidth proposed by Calonico et al. (2014) and Calonico (2019). Panel A summarizes the results using urban population while Panel B reports the rural results. In Panel C, we further split the urban sample into two groups based on the median GDP per capita. Standard errors clustered at the DSP level are reported below the coefficients. * significant at 5% ** significant at 1%.

Table 7. The Impacts of Winter Heating and AQI by Gender and Age Group

	Impact of Winter Heating on Mortality		Impact of AQI on Mortality: Fuzzy RD	
	(1)	(2)	(3)	(4)
Panel A: By Gender				
Male	0.118**	0.125**	0.026**	0.029*
	(0.035)	(0.040)	(0.010)	(0.012)
Female	0.136**	0.143**	0.023**	0.024*
	(0.043)	(0.051)	(0.008)	(0.010)
Panel B: By Age Group				
Old People (>=60)	0.150**	0.158**	0.024**	0.025**

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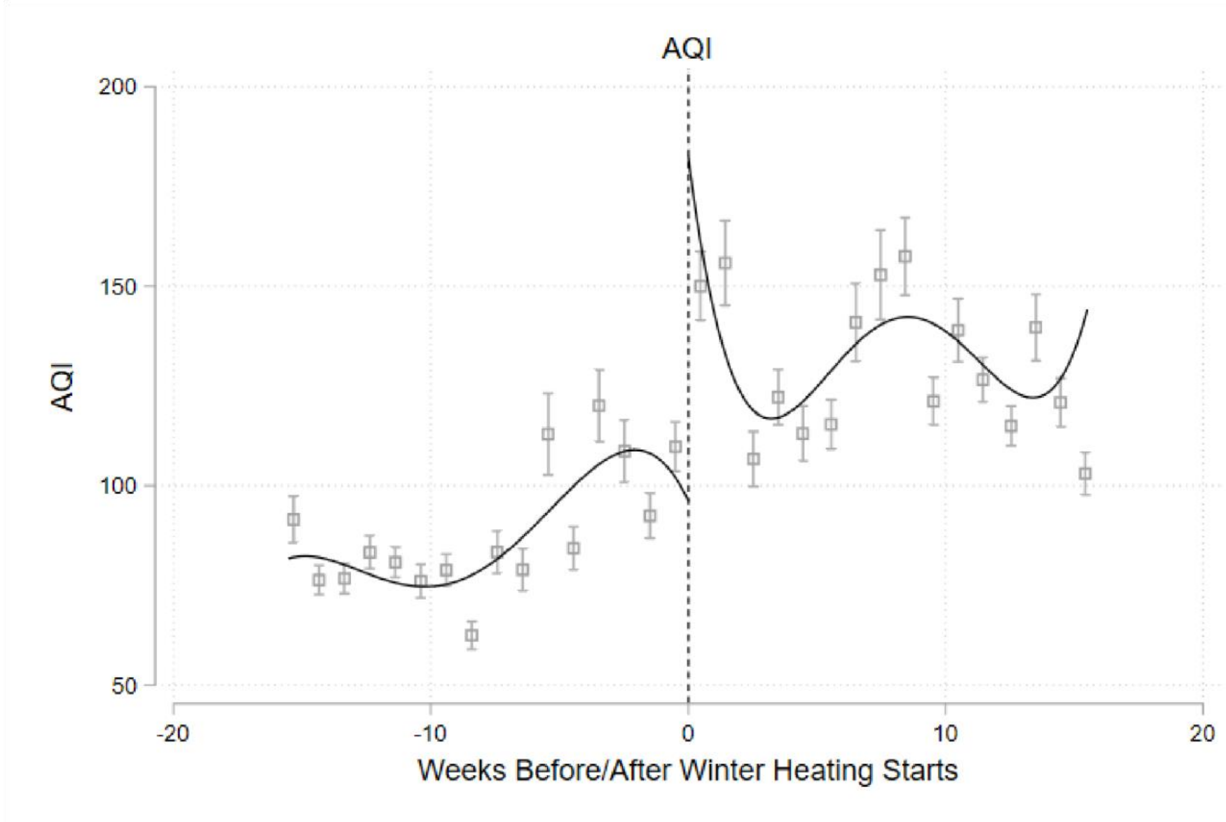
	(0.033)	(0.038)	(0.006)	(0.007)
Young People (<60)	0.058	0.063	0.012	0.013
	(0.034)	(0.041)	(0.007)	(0.008)
RD Estimates	Conv.	Bias-Cor. Robust	Conv.	Bias-Cor. Robust
Weather Controls	Y	Y	Y	Y
DSP Fixed Effects	Y	Y	Y	Y
Kernel	Epanech.	Epanech.	Epanech.	Epanech.
Observations	3,645	3,645	3,645	3,645

Notes: Each cell in the table represents a separate RD estimate. All regressions control for weather conditions (temperature, relative humidity, and precipitation) and DSP fixed effects. Columns (1) to (3) report the RD estimates using local linear regressions and two different MSE-optimal bandwidth selectors proposed by Calonico et al. (2014) and Calonico (2019). Columns (4) to (6) report the fuzzy RD estimates using the same methodology. Standard errors clustered at the DSP level are reported below the coefficients. * significant at 5% ** significant at 1%.

Table 8. Estimated Benefit of Replacing Coal by Natural Gas For Winter Heating

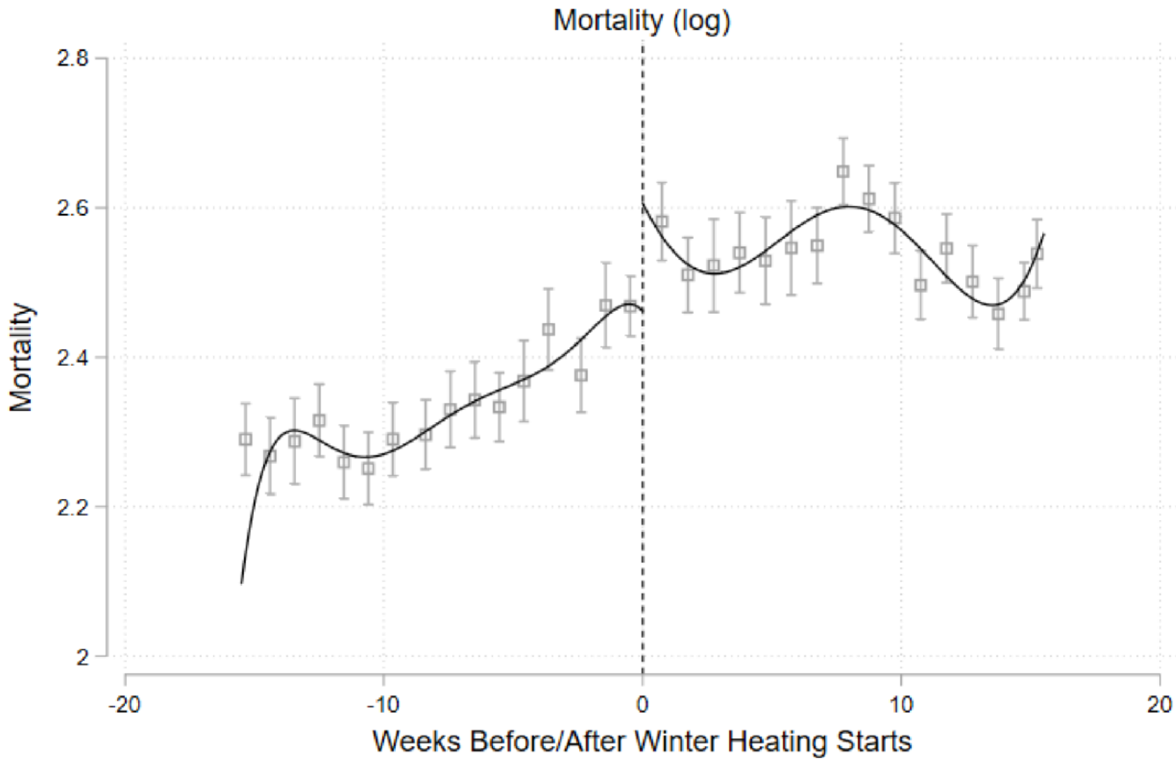
	Effect Size	Source	Costs/Benefits Calculation	Monetary Value
Pane A. Short	*Benefit*			
Pre-mature Deaths	A 10-point increase in the AQI would cause a 3.8% increase in weekly mortality.	Self-calculation	AQI difference between northern and southern China during the winter×the impact of AQI on mortality rate× population in 13 northern Chinese proinvces×16 weeks×VSL (7.46 million CNY)×70% (discounted VSL for the elderly)×89,664 premature deaths = 469 billion CNY	72 billion USD
Defensive Expenditures	A northern household is willing to pay about 43 USD per year to clean the air.	Ito and Zhang (forthcoming)	32.7 USD per year×1/4 (for winter season)×households in 13 northern Chinese provinces = 1.75 billion USD	1.75 billion USD
Medical Expenditures	A reduction of 10 μg/m3 in PM2.5 would lead to total annual savings of 11.7 billion USD.	Barwick et al. (2018)	9 billion USD×1/4 (winter season)×PM2.5 difference between northern and southern China during the winter = 3.6 billion USD	3.6 billion USD
Total				77.35 billion USD
Panel B. Long-term Benefit				
Life Expectancy	Winter heating causes a 3.1-year loss in life expectancy for Northern Chinese people	Ebenstein et al. (2017)	Life years will be saved each year: 3.1 Years/76 Years× population in 13 northern Chinese provinces×= 25.5 million years; Each life year worth: 5.83 million CNY/76 years = 76.7 thousand CNY/year; Total benefit: 25.5 million×76.7 thousand = 1,956 billion CNY/year	266 billion USD

Figure 1. RD Plot for AQI



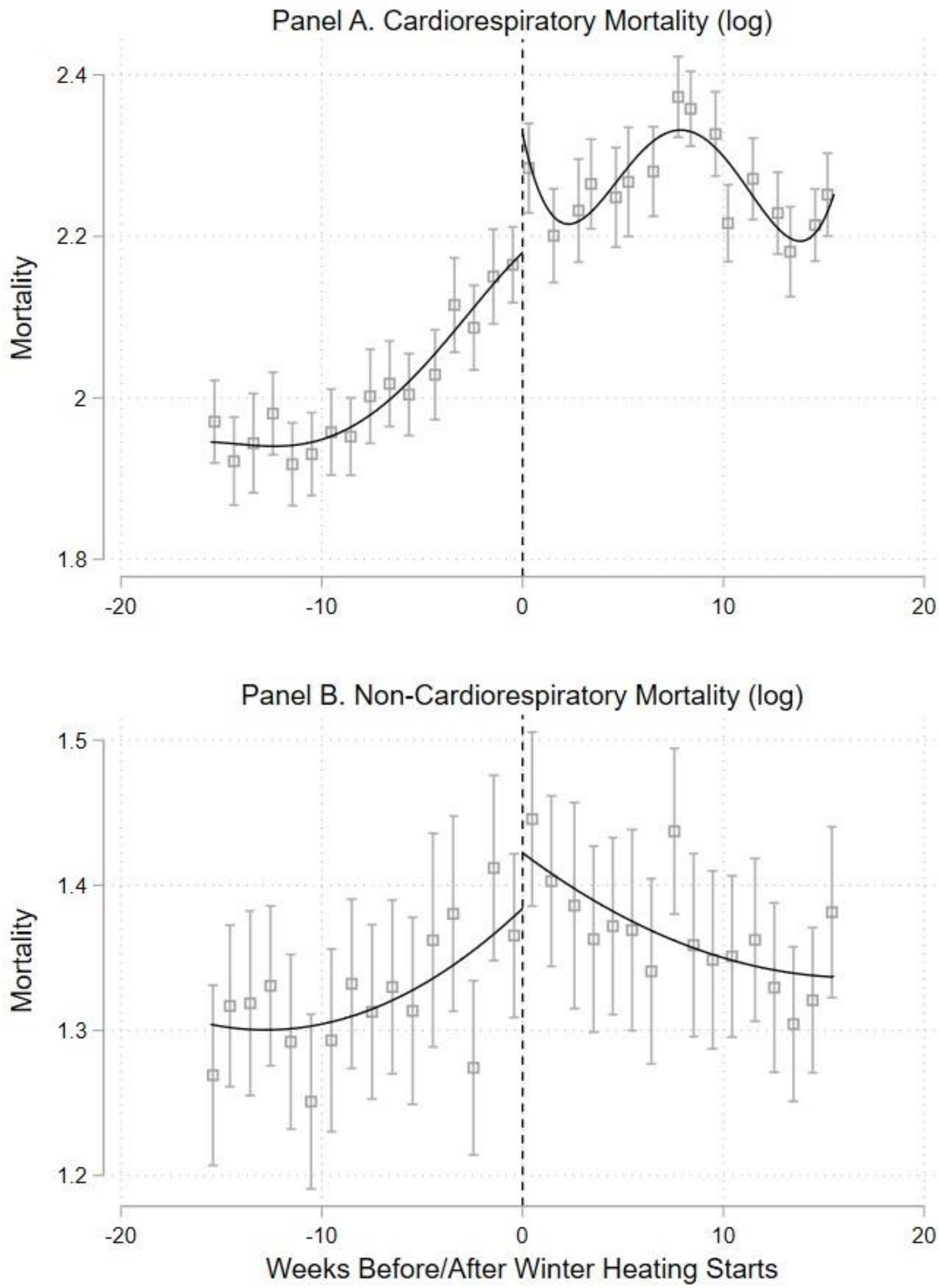
Notes: The figure shows the mean and 95% confidence interval of AQI across the DSP locations within a week. The solid line represents a quartic polynomial fit of AQI separately for each side of the threshold.

Figure 2. RD Plot for Mortality



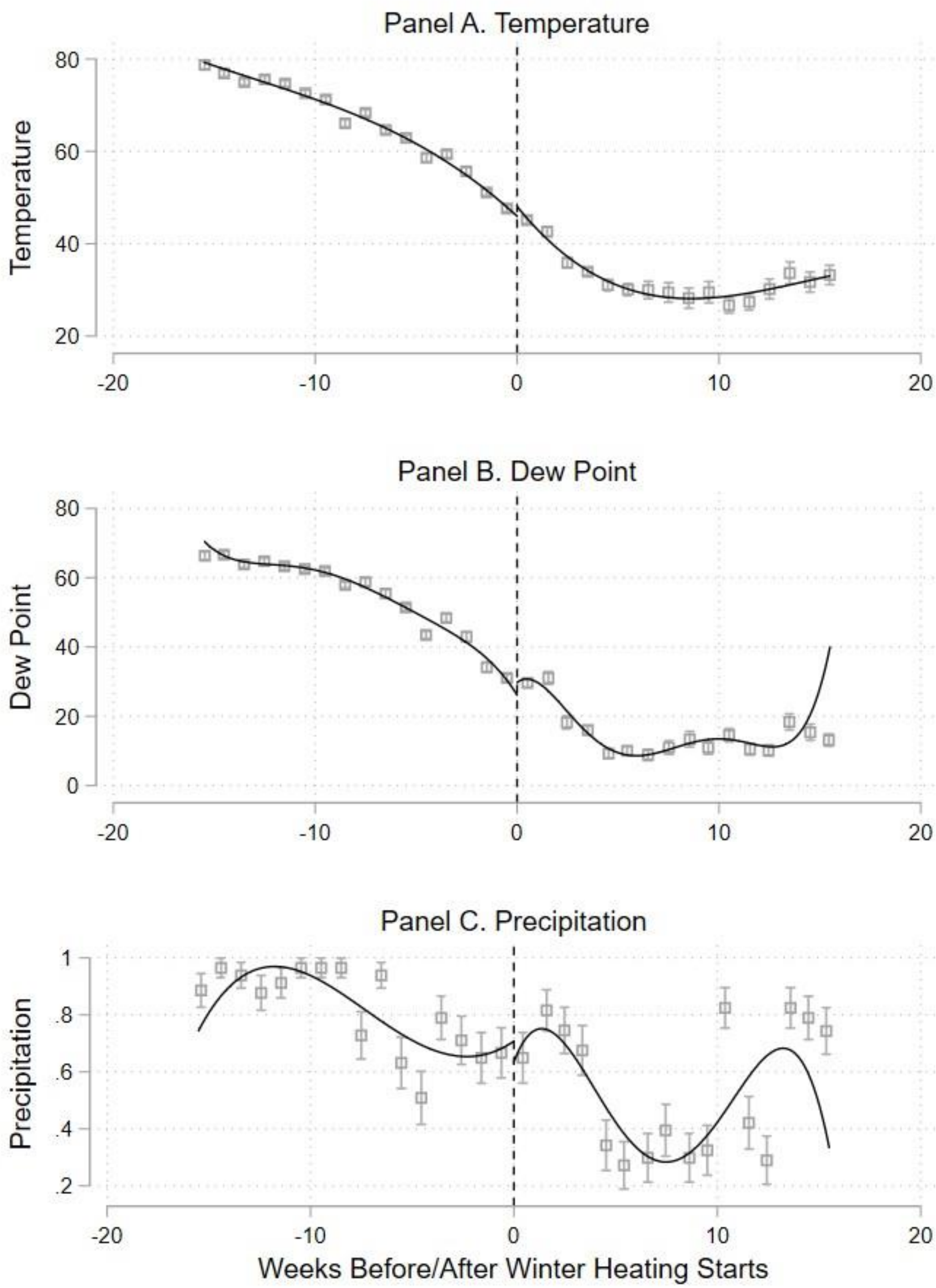
Notes: The figure shows the mean and 95% confidence interval of mortality rate across the DSP locations within a week. The solid line represents a quartic polynomial fit of mortality separately for each side of the threshold.

Figure 3. RD Plots for Cardiorespiratory and Non-Cardiorespiratory Mortality



Notes: The figure shows the mean and 95% confidence interval of CVR and non-CVR mortality rates across the DSP locations within a week. The solid line represents a quartic polynomial fit of CVR (or Non-CVR) mortality separately for each side of the threshold..

Figure 4. RD Plots for Weather Conditions



Notes: Each figure shows the mean and 95% confidence interval of a weather variable across the DSP locations within a week. The solid line represents a quartic polynomial fit of each variable separately for each side of the threshold.

Online Appendix

The Winter Choke: Coal-Fired Heating, Air Pollution, and Mortality in China

A1. Disease Surveillance Point System

Our sample of mortality in China is taken from the Disease Surveillance Points (DSP) system administered by the Chinese Center for Disease Control and Prevention (CCDC). 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 DSP locations 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 ($\mu g/m^3$).

The scale of the 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 (See Table

A1). The pollution concentration between the thresholds is linearly interpolated using the following equation:

$$IIIIIIII_{PP} = \frac{IIIIIIII_{HHHH} - IIIIIIII_{LLLL}}{BBPP_{HHHH} - BBPP_{LLLL}} (CC_{PP} - BBPP_{LLLL}) + IIIIIIII_{LLLL}$$

where

$IIIIIIII_{PP}$: individual air quality index for pollutant *P*.

CC_{PP}: the rounded concentration of pollutant *P*

$BBPP_{HHHH}$: the threshold greater than or equal to CC_{PP}

$BBPP_{LLLL}$: the threshold less than or equal to CC_{PP}

$IIIIIIII_{HHHH}$: the AQI corresponding to $BBPP_{HHHH}$

$IIIIIIII_{LLLL}$: the AQI corresponding to $BBPP_{LLLL}$

The index $IIIIIIII_{PP}$ has a linear relationship with the concentration C_p, with $\frac{IIIIIII}{BBPP_{HHHH}{}^{HHHH}{}_{-}{}^{-}{}_{BBPP}{}^{IIIIIII}{}_{LLLL}{}^{LLLL}}$ as the slope. The AQI is then 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.

$$IIIII = mmmmmm\{IIIIIIII_1, IIIIIIII_2, IIIIIIII_3, \ldots, IIIIIIII_{nn}\}$$

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 $PM_{2.5}$.

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. The Chinese government provides guidelines about the health implications at different levels (Table A2). For example, when the AQI level is between 51 and 100, the air quality

is considered "Good" and only hypersensitive individuals should reduce the time for outdoor activities.

Table A1. The Thresholds of Individual Air Quality Index

IAQI	SO2 24-hour Average (µg/m³)	SO2 1-hour Average (µg/m³)	NO2 24-hour Average (µg/m³)	NO2 1-hour Average (µg/m³)	PM10 24-hour Average (µg/m³)	CO 24-hour Average (µg/m³)	CO 1-hour Average (µg/m³)	O3 1-hour Average (µg/m³)	O3 8-hour Average (µg/m³)	PM2.5 24-hour Average (µg/m³)
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	1000	-	350
500	2620	-	940	3 840	600	60	150	1200	-	500

Source: Ministry of Environmental Protection of China.
http://www.mee.gov.cn/gkml/hbb/bgth/201103/W020110301385498176520.pdf. Accessed on 07/28/2019.

Table A2. AQI and Health Implications

AQI	Air Quality	Health Implications
0–50	Excellent	No air pollution.
51–100	Good	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.

Source: Ministry of Environmental Protection of China. http://www.mee.gov.cn/gkml/hbb/bgth/201103/W020110301385498176520.pdf. Accessed on 07/28/2019.

Table A3. List of Winter Heating Starting Date

Starting Date	Cities
24-Sep	Daxing'anling
26-Sep	Heihe
29-Sep	Yichun
30-Sep	Xilingol, Zhangye, Hami
4-Oct	Ulanqab, Jixi, Wulanchabu,
9-Oct	Baishan, Hegang, Shuangyashan, Daqing, Urumuqi, Changji, Bayingolin, Hetian
13-Oct	Qiqihar
14-Oct	Zhangjiakou, Hohhot, Baotou, Wuhai, Chifeng, Erdos, Bayannur, Hinggan, Alxa, Jiamusi, Qihetai, Mudanjiang, Suihua, Jiuquan, Xining, Haidong, Haibei, Huangnan, Guoluo, Yushu, Haixi, Bortala， Karamay, Huhehaote, Xinganmeng,
19-Oct	Shuozhou, Tongliao, Liaoyuan, Haerbin, Guyuan
22-Oct	Turpan

24-Oct	Datong, Changchun, Jilin, Siping, Songyuan, Baicheng
25-Oct	Aksu
26-Oct	Shizuishan
27-Oct	Chengde
29-Oct	Panjin
30-Oct	Liaoyang
31-Oct	Taiyuan, Yangquan, Jinzhong, Xinzhou, Linfen, Lvliang, Shenyang, Anshan, Fushun, Benxi, Dandong, Jinzhou, Yingkou, Fuxin, Tieling, Huludao, Tonghua, Lanzhou, Jiayunguan, Jinchang, Baiyin, Pingliang, Qingyang, Dingxi, Longnan, Yinchuan, Wuzhong, Zhongwei, Kashi, Yulin
10-Oct	Longjin
15-Oct	Hulunbuir, Yanji
20-Oct	Dunhua
1-Nov	Kangle
4-Nov	Jincheng, Dalian, Chaoyang
6-Nov	Weihai
9-Nov	Hengshui, Jining, Taian, Lingyi
11-Nov	Jinan, Liaocheng
12-Nov	Laiwu
13-Nov	Tianshui
14-Nov	Weinan, Yan'an, Hanzhong, Shangluo, Zhengzhou, Kaifeng, Luoyang, Anyang, Hebi, Xinxiang, Jiaozuo, Puyang, Luohe, Sanmenxia, Nanyang, Shangqiu, Zhumadian,
15-Nov	Hefei, Qingdao, Pingdingshan, Dingzhou, Jiyuan, Beijing, Tianjin, Shijiazhuang, Tangshan, Handan, Xingtai, Baoding, Cangzhou, Langfang, Changzhi, Yuncheng, Huainan, Zibo, Dongying, Yantai, Weifang, Binzhou, Heze, Xian, Baoji,
16-Nov	Wuhan
22-Nov	Xuchang
24-Nov	Rizhao
30-Nov	Xuzhou

Sources: Online information from local governments and various newspapers in 2012-2014.

Table A4. Changes in Weather Conditions before and after Winter Heating Starts

		RD Estimates		
	(1)	(2)	(3)	(4)
Panel A: Winter Heating and Temperature				
Heating On	0.49	1.02	1.14	0.73

	(0.66)	(0.66)	(0.63)	(0.71)
Panel B: Winter Heating and Dew Point			0.00	0.00
Heating On	-0.69	-0.11		
	(0.80)	(0.80)	(0.00)	(0.00)
Panel C: Winter Heating and Precipitation				
Heating On	-0.11	-0.19	-0.11	-0.19
	(0.08)	(0.10)	(0.08)	(0.10)
RD Estimates	Conventional	Bias-Cor. Robust	Conventional	Bias-Cor. Robust
DSP Fixed Effects	Y	Y	Y	Y
Observations	3,647	3,647	3,647	3,647
Kernel	Epanech.	Epanech.	Triangle	Triangle

Notes: Each cell in the table represents a separate RD estimate. The discontinuities are estimated using local linear regressions and MSE-optimal bandwidth selectors proposed by Calonico et al. (2014) and Calonico et al. (2019). Standard errors clustered at the (DSP) county level are reported below the coefficients. * significant at 5% ** significant at 1%.

Table A5. RD Estimates of the Impacts of Winter Heating on AQI and Mortality (Level)

	RD Estimates		
	(1)	(2)	(3)
Panel A. Impact of Winter Heating on Mortality			
Heating On	1.80**	1.78**	1.91**
	(0.60)	(0.54)	(0.54)
Bandwidth (Left)	2.96	2.75	3.04
Bandwidth (Right)	4.17	3.69	3.59
Panel B. Impact of Winter Heating on CVR Mortality			
Heating On	1.44**	1.46**	1.62**
	(0.48)	(0.43)	(0.42)
Bandwidth (Left)	2.90	2.64	2.97
Bandwidth (Right)	3.81	3.38	2.99
Panel C. Impact of Winter Heating on Non-CVR Mortality			
Heating On	0.45	0.42*	0.41*
	(0.23)	(0.21)	(0.20)
Bandwidth (Left)	3.89	3.65	3.82

Bandwidth (Right)	5.25	4.72	4.36
Panel D. Impact of AQI on Mortality: Fuzzy RD Estimates			
AQI (per 10 points)	0.49**	0.52**	0.32**
	(0.18)	(0.18)	(0.11)
Bandwidth (Left)	2.42	2.19	3.10
Bandwidth (Right)	3.66	3.29	3.15
Panel E. Impact of AQI on CVR Mortality: Fuzzy RD Estimates			
$PM_{2.5}$ (per 10 μg/m3)	0.56**	0.59**	0.36**
	(0.19)	(0.20)	(0.12)
Bandwidth (Left)	2.32	2.07	3.03
Bandwidth (Right)	3.81	3.16	2.78
RD Estimates	Bias-Cor. Robust	Bias-Cor. Robust	Bias-Cor. Robust
Weather Controls	N	N	Y
DSP Fixed Effects	N	Y	Y
Observations	3,647	3647	3,647
Kernel	Epanech.	Epanech.	Epanech.

Notes: Each cell in the table represents a separate RD estimate. The discontinuities are estimated using local linear regressions and two different MSE-optimal bandwidth selectors proposed by Calonico et al. (2014) and Calonico (2019). Weather controls include temperature, relative humidity, and precipitation. Standard errors clustered at the (DSP) county level are reported below the coefficients. * significant at 5% ** significant at 1%.

Table A6. Local Linear RD Estimates and IV estimates For Different Tolerance Distances

		Different Tolerance Distances		
	75KM	100KM	125KM	150KM
	(1)	(2)	(3)	(4)
Panel A: RD Estimates of Winter Heating on AQI				
Heating On	49.6**	44.2**	40.8**	40.0**
	(8.0)	(7.5)	(7.1)	(6.8)
Panel B: RD Estimates of Winter Heating on Mortality (log)				
Heating On	0.178**	0.156**	0.143**	0.138**
	(0.037)	(0.036)	(0.036)	(0.035)
Panel C: Fuzzy RD Estimates of the Impact of AQI on Mortality (log)				
AQI (per 10 points)	0.038**	0.025**	0.023**	0.022**
	(0.011)	(0.007)	(0.007)	(0.007)
Panel D: Fuzzy RD Estimates of the Impact of AQI on CVR Mortality (log)				
Heating On	0.031**	0.028**	0.026**	0.027**
	(0.008)	(0.007)	(0.007)	(0.008)
Panel E: Fuzzy RD Estimates of the Impact of AQI on Non-CVR Mortality (log)				
Heating On	0.016	0.013	0.012	0.010
	(0.008)	(0.008)	(0.009)	(0.009)
Weather Controls	Y	Y	Y	Y
DSP Fixed Effects	Y	Y	Y	Y
Observations	3,039	3,295	3,487	3,647
Kernel	Epanech.	Epanech.	Epanech.	Epanech.

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 75 kilometers of a station is assigned the value at the closest station. We report an independent RD estimate in each cell. All regressions control for weather conditions (temperature, relative humidity, and precipitation) and DSP fixed effects. The discontinuities are estimated using local linear regressions and two different MSE-optimal bandwidth selectors proposed by Calonico et al. (2014) and Calonico (2019). BiasCorrected RD estimates are reported with robust standard errors clustered at the (DSP) county level below the coefficients. * significant at 5% ** significant at 1%.

Table A7. Placebo Results Using Southern Cities

		RD Estimates		
	(1)	(2)	(3)	(4)
Panel A: Winter Heating and AQI				
		AQI		
Heating On	9.5*	8.3	2.7	1.8
	(5.5)	(5.9)	(5.2)	(4.3)
Bandwidth (Left)	3.14	2.42	2.13	2.13
Bandwidth (Right)	3.22	3.01	3.70	3.70
Panel B: Winter Heating and Mortality				
		Overall Mortality (log)		
Heating On	0.048	0.078	0.044	0.040
	(0.102)	(0.083)	(0.085)	(0.071)
Bandwidth (Left)	4.30	3.67	3.44	3.44
Bandwidth (Right)	5.40	4.59	5.04	5.04
		CVR Mortality (log)		
Heating On	0.073	0.053	0.033	0.033
	(0.100)	(0.084)	(0.086)	(0.070)
Bandwidth (Left)	5.03	4.39	3.65	3.65
Bandwidth (Right)	5.74	5.14	5.36	5.36
		Non-CVR Mortality (log)		
Heating On	0.054	0.058	0.044	0.020
	(0.151)	(0.135)	(0.137)	(0.113)
Bandwidth (Left)	4.10	3.82	3.66	3.66
Bandwidth (Right)	4.82	4.47	4.51	4.51
RD Estimates	Bias-Cor. Robust	Bias-Cor. Robust	Bias-Cor. Robust	Conventional
Weather Controls	N	N	Y	Y
DSP Fixed Effects	N	Y	Y	Y
Observations	1,184	1,184	1,184	1,184
Kernel	Epanech.	Epanech.	Epanech.	Epanech.

Notes: The table presents placebo tests using cities in the south. We randomly assign the heatingon dates from northern cities to southern cities and estimate the discontinuities using local linear regressions and MSE-optimal bandwidth selectors proposed by Calonico et al. (2014) and Calonico (2019). Each cell in the table represents a separate RD estimate. Weather controls include temperature, relative humidity, and precipitation. Standard errors clustered at the (DSP) county level are reported below the coefficients. * significant at 5% ** significant at 1%.

Table A8. RD Estimates with High-order Weather Controls

	RD Estimates		
	(1)	(2)	(3)
Panel A: Winter Heating and Mortality (log)			
Heating On	0.130**	0.130**	0.130**
	(0.037)	(0.036)	(0.037)
Panel B: Winter Heating and CVR Mortality (log)			
Heating On	0.159**	0.162**	0.163**
	(0.042)	(0.043)	(0.044)
Panel C: Winter Heating and Non-CVR Mortality (log)			
Heating On	0.064	0.070	0.067
	(0.045)	(0.044)	(0.044)
Panel D: Fuzzy RD Estimates of the Impact of AQI on Mortality (log)			
Heating On	0.059**	0.057**	0.062**
	(0.017)	(0.017)	(0.019)
Panel E: Fuzzy RD Estimates of the Impact of AQI on CRV Mortality (log)			
Heating On	0.029**	0.031**	0.051**
	(0.009)	(0.009)	(0.019)
Panel F: Fuzzy RD Estimates of the Impact of AQI on Non-CRV Mortality (log)			
Heating On	0.010	0.009	0.009
	(0.009)	(0.009)	(0.009)

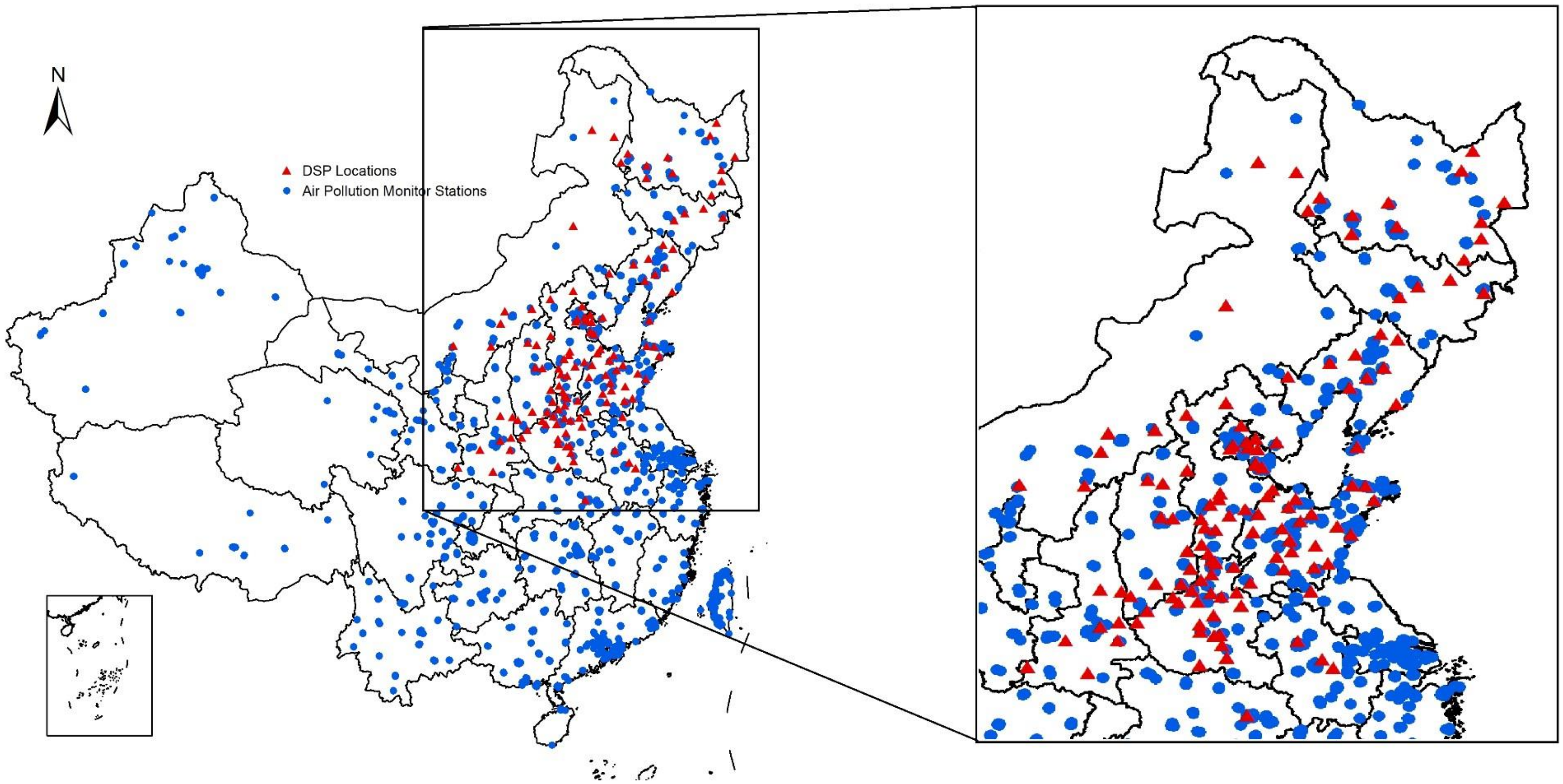
Weather Controls	Quadratic	Cubic	Quartic
DSP Fixed Effects	Y	Y	Y
Observations	3,647	3647	3,647
Kernel	Epanech.	Epanech.	Epanech.

Notes: Each cell in the table represents a separate RD estimate. The discontinuities are estimated using local linear regressions and MSE-optimal bandwidth selectors proposed by Calonico et al. (2014) and Calonico (2019). Weather controls include temperature, relative humidity, and precipitation. Bias-Corrected RD estimates are reported with robust standard errors clustered at the (DSP) county level below the coefficients. * significant at 5% ** significant at 1%.

Table A9. 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 $PM_{2.5}$ concentrations is 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 TimeSeries	A 10-µg/m3 increase in two-day average $PM_{2.5}$ concentrations is associated with a 0.6-0.9% increase in allcause mortality in rural China.
Franklin et al. (2008)	USA	2000–05	Hierarchical Model	A 1.21% increase in all-cause mortality is associated with a 10-µg/m3 increase in previous day's $PM_{2.5}$ concentrations. Composition of $PM_{2.5}$ helps explain the association.
Kloog et al. (2013)	USA	2000–08	Time-Series	For every 10-µg/m3 increase in $PM_{2.5}$ exposure, PMrelated mortality increases by 2.8%.
Atkinson et al. (2014)	World	-	Meta Analysis	A 10-µg/m^3 increment in $PM_{2.5}$ is associated with a 1.04% increase in the risk of death. Substantial regional variation observed around the globe.
Deryugina et al. (forthcoming)	USA	1999-2013	Instrumental Variable	A 10 µg/m^3 increment in $PM_{2.5}$ is associated with 1.8% increase in three-day mortality rate per million people aged 65+.

Appendix Figure A1. Distribution of DSP Locations and Air Pollution Monitor Stations



Notes: The red triangles are the DSP locations. The blue dots are the locations of the air pollution monitor stations. In our analysis, we include 144 DSP locations where centralized winter heating is provided. The winter heating periods of those locations are confirmed by government websites.

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